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# Artificial Intelligence and Education

Shaping the Future of Learning

*Edited by Seifedine Kadry*





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# Artificial Intelligence and Education - Shaping the Future of Learning

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IntechOpen Book Series

# Artificial Intelligence

Volume 28

## Aims and Scope of the Series

Artificial Intelligence (AI) is a rapidly developing multidisciplinary research area that aims to solve increasingly complex problems. In today's highly integrated world, AI promises to become a robust and powerful means for obtaining solutions to previously unsolvable problems. This Series is intended for researchers and students alike interested in this fascinating field and its many applications.



# Meet the Series Editor



Andries Engelbrecht received the Masters and Ph.D. degrees in Computer Science from the University of Stellenbosch, South Africa, in 1994 and 1999 respectively. He is currently appointed as the Voigt Chair in Data Science in the Department of Industrial Engineering, with a joint appointment as Professor in the Computer Science Division, Stellenbosch University. Prior to his appointment at Stellenbosch University, he has been at the University of Pretoria, Department of Computer Science (1998-2018), where he was appointed as South Africa Research Chair in Artificial Intelligence (2007-2018), the head of the Department of Computer Science (2008-2017), and Director of the Institute for Big Data and Data Science (2017-2018). In addition to a number of research articles, he has written two books, *Computational Intelligence: An Introduction and Fundamentals of Computational Swarm Intelligence*.



# Meet the Volume Editor



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# Preface

In today's rapidly evolving 21st-century landscape, artificial intelligence (AI) has become a transformative force across various sectors, including education. Our book *Artificial Intelligence and Education – Shaping the Future of Learning* explores the significant impact of AI on educational paradigms, discussing both the opportunities and challenges it brings.

This book aims to provide educators, policymakers, students, and technology enthusiasts with a comprehensive understanding of how AI is reshaping the educational environment. From personalized learning experiences and intelligent tutoring systems to administrative efficiencies and new ethical considerations, the integration of AI in education is paving the way for a future where learning is more accessible, engaging, and tailored to individual needs.

As we navigate this transformation, it's crucial to address the implications of AI on traditional educational models and the broader societal context. This book seeks to spark a thoughtful dialogue about the role of AI in education, encouraging readers to reflect on its potential for enhancing learning outcomes and preparing students for an AI-driven world.

By combining theoretical insights, practical examples, and visionary perspectives, the book aims to inspire innovation and critical thinking. We hope that this book will serve as a valuable resource for those dedicated to advancing education in an era defined by technological progress and human ingenuity. Welcome to a journey into the future of learning.

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## Chapter 1

# Utilization of Artificial Intelligence in Education: A Perspective on Learning Strategies

*Serpil Yalcinalp, Hacer Türkoğlu, Serdar Engin Koc  
and Halil Ersoy*

### Abstract

When considered in scope of our digitally surrounded world, new approaches unavoidably find their places in education as well as other fields in society. In such a world, AI is one of the recent and most sound technical developments with its fast widespread at an unprecedented pace in all educational levels. Students, who did not even know the name of a specific generative AI, are starting to use it as soon as they hear about it. A vast variety of rich resources for learning exist and approaches in learning like individual learning, personalized learning, and connected learning are gaining considerable importance. While there is a strong emphasis on learning based on learners' own needs and their freedom in the selection of their own strategies, we need to consider the place of AI as the facilitator of such trends so that learning could be implemented effectively. With this in mind, this section aims to present and discuss how AI tools and applications could be used in accordance with learning strategies to give chances to learners to learn efficiently in their way. Within that perspective connected learning and cognitive-affective strategies in AI environments were also elaborated with sample scenarios of cases provided.

**Keywords:** AI in education, AIED, learning strategies, connectivism, personalized learning

### 1. Introduction

This chapter aims to introduce and categorize Artificial intelligence (AI) technologies both in general and within the educational context and explore their use in education with a focus on implementing appropriate learning strategies. First, definitions of AI from the literature were given, reflecting various considerations in categorizing AI from technological and educational perspectives. After providing a brief overview of learning strategy definitions, this chapter highlights connected learning as one of the most crucial strategies in today's digitally immersive educational environments. The discussion delves into the advantages and disadvantages of its implementation. Specifically, personalized and deep learning emerge as central themes, with a focus on these approaches dominating the discourse.

Section 4 of this chapter shows examples of popular AI tools, as categorized by Zawacki et al. [1], with a primary focus on their educational utility. These tools include ChatBots, visual and design aids, lesson design and content creation tools, teaching aids, quiz and assessment generators, collaboration and communication platforms, and learning platforms. Furthermore, appropriate learning strategies tailored to each category are proposed with the aim of maximizing learning efficacy. In Section 5, scenarios and case studies are developed to illustrate the effective utilization of AI tools within exemplary domains and to show the implementation of effective learning strategies.

## **2. What is the scope of artificial intelligence?**

### **2.1 Main definitions of artificial intelligence**

Artificial intelligence (AI) spans numerous research and application domains. Among these, ChatGPT and other popular ChatBots have emerged since 2022, finding application in various fields such as economics, business, and, notably, education. To understand those applications, we need to pay attention to the following definitions and descriptions.

*ChatGPT*: is an AI tool, developed by OpenAI company, that uses a generative pre-trained transformer model (GPT) as a large language model (LLM) to understand and generate text in human languages. Users enter their questions, called prompts, into a text box on the ChatGPT website. ChatGPT performs input processing by tokenization and segmentation, and unnecessary words are removed based on the generative pre-trained transformer (GPT) model. Next, ChatGPT encodes these meaningful pieces of data into a vector format to see what the input means [2]. Then, based on its trained GPT model and a huge dataset collected over the Internet, a response in human language is given to the user. The user may provide extra prompts to reflect on the responses or to change the direction of the conversation.

One of the important features of ChatGPT is its dataset and GPT model. OpenAI provides different versions of ChatGPT based on different datasets and models covering recent information on the Internet and is capable of more diverse analysis of input [3].

*Natural Language Processing (NLP)* is a research area in computer science that aims to create computers or applications that understand and generate responses for human language in textual, auditory or speech forms [4]. NLP is being used in many diverse areas such as speech-to-text or text-to-speech engines, translators among languages, etc. [4].

*Large Language Models (LLM)* are a kind of NLP models that are trained with a rich dataset of a specific language to understand the input and generate proper output in that language. The generation process is aimed at getting the most expected or proper token (smallest unit of meaningful words or phrases) in the context [5].

*Generative Pre-Trained Transformer (GPT)* is a specific type of LLM created by OpenAI in 2018 (version 1). The main purpose was to generate output by predicting the next word in a sentence. In 2019, the second version, GTP-2, and in 2020, the third version, GTP-3, were introduced with larger datasets and parameters. Open AI continued enlarging the size and diversity of the training dataset and released GTP-3.5 in 2022 and GTP-4 in 2023 so that it is almost impossible to distinguish if the output is generated by a ChatBot or a human [6].

Every definition of artificial intelligence makes some assumptions. The first assumption is that it is modeled by a set of programmes, the second assumption is

that it has input and output as a set of information, and the third assumption is that it exists in a world of some type which is also influenced by the output of the information. From a different perspective, Ng et al. ([7], p. 1) state AI as “intelligent machines and algorithms that can reason and adapt based on sets of rules and environment which mimic human intelligence.” Furthermore, AI is termed as machines emulating human behaviour [8]. Dobrev ([9], p. 2) defines AI as “...such a program which in an arbitrary world will cope not worse than a human” [10] sees no correct definition of AI due to the wide research field that AI covers and AI still remains a label for historical reasons, whereas Baker and Smith ([11], p. 10) define AI as “Computers which perform cognitive tasks, usually associated with human minds, particularly learning and problem-solving.”

## **2.2 Criteria for categorizing AI systems in literature**

The above definitions lead us to believe that there are two types of AI; one being the learning machine that is open to evolve, and the other is trained on sets of knowledge and statistics with limited memory and limited to a single medium or field lacking the cognitive abilities of a human. The latter is categorized as narrow or weak AI that is designed for specific tasks and effective only in a certain domain. The former is only in theory, and the closest thing to a strong AI is Elon Musk’s self-driving car. The reason is that while it is possible to train AI using datasets and all sorts of information, programmes do not learn, but they try to perfect their operations using repetition over finely grained data and tasks.

Based on functionality, AI is divided into being reactive and having limited memory with a theory of mind. Reactive machines cannot learn from past experiences but only respond to a certain set of rules. Some AI such as self-driving cars use past experiences to make better decisions and improve performance. On the other hand, AI that understands human emotions, intentions, beliefs, and mental states sets the theoretical mind of AI, which only exists in the form of understanding facial expressions with the help of input devices till today. In the category of AI learning approach, that is, the way AI is supposed to be trained, there are four types of approaches: supervised, unsupervised, semi-supervised, and reinforcement learning. Supervised learning refers to approximating the behaviour of the function or imitation by analyzing labeled examples in the data. Supervised learning leverages datasets that contain images and labels. According to data, generally, supervised learning requires first training using large and unrelated data and then fine-tuning with data of interest. Unsupervised learning is for training without labels, and AI trying to find patterns and relationships that exist within the data provided. In semi-supervised learning, small portions of labelled data are used as a primer for the large unlabeled data. Reinforcement learning occurs when AI learns a policy of action depending on observation and feedback from its environment, leading to rewards or punishments and, hence, reinforcement. Based on the way the applications of AI operate, we see categories such as natural language processing, computer vision, robotics, and expert systems. Natural language processing models lead to large language models (LLMs), which are capable of self-learning with annotated data and accordingly imitate texts that are written by humans. They can learn more efficiently and generate output specified by users [12]. LLMs use relevant predictions to generate long texts. While LLMs can summarize, and expand texts, it is not clear how to produce reliable outputs from them [13]. GPT, BERT, and RoBERTa are some of the models mentioned that made it possible for further research in natural language processing [14]. Computer vision is the ability of AI to perceive

visual stimuli meaningfully. Objects are classified and localized to identify their types through image processing. Recently, medical imagery has advanced in detection with the help of deep learning and visual pattern recognition up to an accuracy that matches or surpasses the level of expert physicians [15]. AI takes forms that are used in robots (Robotics) that can offer enhancement in precision and less error in all kinds of operations. AI helps robots in decision-making and learning algorithms with the ultimate purpose of autonomous robotic systems. Lately, AI techniques have made it possible for robotics to connect wirelessly with applications, increasing efficiency and optimization [16]. Expert systems were built to provide aid in decision-making processes. To conclude, expert systems have to be able to reason and generate explanations. The introduction of machine learning enhanced the capturing process of data patterns for knowledge acquisition. The explanation is generally a compromise between precision and understandability, depending on the audience. Based on the time horizon, batch learning refers to learning from a fixed dataset without further interactions with the world, whereas online learning indicates continuous learning with data updates. Batch learning is advantageous in that it is cheaper, faster, has better sample efficiency and has algorithms that are model-free [17].

### **3. Utilization of AI in education and learning strategies**

#### **3.1 AI in education**

Based on the aforementioned categorizations of AI systems such as machine learning, personalized learning, deep learning, learning analytics, and more, Artificial Intelligence in Education (AIEd) has also been categorized in various ways according to different criteria (AIEd) were categorized into three paradigms by Ouyang and Jiao ([18], p. 2) as (i) “AI-directed (learner-as-recipient and AI is used to represent knowledge models and direct cognitive learning). (ii) AI-supported (learner-as-collaborator, AI is used to support learning) while learners work as collaborators with AI, and (iii) AI-empowered (learner-as-leader, AI is used to empower learning) while learners take agency to learn.”

Chaudhry and Kazim [19] categorized the work of AIEd as (i) reducing teachers’ workload, (ii) contextualized learning for students (providing customized and/or personalized learning), (iii) revolutionizing assessments (knowing how learners learn and pedagogies apply to them individually), and (iv) intelligent tutoring systems (ITS).

In general, the trajectory of AIEd’s development has been aimed at empowering learner autonomy and personalization, facilitating learners’ reflective processes, and guiding AI systems to adapt accordingly in light of such reflections. This progression has fostered iterative enhancements towards learner-centred and personalized learning approaches.

The educational value of AI is continuously being watched and scrutinized, and educators remain doubtful about the adoption of AI, which is lagging except in fields such as medicine and finance.

Adnan et al. [20] carried out an experiment on 425 students and found that using deep learning techniques and giving learners adaptive, motivational triggers and adaptive learning content had a significant effect on the experimental group. Fryer et al. [21] found that students benefited from the ChatBot system by monitoring their learning behaviour and assigning speaking tasks via ChatBot. Baillifard et al. [22] used

an AI Tutor to assess and understand concepts understood by students for further personalization of practice to each learner. The results showed significantly increased achievement compared to the control group and 15% more active engagement.

We cannot deny the disconnect between vision and the present status of AI in educational systems as they are not being practised on large scales and use simple methods for testing student mastery. However, the use of intelligent tutoring systems includes the integrated form of AI, so the spread of ITS in time will further disseminate these systems that are being used in education. These systems are used for adaptive feedback [23–28], presenting and recommending content [24, 27, 29, 30].

### **3.2 Learning strategies**

Duffy ([31], p. 368) defines learning strategies as algorithmic “secrets.” In the student-centred approach, it is up to the learner to choose which strategy to learn effectively. Mariani [32] explains learning strategies as “the processes (or sequences of processes) that, when matched to the requirements of tasks, facilitate performance.”

Focusing on learning strategies and their place in educational phenomena, it is important to keep in mind that;

- There are many ways to classify and categorize learning strategies. This varies from the point of view of the educators, instructors, and even the learner himself.
- Selection of learning strategies is up to the learner, so it is not convenient to label strategies as best or worse.
- Learning and instructional strategies overlap generally. It is important to note that the use of learner strategies varies in situations in which (i) the learner has full autonomy on his learning (learning strategies), (ii) the learner has half autonomy but is guided by instructor-tutor (learning and instructional strategies), and (iii) the learners have no autonomy; instructional strategies are dominant (instructional strategies).

It must be kept in mind that (i) learner-centred education, learner autonomy, and increasing emphasis on learning strategies, (ii) technological developments such as in AI, and (iii) new approaches and theories like connected learning are the key points for consideration in today’s educational phenomena and technology-driven world.

Learning activities, which were the first indications for categorizing learning strategies, were identified as (i) cognitive, (ii) affective, and (iii) metacognitive-regulation by educators in the field [33–35]. Boekaerts’ [36] explanation of those strategies with examples fits well with learning activities as cognitive strategies like elaboration to deepen the understanding of the domain, metacognitive strategies like planning to regulate the learning process, and motivational strategies like self-efficacy to motivate oneself to engage in learning.

New categories of learning strategies also appeared in parallel to developments in technology, especially with the wide use of the Internet and increased autonomy of learners in that environment. For example, Dignath et al. [37] added a fourth category—management strategies such as finding, navigating, and evaluating resources.

Dunlosky et al. [38] provided an overview of the most common effective cognitive learning strategies as practice testing (or retrieval practice), distributed practice,

|   | Theoretical underpinning              | Implementations  | AI techniques  |
|---|---------------------------------------|--|--|
| Paradigm One:<br><i>AI-directed,<br/>learner-as-recipient</i>     | Behaviorism                           | Earlier work of Intelligent Tutoring Systems (ITSs)                              | AI based on statistical relational techniques                        |
| Paradigm Two:<br><i>AI-supported,<br/>learner-as-collaborator</i> | Cognitive, social constructivism      | Dialogue-based Tutoring Systems (DTSs); Exploratory Learning Environments (ELEs) | Bayesian network, natural language processing, Markov decision trees |
| Paradigm Three:<br><i>AI-empowered,<br/>learner-as-leader</i>     | Connectivism, Complex adaptive system | The human-computer cooperation; Personalized/ adaptive learning                  | The brain-computer interface, machine learning, deep learning        |

**Table 1.**  
*Three paradigms of artificial intelligence in education ([18], p. 3).*

elaborative interrogation, self-explanation, interleaved practice, summaries, mental imagery, keyword mnemonics, highlighting or re-reading.

In their study, Hattie and Donoghue ([39], p. 2) identified the most effective learning strategies based on the synthesis of 228 meta-analysis studies among more than 400 learning strategies based on a model. Their model described those strategies as “three inputs and outcomes (skill, will and thrill), success criteria, three phases of learning (surface, deep and transfer) and an acquiring and consolidation phase within each of the surface and deep phases.” In this section in **Table A1**, learning strategies were mainly suggested by selecting from Hattie and Donoghue’s [39] list of such strategies.

Educational technology can hardly receive the adequacy and robustness for integration with educational and learning theories and needs good examples of applications rather than just using AI for the prospect of transforming education [40, 41]. Blayone [41] thinks that theories that depend on technology such as technology-mediated learning theory and activity theory can shed light on AI education.

According to Vygotsky’s zone of proximal development, children learn by initiating and interacting with others. As the school’s grip over technology loosens, children learn from technology and resources, problem-solving under guidance or in collaboration with peers. Cognitive development is in conjunction with other kinds of development in children, and the learning internalization process shows itself when children solve problems. To realize their potential, children need assistance, consolidation, and cooperation. Given that interaction primarily occurs through language, it is imperative for intellectual development, beginning from early childhood education and extending to all levels of education. This is where AI-related technologies come in handy in aiding students with new concepts exemplified in different contextualized situations. Both children and adults need a learning companion to gain critical thinking skills. They need a safe environment to evaluate their peers and they can deepen their understanding of concepts by conversing with agents of AI.

Generally, AI applications were used to enrich students’ online learning experience through teaching robots, learning recommendations, and detecting progress, all under the name of natural language processing. Ouyang and Jiao [18] represented three AI Education paradigms such as AI-directed, AI-supported, and AI-empowered, where learners take the role of recipients, collaborators, and empowered agents that in ways adapt, personalize, and reflect learning. To achieve this goal, ChatBots have made significant progress, particularly in providing assignments, resources,

and individualized interactions. Wollny et al. [42] examined the pedagogical role of ChatBots and identified four roles: supporting learning, assisting, and mentoring roles. It can be seen that ChatBots are also in line with self-directed learning, metacognitive theories, and motivational theories, which cover a large part of the educational framework. According to [43], almost all studies related to the use of ChatBots in education adopted guided learning, so they decided that research in this area and the use of artificial intelligence are still in their early stages.

So, what does AI-supported learning entail? Integration of AI technologies must consider learning strategies that include pedagogy. At this juncture, it is worth questioning how effectively AI can incorporate human-like elements to address pedagogical issues ([44], p. 108). Yang [44] suggests that “AI may be able to imitate human emotions; however, imitating human feelings is difficult for AI.”

Some models intensively explain the attributes of integrating AI into education. According to Zhai et al. [45], AI-integrated systems are developed for the classification of content, matching of content to learners, recommendations for learners, and for deep learning purposes. In their literature review, they found studies of pedagogical applications under feedback, AI-supported reasoning, and adaptive learning. They also found that applications of AI carried the labels of immersive learning, affection computing, gamification, and role-playing. As technology develops, AI can also take roles that are finely grained in teaching situations that are necessary for visualization and task-specific procedures such as highlighting concept map nodes or reasoning [46, 47].

As seen in **Table 1**, Ouyang and Jiao’s [18] separation of AI in Education is historically grounded and goes from behaviourism into cognitive and constructive theoretical foundations and lastly to connectivism where the learner is seen as the leader and has the capability to monitor and evaluate his own learning making personalized content possible. With its possible connections and large application field of choice, AI is seen as a novelty in education that can take part in differing roles to supplement learners.

Interactive learning, feedback and assessment, and personalized learning are essential features to be considered in the scope of AI applications in education.

*Interactive Learning:* Bhuthoria [48] linked the capability of AI to transform education to both being the judge and the helper in learning with optimization and algorithms on both ends. The role of AI in active teaching manifests itself through ChatBots and intelligent agents, which help learners receive feedback [49] and hints [46], as well as general classroom purposes [50] through natural language processing, machine learning, and deep learning.

Kong et al. [51] developed the Virtual Integrated Patient (VIP) that can mimic realistic conversations that take place between a doctor and patient via a natural language processor. With AI technologies, it is guaranteed that no two patients are the same, and the students are surrounded by a safe environment where they can make mistakes and learn from them. Yang and Shulruf [52] used artificial skin that was connected to an AI system for suture and ligature training of medical students.

This AI-assisted and expert-led tutoring increased the students’ performance as well as confidence due to real-time feedback. Kim et al. [53] used different interaction modes such as AI text, AI voice chatting, and face-to-face chatting to test the speaking performance of students. Voice chatting pairs outperformed the two other modes of interaction in speaking tasks. Vasquez-Cano et al. [54] compared two teaching methods, one being exercises written on paper and the other interaction with a ChatBot, and the results showed that the ChatBot group improved their punctuation skills significantly. Vahabzadeh et al. [55] used the Empowered Brain, which is a conveyor

of socioemotional and behavioural skills using augmented reality and artificial intelligence to decrease the irritability, hyperactivity, and social withdrawal of subjects. The results were decreased symptoms in all aspects.

*Feedback and Assessment:* AI can help create feedback and scaffold content according to the continuous assessment from adaptive learning systems and, in a way, reduce teacher burnout to compensate for problems in learning. The AI uses machine learning and deep learning-based models or techniques to balance learner content as it is most effective in outputting the most effective mode of learning for the specific learner at his level. We can mostly see the combined form of AI, personalized, and adaptive learning systems in intelligent tutoring systems, which derive these technologies to provide support in monitoring, deliverance, feedback and interface to learners [56].

*Personalized learning:* Personalization refers to individual assessment and teaching, so it needs to be handled with learning content and assessment, which AI today is fit to provide with proper integration. After that repetition or introduction of the next level of content is provided depending on the progress of the learner, adaptive learning is a way to personalize learning, and it can be different for each learner to focus on problematic areas in a customized form. Personalized learning centres around the task of connecting the learner's previous knowledge, experience, and abilities with training materials that link that understanding to new information. Edula et al. [57] see the key to personalized learning as levelling prior knowledge and skills of the learner to link to new knowledge.

Murtaza et al. [58] commented on how a personalized e-model should state that a trained machine learning model and adaptive learning model create the past and future behavior of learners through sequential assessment. They added that continuous e-learning data provides information for the recommendation module, and other modules can help to create personalized learning. Peng et al. [59] thought that to achieve personalized adaptive learning, one must rely on teaching strategies, whether based on differences in individual characteristics, differences in individual performance, or differences in personal development vision. These strategies should also rely on data-driven decision-making.

Educause Learning Initiative ([60], p. 1) explains the relationship between adaptive learning and personalized learning as “*Adaptive learning is one technique for providing personalized learning, which aims to provide efficient, effective, and customized learning paths to engage each student. Adaptive learning systems use a data-driven and, in some cases, nonlinear approach to instruction and remediation.*” In addition to that, adaptive learning works by creating paths of learning for students according to their knowledge, skills, and learning speed. Adaptive learning environments also depend on monitoring and drawing results of student activities to supplement their learning [61]. There are examples of using personalized learning that could positively affect learning and reduce anxiety and stress among learners [21, 62, 63] with promising results, but these studies need more proof and a larger sample size to be generalized.

### **3.3 Use of AI to learn: in scope of learning strategies**

Using technology to effectively teach and learn has become one of the most critical issues since the first time people needed to integrate them into educational settings. Today, we grapple more with the dilemma of effectively integrating educational technology, even as intelligent systems continue to evolve, supporting and enhancing educational progress across all levels. While teachers are irreplaceable by computers and AI systems from various perspectives, including pedagogical considerations,

advancements in AI systems' capabilities have reached a point where they can assist teachers in sequencing, adjusting, and organizing instruction. This support extends to creating learning activities, measurement tools, and more, shifting this dilemma in a completely new direction to the real roles of teachers. It is evident that teachers cannot be replaced by AI when it comes to applying pedagogy in real-life situations, which underscores the increasing importance of recent human-AI studies. On the flip side, AI systems are revolutionizing learning by providing substantial support for personalized learning in many aspects. These new insights necessitate new roles for learners, not only in effectively utilizing supportive tools and systems but also in engaging with them through constructive and meaningful dialogs.

As we, as instructors and learners, faced with AI more intensively in our educational activities, we get familiar that such technology is assisting and guiding us instead of displaying information and is planning and adapting learning activities instead of sequencing them [64].

In situations where learners have complete autonomy over their learning, the skills and knowledge to select and apply appropriate learning strategies have become increasingly critical, particularly following the emergence of generative AI technologies (see Appendix 1).

One of the reasons why the connected learning paradigm has become such a hot topic today is the increasing autonomy of learners in determining and directing their learning processes. This departure from traditional educational models allows for a greater focus on learners' interests, needs, and learning styles. Additionally, with the emergence of generative artificial intelligence technologies, learners have more choice and control over their learning processes and can personalize their learning experiences. This makes the skills of selecting and applying their own learning strategies increasingly critical. In this context, the connected learning paradigm has become a significant topic of discussion in the field of education today.

In the upcoming section, we will delve into connected learning and its critical role in contemporary education within the context of AI, highlighting its significance as one of the foremost learning paradigms in our digitally interconnected world.

### **3.4 Learning paradigm in today's world of technology: connected learning**

Surrounded by a huge amount of educational resources, easy access to those resources, easy access to educators and specialists in the area, increased interaction with people and the content, and challenges to tracking learners digitally all opened a new area for learners to learn. Such learning allows learners to select their way of learning in line with a lot of choices in their way of learning, or in other words, in controlling their learning.

Moreover, the rapid development and progress in AI technologies in recent years have significantly accelerated such learning phenomena. As a result, the future is now more unpredictable than at any other time in history.

The theory of connectivism was first proposed by Siemens [65] and Downes [66]. It was almost the first theory of Internet-related learning. They identified connectivism as a set of principles. Those principles still have strong ties with generative AI today, and now we discuss them with insights in examples in light of today's AI systems ([65], p. 5).

#### *3.4.1 Learning and knowledge rest in a diversity of opinions*

Today's capabilities in generative AI, such as ChatGPT, could enhance learning by swiftly gathering and presenting a multitude of alternative opinions, saving learners

the time and effort of searching for sources themselves. However, there are some issues to consider.

On one hand, this convenience might lead students to passively accept information without critically engaging with it, potentially fostering a sense of intellectual laziness. On the other hand, proper training in critical thinking and effective inquiry techniques is crucial for students to engage in meaningful dialog with these systems and extract valuable insights from the wealth of information provided. Thus, while generative AI technologies offer great potential for deepening learning, it is essential to balance convenience with the development of critical thinking skills in learners.

#### *3.4.2 Learning is a process of connecting specialized nodes or information sources*

Before the advent of generative AI and personalized tutorials, it was crucial for learners to possess the ability to connect specialized nodes or information sources. This required the application of a series of learning strategies, including self-acquisition, metacognition (such as reflecting on their learning processes), decision-making, problem-solving, questioning, and more. These skills empowered learners to navigate through vast amounts of information, critically assess its relevance and reliability, and synthesize knowledge from various sources. This active engagement in the learning process not only deepened their understanding of the subject matter but also honed their cognitive abilities essential for lifelong learning and success in various endeavours.

Again, generative AI, instead of requiring students to track and connect specialized nodes, may inadvertently foster a sense of laziness. When students can rely on AI to gather and present information, they might become less inclined to actively engage in the process of seeking out diverse perspectives and making connections themselves. This passivity could hinder their development of critical thinking skills and their ability to deeply understand complex topics. These issues could be addressed through careful instructional design, which includes projects requiring students to engage in self-reflection and compare results from AI systems.

#### *3.4.3 Learning may reside in non-human appliances*

Day by day, non-human appliances are increasingly entering the scene through generative AI systems that continuously learn from previous interactions and data, as such systems are encountering our daily lives immensely, including educational settings. Here, all issues, including ethical, replacement, social equity and more, must be considered.

#### *3.4.4 Capacity to know more is more critical than what is currently known*

For sure, the primary role of generative AI is continuous learning. How do we encourage students to see learning as an ongoing journey where mastering the skill of learning itself is paramount?

#### *3.4.5 Nurturing and maintaining connections is needed to facilitate continual learning*

While strong connections between nodes are critical, even more important is the presence of activities and tasks within each node that necessitate actions in other nodes. Designing such connections and maintaining them can be achieved through careful instructional design, emphasizing instructional control. While learners have full autonomy in selecting and following these actions, developing skills and

knowledge to manage their learning is crucial. On the other hand, personalized AI systems that provide support and manage the entire learning process for the learner represent significant progress. The question arises: will there be no need for learners to possess such skills in the future, given that AI handles all tasks? Alternatively, could AI potentially undermine the development of these skills, thereby impacting the profile of the next generation of learners?

#### *3.4.6 Ability to see connections between fields, ideas, and concepts is a core skill*

Similar questions arise here: how can such skills be enhanced when various AI systems are performing tasks instead of learners? What strategies could be employed to leverage AI systems at this juncture without impeding the development of these skills in learners?

#### *3.4.7 Currency (accurate, up-to-date knowledge) is the intent of all connectivist learning activities*

While the primary responsibility for this lies with instructional designers creating learning environments and learners utilizing these environments for learning, contemporary AI systems like ChatGPT may base decisions on a limited timeframe, excluding recent years. Even more so, the occurrence of mistakes and errors is inevitable in such systems, underscoring the need for students' care and inquiry now more than ever. It is inevitable to develop learners' skills and abilities by comparing results from AI systems and reflecting on them.

#### *3.4.8 Decision-making is itself a learning process*

In our digitally immersed and AI-enhanced educational landscape, learners are not only equipped with decision-making skills but also have questioning, problem-solving, self-assessment, self-regulation, and decision-making skills that remain essential as cornerstones for healthy societies and individuals. Therefore, in all educational systems, the appropriate integration of AI into learning approaches and tasks, as well as the promotion of effective application of learning strategies, must be the focal point for educators in the field.

## **4. Exemplary AI tools in education with recommended strategies for implementation**

This section introduces several popular AI tools, providing explanations of their general features (in Appendix 1), and recommends learning strategies for their application. The table categorizes AI tools based on the literature review by [1, 63] and for educational use into (i) ChatBots, (ii) visual and design tools, (iii) lesson design and content creators, (iv) teaching aids, (v) quiz/assessment generators, (vi) collaboration-communication, and (vii) learning platforms. In the last column, we suggest learning strategies from [39], which are deemed most suitable for each respective tool.

It is important to note that the selection and implementation of learning strategies for each tool may vary depending on the specific domain and learning objectives. Our suggestions are intended to provide a general framework for effectively integrating AIED into practice.

## 5. Exemplary case scenarios for implementing AI tools in education

In this section, exemplary case scenarios were created for implementing AI tools across various domains.

### 5.1 Case 1: the category of ChatBots - ChatGPT

Anna aims to teach sixth-grade students how to create formulas in Microsoft Excel and utilize the natural language processing capabilities of ChatGPT for *interactive learning*. The goal is to empower students with the ability to use ChatGPT to calculate sales tax, seller's commission, and total, as well as the remaining inventory, in an imaginary Excel table containing January 2023 inventory data. Students will use ChatGPT to write formulas for sales tax and commission, then apply these formulas correctly in Excel by pasting them. Additionally, students will be encouraged to explore creating new formulas with different values using both ChatGPT and external sources. This learning experience not only equips students with the skills to effectively use Excel formulas but also provides them with hands-on experience in natural language processing with ChatGPT.

### 5.2 Case 2: the category of visual and design - Adobe express with firefly

Graham, contemplating the integration of technology into K-12 education to *enhance students' creativity and storytelling skills*, suggests various methods by combining Generative AI with Adobe Firefly. Initially, students are tasked with using descriptive words to create opening scenes for their stories before even starting to write. Subsequently, the teacher recommends using generative AI for formative assessment, where students input descriptive text to swiftly generate corresponding visuals, saving time and offering a visual representation for assessment and improvement. Finally, students utilize additional keywords obtained from the created visuals to review and enhance their stories, fostering continuous reflection and improvement in storytelling skills through the effective use of technology (Figure 1).



**Figure 1.**  
*Created the cute little giant by adobe firefly.*

### 5.3 Case 3: the category of lesson design and content creator - Curipod AI

David wants to design a lesson on historical figures. He needs more interactive materials to engage students actively and give them instant feedback. He first creates the classroom with a Curipod. He enters the topic to be taught, and the AI generator creates the interactive slides. The teacher can edit these slides if he wishes. The teacher sends a team code to his students so they can access the presentation. By entering this code at [curipod.live](http://curipod.live), students can access the interactive presentation. The teacher can ask the students questions during the slide transitions and have them log in with the team code to answer the question. The teacher can set the time and duration while the students are replying to the questions. AI gives instant feedback to the students' answers to the question. The teacher can review the feedback, accept it after checking its accuracy, and let the student see it. At the end of the last slide, the student is asked questions to self-evaluate what they learned at the end of the lesson, and all the answers are displayed on the teacher's screen (Figure 2).

### 5.4 Case 4: the category of teaching aid - MagicToDo

Susan, a pre-service teacher, wants to create a lesson plan but does not know how to break down the process. So she writes to MagicToDo about the task she wants to do, but she cannot. MagicToDo explains step by step how to create the lesson plan. If Susan wants, she can ask MagicToDo to explain each sub-task again and decrease or increase by adjusting the spicy ordinal level. So she can plan her time more effectively and find a guide to help her complete the task (Figure 3).

### 5.5 Case 5: the category of quiz/assessment generators - Quizizz

Ivana wants to evaluate her students at the end of the Addition and Subtraction of Fractions lesson. She decides to use Quizizz for this. She types the topic of the test she wants to create in Quizizz, and AI creates the test. The teacher, Ivana, can edit the questions, correct grammatical errors in the wording of the questions, replace the

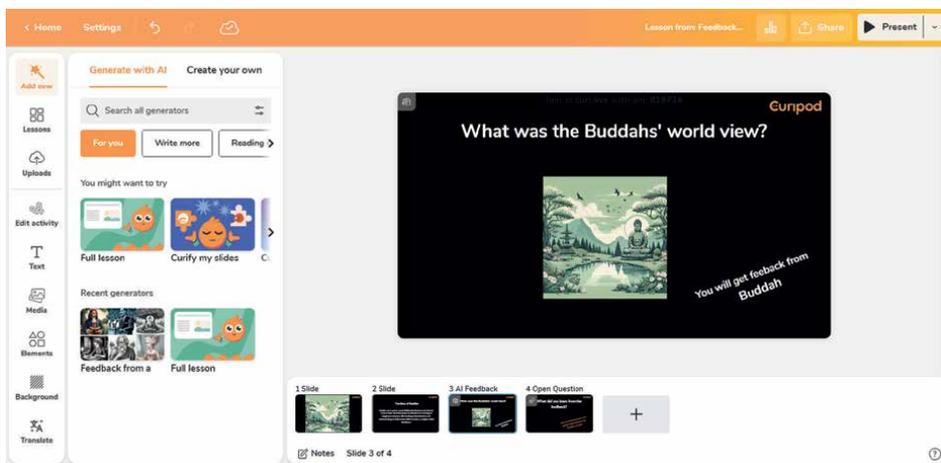


Figure 2.  
Created a lesson tutorial about historical figures by Curipod.



**Figure 3.**  
Created the stages of lesson plan creation with MagicToDo.

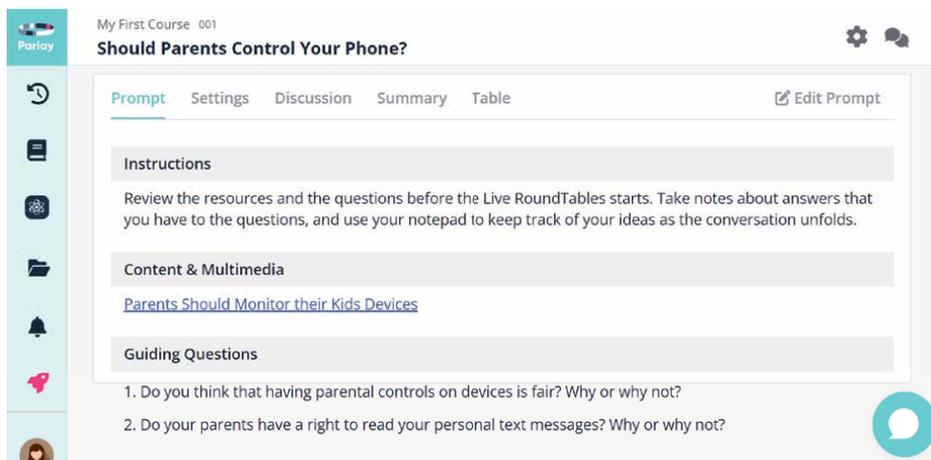
questions with a similar question, adapt them to a daily life problem, or add feedback to the options in a way that the student can see. If the teacher wishes, he/she can start and solve the test live with his/her students or give homework to be assigned at a certain time. It is also possible for students to take the test without a mobile device. The teacher distributes Q cards and students can mark the answers on the Q cards. The teacher can scan the cards with the mobile app and see the results.

### 5.6 Case 6: the category of collaboration and communication - Parlay

Sophie planned to discuss the safe use of the Internet by asking her students the question, “Should parents control your phone?” She decided to use the Parlay app to monitor the discussion. First of all, she created a course and invited her students. Then, she created a verbal discussion activity. She deepened the discussion by asking the questions: “Do you think that it is fair for your parents to control your phone?” and “Do parents have the right to read your text messages?” Discussion rules and evaluation criteria were added with Parlay. In Parlay, students are allowed to express their opinions verbally around a round table by turning on the camera and audio to the student whose turn it is. Parlay also allows students to construct their ideas by posing discussion questions to the students and asking them to respond in writing. At the end of the discussion, the teacher can see a summary report and a table with each student’s opinion and the time spent in the discussion. Students can also see the feedback written by the teacher (**Figure 4**).

### 5.7 Case 7: the category of learning platform - RiPPLE

The teacher gives an assignment using RiPPLE.  
This tool helps you study more effectively, actively, and socially.



**Figure 4.**  
*Created a discussion activity with parlay.*

RiPPLE will help you learn by involving you in:

Creating study resources. Creating study resources can improve your mastery and metacognition and encourage higher-order thinking as it requires you to process, organize, integrate, and reconstruct knowledge.

1. Moderation of your peers' resources. Moderating (or checking) your peers' study resources and providing critical feedback encourages self-reflection, communication, and problem-solving skills.
2. Adaptive practice. RiPPLE will provide you with study resources to view and practice based on your current level of knowledge on each course topic. Over 100 years of educational research demonstrates practicing is one of the most effective study techniques – far more effective than re-reading lecture notes or re-watching lectures.
3. Live formative quizzes. Participating in quizzes during lectures or while studying can improve your memory, attention, and engagement while also reducing mind-wandering.

### 5.7.1 Assessment

There will be a total of four rounds of RiPPLE assessment throughout the semester. In each round, you can earn up to 2.5 marks for correctly creating, moderating, and practicing study resources.

### 5.7.2 Task details

Creating one or more effective resources.

For a learning resource to be considered effective, it must:

- align with the course content and objective,
- be correct, clear, and easy to understand,

- be appropriately difficult, and
- encourage critical thinking and reasoning.

Your peers and teaching team will decide if your resource meets these criteria.

### *5.7.3 Moderating four or more resources effectively*

An effective moderation is one where you have:

- completed the moderation rubric,
- provided a detailed justification for your judgement, and
- provided constructive feedback on how the resource can be improved.

Simply writing feedback such as “good job” does not qualify. Again, teaching staff will be spot-checking the quality of moderation and change the outcome when necessary.

### *5.7.4 Answering 10 or more questions correctly*

To answer a resource correctly, your first response must be correct. You can attempt as many questions as you want. Only answers from the practice page are counted. Answering questions in an activity or moderation does not count. <https://itali.uq.edu.au/digital-learning/learning-analytics/ripple/ripple-guides>.

## **6. Ethical considerations in AI**

There are also issues about plagiarism, ethics, and misuse of ChatGPT that are unrelated to normal usage since it is in ChatGPT’s natural form to fabricate results in certain situations in the form of annotations, resources, and assumptions.

Li et al. [67] found that ChatGPT gave correct answers to questions but made wrong explanations. In their work, Belletini et al. [13] looked for the problem-solving ability of ChatGPT using the Bebras International Challenge on Informatics and Computational Thinking as background, and it was found that ChatGPT had poor performance and had no confidence in its answers. While it had better answers for procedural knowledge, it had difficulty with tasks requiring knowledge synthesis. Furthermore, the reliability of ChatGPT was in question as it did not provide sources of information but gave accurate answers [68]. Likewise, ChatGPT provides non-academic resources and annotations depending completely on what is available on the web [69]. Jalil et al. [70] showed that for software testing education and software processes, ChatGPT was not well-calibrated, lacked knowledge, and made wrong assumptions. Bordt and Luxburg found that the success of ChatGPT depends on quality entries on the web as the concepts they were investigating were common knowledge, and they warned that if there were not quality information on the web, the results would have been incorrect or poorer [71].

Overuse of ChatGPT would prevent learning, and learning how to use prompts must be a high priority for users [72]. Furthermore, Castillo et al. [73] declared that

with such detailed and long answers, ChatGPT can promote laziness among students and can cause decreased learning. The same results can be seen in another study [74], where they thought ChatGPT overuse interferes with critical thinking and problem-solving skills, which are essential and prevent them from seeking alternative solutions to problems, reducing their vision. Using ChatGPT to write term papers and code is plagiarism, and it reduces the experience and knowledge of students [75]. They warned that the students' lack of previous information would undermine their ability for upcoming challenges and declared the best usage of ChatGPT would be as an assistant role as it would lead to personal learning and negate differences between students.

Perceptions of math, science, art, school, and teachers by ChatGPT mirroring the students' perceptions [76]. The used LLMs were GPT-3 and ChatGPT-4, and it was found that they perceived math much more negatively than science, and GPT-3 perceived schools and teachers more negatively than ChatGPT-4. Also, math was viewed as detached from scientific advancements and real-world understanding. The authors suggest a cognitive psychology approach to these perceptions and to understand the behavioural patterns shown by LLMs.

It was very easy to get a university degree using ChatGPT, and the integrity of the academic area was under threat, and that is why changes have to be made in the education system for prevention [75]. Similarly, the study [74] stated that without proper prevention, ChatGPT can weaken the validity of assessments, and it is effortless to create considerable work without attribution and showing resources. Supporting these findings, plagiarism detection is unable to detect ChatGPT-generated content [77].

These results all show that ChatGPT depends more on the user than on itself and can be misunderstood easily. That is why there should be precautions for using ChatGPT or for better results; before experiments of any sort, ChatGPT should be trained with the data that the experiment will be about.

## **7. Conclusion**

In summary, while the integration of AI technologies into education is inevitable, given recent advancements and contemporary approaches to learning and teaching, attention must be paid to several critical issues:

- i. AI technologies are not yet sufficiently advanced to address all pedagogical concerns. Therefore, it is essential to recognize that these technologies cannot replace human educators entirely. Research into human-AI systems should be prioritized.
- ii. The difference between the success of AI on its own and as a teaching/learning aid should also be realized. AI systems that provide feedback and assessment should be used with larger samples, whereas AI that is used with more specialized purposes that help the learner at every step of learning should continue to determine effectiveness for generalization.
- iii. The development of critical skills in students, such as inquiry, problem-solving, metacognition, cooperation, group work, and emotional intelligence, should take precedence over-reliance on AI systems. Over-reliance on AI could lead to a decline in student initiative and engagement.

- iv. Ethical considerations, including the prevention of plagiarism, must be carefully addressed with appropriate safeguards.
- v. In-service training on AI features and usage should be provided to all stakeholders, including instructors, students, educational professionals, and academics. This training should include guidance on interacting with large language models, which calls for prompt engineering features.

## **Acknowledgements**

ChatGPT is used in language editing in cooperation with an English language specialist.

## **Conflict of interest**

The authors declare no conflict of interest.

## **Appendix 1**

| AI categories for education   | AI tools                          | How it works  | Pricing                       |
|---|-----------------------------------|---|-------------------------------|
|   | BingChat                          | It can be accessed through the Bing website or Microsoft Edge browser and can be used to ask both simple and complex questions, and request summaries of articles, books, events, news, sports results, and more. Bing Chat can also be used as a creative tool, helping you write poems, and stories, or even share ideas for a project. | Free                          |
|   | ChatGPT                           | ChatGPT is a generative AI ChatBot that interacts with you conversationally, the way a human would. It is trained with information from all over the Internet and tonnes of other sources – and it is been trained by humans to interact with you authentically.  | Freemium (free+ premium plan) |
|   | Perplexity                        | Perplexity is another generative AI ChatBot that lets users ask questions and get responses conversationally. What seems to set Perplexity apart is that it cites sources, which are easily clickable to get more context and more information.   | Free                          |
|   | Google Bard                       | Google Bard is an experimental conversational AI chat service developed by Google. Google Bard is designed to engage in text-based conversations with users, offering responses and generating human-like dialog  | Free                          |
|   | Pi                                | To use Pi, you can interact with it through text or voice commands. You can ask questions, seek advice, or simply engage in conversation with the AI.   | Free                          |
| <i>Which learning strategies could be supported by using ChatBots?</i>  |                                   |   |                               |
| <b>Skill:</b> Prior achievement   |                                   |   |                               |
| <b>Will:</b> Using trial and error with computer support can increase self-confidence and competence by coping with mistakes. |                                   |   |                               |
| <b>Environment:</b> The students control their overlearning at any time and anywhere  |                                   |   |                               |
| <b>Acquiring surface learning:</b> Activate prior knowledge; summarization; organization; note taking; highlighting.          |                                   |   |                               |
| <b>Acquiring deeper learning:</b> A synthesis of what they have learned at the surface phase                                  |                                   |   |                               |
|   | Adobe Express with Firefly (free) | With generative AI, you can create custom images and text effects using text prompts. As an educator you can use this feature to generate unique and engaging visuals for your lessons and activities.  | Free                          |
|   | Bing Image Creator (limited)      | Type in a description of an image you would like to see. Take the resulting images and download or save them – or ask for an adjustment to them.  | Free                          |
| <b>Visual and Design</b>  | Canva Classroom Magic             | Canva Classroom Magic is a suite of AI tools designed for educators. It includes features such as Magic Design, a free AI design tool for creating visual content, and Magic Write, an AI text generator and writer that assists in generating written content.   | Free                          |
| <i>Which learning strategies could be supported by using visual and design tools?</i>   |                                   |   |                               |

| AI categories for education   | AI tools          | How it works  | Pricing            |
|---|-------------------|---|--------------------|
| <p><i>Skill:</i> Prior achievement</p> <p><i>Will:</i> Increasing self-efficacy, reducing anxiety and self-blame by increasing social support</p> <p><i>Thrill-motivation:</i> Achieving approach</p> <p><i>Management of the environment:</i> The students control their overlearning at any time, anywhere</p> <p><i>Acquiring surface learning:</i> Activate prior knowledge; summarization; organization; note taking; highlighting</p> <p><i>Consolidating surface learning:</i> Giving-receiving feedback, help-seeking, effort.</p> <p><i>Acquiring deeper learning:</i> A synthesis of what they have learned at the surface phase</p> <p><i>Consolidating deep learning:</i> critical thinking, evaluation and reflection, seeking help from peers</p> <p><i>Transfer adapted learned skills and knowledge to the different tasks.</i></p> |                   |   |                    |
|   | Curipod           | Give Curipod a topic, and it will generate an interactive slide deck for you in seconds, including: polls, word clouds, open-ended questions, a drawing tool, etc.  | Freemium           |
|   | Diffit            | Diffit allows you to get levelled resources for literally anything. You can adapt existing materials for any reader, generate “just right” resources for any topic and then edit and share resources with students.   | Freemium           |
|   | MagicSchool.ai    | MagicSchool.ai is an AI-powered educational platform designed to help teachers save time by automating tasks such as lesson planning, grading, and generating educational content. It offers over 40 AI tools that are searchable by keyword and categorized for planning, student support, community, productivity, and community tools. | Free               |
|   | Education Copilot | Education Copilot provides you with AI-generated templates for lesson plans, writing prompts, educational handouts, student reports, project outlines and lots more.  | 30-day free trial. |
| <i>Lesson Design and Content Creator</i>  | Nolej             | Provide content (like text, videos, audio, YouTube, websites, etc.). AI analyzes it and generates educational content. After that, you can embed, export, or integrate with your learning management system (LMS).  | Freemium           |
|   | Eduaide.ai        | Eduaide.ai is an AI-powered teaching assistant designed to help teachers with lesson planning, instructional design, and generating educational content. It offers a resource generator, teaching assistant, feedback bot, and AI chat.   | Freemium           |
|   | Khanmigo          | Khanmigo is an AI-powered learning tool developed by Khan Academy that can be used as a virtual tutor and debate partner. It can also be used by teachers to generate lesson plans and assist with other administrative tasks.  | Monthly donation   |
|   | Copy.ai           | Copy.ai is an AI-powered writing tool that uses machine learning to generate various types of content, including blog headlines, emails, social media content, web copy, and more. Educators can use it to generate lesson plans, substitute teaching plans, newsletter copy, email, writing prompts, and more.                           | Freemium           |
|   | PopAI             | A powerful AI tool that boosts productivity. Besides instant answers, explore search engine integration, PDF reading, PowerPoint generation, and more   | Freemium           |
|   | Tutor AI          | TutorAI. Author: Sign In. Learn anything. What do you want to learn about? Start learning. Try topics like physics, history, or your own name!  | Freemium           |

| AI categories for education   | AI tools                    | How it works  | Pricing  |
|---|-----------------------------|---|----------|
| <i>Which learning strategies could be supported by using lesson design and content creator tools?</i>           |                             |   |          |
| Skill: Prior achievement  |                             |   |          |
| Will: Increasing self-efficacy, reducing anxiety and self-blame by increasing social support                    |                             |   |          |
| Thrill-motivation: Achieving approach, goals,   |                             |   |          |
| Management of the environment: The students control their overlearning at any time and anywhere, social support |                             |   |          |
| Acquiring surface learning: Activate prior knowledge; summarization; organization; note taking; highlighting    |                             |   |          |
| Consolidating surface learning: Giving-receiving feedback, help-seeking, effort                                 |                             |   |          |
| Acquiring deeper learning: A synthesis of what they have learned at the surface phase                           |                             |   |          |
| Consolidating deep learning: Critical thinking, evaluation and reflection, seeking help from peers              |                             |   |          |
| Transfer Adapted learned skills and knowledge to the different tasks  |                             |   |          |
|   | gotFeedback by got learning | Choose what you want gotFeedback to provide feedback on. Upload a Word document or PDF file – or paste it into text. It provides an evaluation that you can use as a teacher – or copy/paste to give to a student.  | Freemium |
|   | Grammarly                   | Grammarly is your online writing assistant. Using artificial intelligence helps you compose bold, clear, mistake-free writing. It can work inside your email client, your productivity suites, and even your social media. Grammarly's AI checks grammar, spelling, style, tone, and more | Freemium |
| <i>Teaching Aid</i>   | Goblin tools                | Goblin Tools is a collection of small, simple, single-task tools designed to help neurodivergent people with tasks they find overwhelming or difficult. The tools include MagicToDo, Formalizer, Judge, Estimator, and Compiler.  | Free     |
|   | Hello History               | Hello History is an app that lets you have life-like conversations with historical figures. Get a personal perspective on life, history, and the world from some of the most influential figures of all time – Cleopatra, Einstein, Buddha, and more.                                     | Freemium |
|   | Chat PDF                    | ChatPDF is an AI-powered tool that allows users to interact with PDF documents in a conversational format. From the website "ChatPDF in a Nutshell" Your PDF AI-like ChatGPT but for PDFs. Summarize and answer questions for free."  | Freemium |
| <i>Which learning strategies could be supported by using Teaching Aid AI Tools?</i>                             |                             |   |          |

| AI categories for education   | AI tools     | How it works  | Pricing  |
|---|--------------|---|----------|
| <p><i>Skill:</i> Prior achievement</p> <p><i>Will:</i> Increasing self-efficacy, reducing anxiety and self-blame by increasing social support</p> <p><i>Thrill-motivation:</i> Achieving approach, goals,</p> <p><i>Management of the environment:</i> The students control their learning any time, anywhere; social support</p> <p><i>Success criteria</i> Planning and prediction; setting standards for self-judgment</p> <p><i>Acquiring surface learning</i> Activate prior knowledge; summarization; organization; note taking; highlighting.</p> <p><i>Consolidating surface learning</i> Giving-receiving feedback, help-seeking, effort</p> <p><i>Acquiring deeper learning:</i> A synthesis of what they have learned at the surface phase</p> <p><i>Consolidating deep learning</i> Critical thinking, evaluation and reflection, seeking help from peers</p> <p><i>Transfer</i> Adapting learned skills and knowledge to the different tasks</p> |              |   |          |
|   | QuestionWell | QuestionWell generates an endless supply of questions so teachers can focus on what matters. Just input some reading, and the AI will write essential questions, learning objectives, and aligned multiple-choice questions.  | Free     |
|   | Formative AI | Formative has been an assignment and quiz platform for a long time, allowing teachers to ask students a variety of question types. Now, it has incorporated the power of ChatGPT to generate new standard-aligned questions and hints for learners as well as student feedback.   | Freemium |
|   | Quizizz AI   | Quizizz AI is an artificial intelligence-powered tool that can generate multiple-choice questions with four answer options, of which one is the correct answer. Quizizz AI can automatically determine the appropriate number of questions to generate from the content provided. | Freemium |
| Quiz/Assessment Generators  | Quizizz AI   | Quizizz AI can also modify existing quizzes, both manually created and AI-generated, with Enhance to customize activities according to students' needs.   |          |
|   | Conker       | Conker lets you create multiple-choice, read-and-respond, and fill-in-the-blank quizzes for students at a variety of levels on specific topics. It will also let you copy/paste reading material to generate quizzes.   | Free     |
|   | Twee         | Twee is an AI-powered tool designed to simplify lesson planning for English teachers by generating questions, dialogs, stories, letters, articles, multiple-choice questions, true/false statements, and more.  | Free     |
|   | Gradescope   | It allows students to submit their assignments online and automatically grades multiple-choice, fill-in-the-blank, and coding questions.<br>With Gradescope, students can receive instant feedback on their work and track their progress throughout the semester.                | Freemium |
| <i>Which learning strategies could be supported by using Quiz/Assessment Generators AI Tools?</i>   |              |   |          |

| AI categories for education  | AI tools                          | How it works   | Pricing                         |
|--|-----------------------------------|--|---------------------------------|
| <p><i>Skill:</i> Prior achievement</p> <p><i>Will:</i> Increasing self-efficacy, reducing anxiety and self-blame by increasing social support</p> <p><i>Thrill-motivation:</i> Achieving approach, goals,</p> <p><i>Management of the environment:</i> The students control their learning at any time and anywhere; social support</p> <p><i>Success criteria</i> Planning and prediction; setting standards for self-judgment</p> <p><i>Acquiring surface learning</i> Activate prior knowledge; summarization; organization; note taking; highlighting.</p> <p><i>Consolidating surface learning</i> Giving-receiving feedback, help-seeking, effort</p> <p><i>Acquiring deeper learning:</i> A synthesis of what they have learned at the surface phase</p> <p><i>Consolidating deep learning</i> Critical thinking, evaluation, and reflection, seeking help from peers</p> <p><i>Transfer</i> Adapting learned skills and knowledge to the different tasks</p> | <p>FigJam</p> <p>Jambot</p>       | <p>Jambot is a FigJam widget that brings the power of ChatGPT's AI to your boards. To find and run the Jambot widget:</p> <ol style="list-style-type: none"> <li>1. Hover over the pile of recently used icons in the toolbar, then click More.</li> <li>2. From the Widgets tab, search Jambot.</li> <li>3. Click or drag to add the widget to the board.</li> <li>4. Add text to the input sticky.</li> <li>5. Select a function.</li> </ol>   | <p>Freemium</p>                 |
| <p><i>Collaboration and Communication</i></p>  | <p>Parlay Genie</p> <p>Notion</p> | <p>Parlay Genie (part of Parlay) is a discussion prompt generator. It generates higher-order thinking questions for your class based on a topic, a YouTube video, or an article. It uses ChatGPT to generate prompts for your students.</p> <p>To manage and organize tasks, projects, and notes.</p> <ul style="list-style-type: none"> <li>• Create to-do lists</li> <li>• Take class notes</li> <li>• Collaborate with classmates</li> <li>• Stay organized throughout their studies</li> </ul> | <p>Freemium</p> <p>Freemium</p> |
| <p><i>Which learning strategies could be supported by using Collaboration and communication AI Tools?</i></p>  |                                   |  |                                 |

| AI categories for education  | AI tools | How it works  | Pricing       |
|--|----------|---|---------------|
| <p><i>Skill:</i> Prior achievement</p> <p><i>Will:</i> Increasing self-efficacy, reducing anxiety and self-blame by increasing social support</p> <p><i>Thrill-motivation:</i> Achieving approach, goals,</p> <p><i>Management of the environment:</i> The students control their over learning any time and anywhere; social support</p> <p><i>Success criteria</i> Planning and prediction; setting standards for self-judgment</p> <p><i>Acquiring surface learning</i> Activate prior knowledge; summarization; organization; note taking; highlighting.</p> <p><i>Consolidating surface learning</i> Giving-receiving feedback, help-seeking, effort.</p> <p><i>Acquiring deeper learning:</i> A synthesis of what they have learned at the surface phase</p> <p><i>Consolidating deep learning</i> Critical thinking, evaluation and reflection, seeking help from peers</p> <p><i>Transfer</i> Adapting learned skills and knowledge to the different tasks</p> |          |   |               |
|  | Ripple   | <p>RIPPLE is predominantly a course-level platform that instructors can incorporate into their teaching. to help students with their learning. Includes metacognition, higher-order thinking, evaluative judgment, and retrieval practice. It also has a classroom response system, peer learning, learning analytics, assessment tools and gamification elements.</p>            | Paid platform |
| <p><i>Learning Platforms</i></p>   | Fuma     | <p>FUMA uses a range of machine learning models to discover classes of exploratory learning behaviors. These behaviors can then be used to classify users based on their learning needs and to generate personalized hints in real-time that guide the student towards a more effective usage of the tools and affordances available in the OLE (open learning environments).</p> |               |
| <p><i>Which learning strategies could be supported by using Learning Platforms that use AI?</i></p>  |          |   |               |
| <p><i>Skill:</i> Prior achievement</p> <p><i>Will:</i> Increasing self-efficacy, reducing anxiety and self-blame by increasing social support</p> <p><i>Thrill-motivation:</i> Achieving approach, goals,</p> <p><i>Management of the environment:</i> The students control their learning anytime, anywhere; social support</p> <p><i>Success criteria</i> Planning and prediction; setting standards for self-judgment</p> <p><i>Acquiring surface learning</i> Activate prior knowledge; summarization; organization; note taking; highlighting.</p> <p><i>Consolidating surface learning</i> Giving-receiving feedback, help-seeking, effort</p> <p><i>Acquiring deeper learning</i> A synthesis of what they have learned at the surface phase</p> <p><i>Consolidating deep learning</i> Critical thinking, evaluation, and reflection, seeking help from peers</p> <p><i>Transfer</i> Adapting learned skills and knowledge to the different tasks</p>           |          |   |               |

**Table A1.** Exemplary AI tools in education with recommended strategies for implementation.

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## Chapter 2

# Generative AI in Education: Technical Foundations, Applications, and Challenges

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### Abstract

Generative artificial intelligence (AI) (GenAI) has emerged as a transformative force in various fields, and its potential impact on education is particularly profound. This chapter presents the development trends of “GenAI in Education” by exploring the technical background, diverse applications, and multifaceted challenges associated with its adoption in education. The chapter briefly introduces the technical background of GenAI, particularly the development of large language models (LLMs) such as ChatGPT & Co. It provides key concepts, models, and recent technological advances. The chapter then navigates through the various applications of GenAI or LLMs in education, examining their impact on different levels of education, including school, university, and vocational training. The chapter will highlight how GenAI is reshaping the educational landscape through real-world examples and case studies, from personalized learning experiences to content creation and assessment. It also discusses various technical, ethical, and organizational/educational challenges to using technology in education.

**Keywords:** generative AI, large language models, ChatGPT, generative AI in education, educational technologies

### 1. Introduction

In recent years, artificial intelligence (AI) has made remarkable progress in all areas of life, including education. Particularly with advances in generative AI (GenAI), its applications in teaching and learning have attracted stakeholders like students, educators, researchers, and educational institutes worldwide [1]. The development of tools, such as ChatGPT and Dall-E, has further enriched the field by engaging students and teachers in real-time conversations with large language models (LLMs) to create expressive artwork and digital images. Generative artificial intelligence (GenAI) is at the forefront of artificial intelligence and machine learning, focusing on generating new content, such as text, images, music, video, code, or other data types. Unlike traditional AI methods that categorize data into predefined classes, GenAI models learn the underlying patterns and relationships within data to generate entirely new content. This ability

of GenAI models to create new content offers immense potential for revolutionizing the educational landscape. Some examples include applications that facilitate personalized learning experiences tailored to the unique needs of each learner; increased accessibility for students facing challenges, such as learning disabilities, anxiety, or language barriers; and support for a variety of tasks, such as coding, writing, art, music, etc. In addition, GenAI enables teachers to provide constructive feedback at scale, fostering iterative learning and improving writing skills. Furthermore, GenAI helps educational institutions provide customized support and information to students, automate tasks such as scheduling events, and generate promotional content, etc.

Despite the potential innovations and opportunities, concerns and risks are also associated with using GenAI in education. For example, the ability of ChatGPT to correctly answer many practice and exam questions has raised concerns among many educational stakeholders about the use of artificially generated solutions [2]. Teachers' initial concerns are that students may use ChatGPT to cheat on their assignments. Teachers may struggle to determine the difference between artificially generated and human-generated content. This scenario leads to undermining the whole assessment and grading process, and a natural demand has arisen to detect the content of GenAI via some other AI tools, such as TurnItIn, GPTZero, or OpenAI's classifier. However, in the absence of other evidence, technical methods currently need to be more helpful in regulating the use of AI in the classroom. The Education Technology Lab (EDTec Lab), German Research Center for Artificial Intelligence (DFKI) Berlin, advocates an objective assessment of the potential and limitations of the technology and warns against software that claims to be able to automatically recognize text generated by ChatGPT [3]. Other concerns include personal data privacy and security, academic dishonesty's consequences, students' overestimation of GenAI's capabilities and trustworthiness, and the inadvertent reinforcement of biases through system output and user interaction. It has led to a debate, in which some educational institutions have banned the use of ChatGPT or similar GenAI tools for students. In contrast, others have welcomed the ethical and transparent use of GenAI tools in education. Policymakers and educators have initiated disseminating guidelines for students, teachers, and educational institutions aiming to promote academic integrity, ensure accessibility, and encourage ethical applications of this technology in educational settings [4–6].

Generative AI (GenAI) has the potential to formulate knowledge models and guide cognitive activities, aid learning while learners actively engage as collaborators, and empower learners to control their own learning experiences. These tools reflect complex thought processes fundamental to human understanding and are potent resources for students and educators. Innovations like AI-generated content and adaptive learning platforms are reshaping how educational content is delivered and consumed, making learning more accessible and tailored to individual learner's needs [1]. This chapter aims to provide a comprehensive overview of GenAI in education, briefly describe technical foundations, and highlight its emergent opportunities while acknowledging the challenges that must be addressed to ensure its responsible and equitable implementation.

## **2. Technical foundations of generative AI**

### **2.1 What is generative AI?**

Before ChatGPT was launched in late 2022, the public domain was primarily influenced by what's known as discriminative AI. This form of AI specializes in

sorting and categorizing information, serving as a foundational tool in many applications. However, the narrative began to shift with the rise of generative AI, particularly marked by the public availability of models like ChatGPT. Despite sharing common technological underpinnings, generative and discriminative AI diverge significantly in their objectives. Discriminative AI is adept at discerning and differentiating between various data categories. In contrast, generative AI aims to synthesize new content or outputs, drawing upon the inputs it receives and the extensive data understanding it has developed through its training [7].

Generative AI is a type of AI technology that autonomously creates content in response to natural language prompts through conversational interfaces. Unlike traditional methods that mainly curate content from existing web sources, generative AI actively generates new material. This content spans various formats embodying different aspects of human cognition, including natural language texts, images, videos, music, and even software codes. Training generative AI models frequently involve unsupervised learning methods, which allow these models to process and comprehend large volumes of data autonomously. The goal is to discern patterns in the structure or creation of these data, enabling the AI to emulate and reproduce these patterns.

## **2.2 Text generative AI**

Text generative AI employs a specific type of artificial neural network (ANN) called a general-purpose transformer. Within this category, a particular form called a large language model (LLM) is prevalent. These systems are often called LLMs due to their extensive linguistic capabilities. The type of LLM utilized in text generation AI, such as ChatGPT, is known as a generative pre-trained transformer, or GPT. The 'GPT' in 'ChatGPT' reflects this underlying technology.

ChatGPT is built on GPT-4, a version developed by OpenAI, which represents the latest evolution in their GPT series (as of the time the book chapter was written). Each new iteration of OpenAI's GPT has shown significant improvements over its predecessors, driven by advancements in AI architectures, training methodologies, and optimization techniques. A notable aspect of its continuous development is the increasing scale of data used for training and the exponential growth in the number of parameters.

These parameters are akin to metaphorical knobs, fine-tuning the performance of the GPT. They include the model's 'weights', and numerical values dictating how it processes input data and generates output. As of GPT-4, the model substantially increases these parameters, enabling more nuanced and sophisticated responses than earlier versions. This evolution reflects OpenAI's commitment to enhancing the capabilities and accuracy of its language models, ensuring they remain at the forefront of AI technology in text generation.

## **2.3 Image generative AI**

Image generative AI, such as Dall-E and Stable Diffusion, primarily leverage Diffusion Models, a type of ANN that differs from traditional generative adversarial networks (GANs). These Diffusion Models operate by gradually learning to reverse a process that adds random noise to an image. Initially, the model introduces noise to a clear image, transforming it into a completely random pattern. It then learns to

reverse this noise addition during generation, effectively reconstructing the original image from randomness.

This process begins with a random pattern and then iteratively refines this pattern into a coherent image that aligns with a given prompt. Unlike GANs, which involve a generator and discriminator working in opposition, Diffusion Models rely on a single neural network that predicts how to remove noise at each step. Over numerous iterations, this network becomes adept at creating detailed and realistic images from noisy inputs.

Diffusion Models have shown remarkable capability in generating high-quality images that are often more detailed and varied than those produced by GANs. They excel in creating diverse outputs based on textual descriptions, from realistic photographs to artistic renderings. This advancement in AI-driven image generation represents a significant shift from the GAN-based approach, offering more flexibility and potential for creative applications.

## **2.4 Preliminary of multimodal generative AI**

Text and image-generative AI models excel in text-image-based tasks but are limited to their specific data types and cannot simultaneously process images, videos, or audio. This limitation is crucial in real-world applications where multimodal data are shared. To bridge this gap, Multimodal Large Language Models (MLLMs) [8] and Large Vision Models (LVMs) [9] have been developed. MLLMs and LVMs combine a large language model with multimodal adaptors and various diffusion decoders, allowing them to process and generate outputs across different media formats.

The concept of multimodality in these models is inspired by human communication, which often involves multiple channels. MLLMs and MLVMs are trained on extensive multimodal datasets, including image captions, video descriptions, and audio transcripts. They can recognize patterns in these data and generate coherent outputs that match the input modality. Despite these advancements, integrating new modalities into existing models remains challenging. It requires extensive data that include the new modality and often necessitate retraining from scratch, demanding significant computational resources and data quality efforts. Several recent frontier research studies have been devoted to this future direction, for example, Emu2 [10] and Google Gemini [11].

Overall, AI is moving towards more adaptable, efficient, and versatile systems capable of handling a broader range of tasks and data types, reflecting a more holistic approach to artificial intelligence.

## **3. Applications of generative AI in education**

Generative AI (GenAI) can be used in a variety of educational contexts, from creating innovative content and generating personalized learning materials to automating assessment and feedback. For example, students can use GenAI to help with homework or explore creative writing and art, educators can use these tools to create engaging teaching materials or to provide personalized learning experiences, and institutes can use GenAI to improve their administrative and educational services. GenAI applications can be used as standalone tools or integrated into other systems or platforms. In conjunction with different forms of AI, GenAI models, especially LLMs, can enhance and support learning activities at all levels of education. A recent report

published jointly by the German Research Center for Artificial Intelligence (DFKI) and mmb Institut GmbH for the Deutsche Telekom Foundation highlighted applications of AI in school education [12]. The report mentions the practical use cases of GenAI models like ChatGPT in school education. It provides a structured overview of AI systems benefiting learners, educators, and institutes and shaping everyday school life in the future. In the context of INVITE -innovation competition funded by the German Federal Ministry of Education and Research (BMBWF), VDI/VDE-IT comprehensively introduces LLMs and their transformative impact on continuing vocational training [13]. Kasneci et al. presented many possibilities that can be realized using GenAI models such as ChatGPT or other LLMs [14]. They highlighted how these models can be used to create educational content, improve student engagement and interaction, and personalize learning experiences while emphasizing that the use of LLMs in education requires students and teachers to develop a set of competencies and literacies necessary to understand both the technology and its limitations, as well as the unexpected brittleness of such systems.

The applications of AI in education can be divided into three categories: student-supporting applications, teacher-supporting applications, and institute- or system-supporting applications [15]. In addition to providing support in these three categories, they also have the potential to promote learning activities for children with disabilities, support online and collaborative learning, and boost professional development and training. This section provides an overview of some of the applications of GenAI supporting learning and educational activities in these directions.

### **3.1 Student-supporting applications**

Generative AI (GenAI) has the potential to serve as a learning companion and support educational activities at all levels. Students can use GenAI as a general search tool to get answers to their immediate questions about a specific topic, get support in completing homework or preparing for their exams, and learn new skills.

#### *3.1.1 Support in primary to higher education*

In primary school education, GenAI can help children improve their reading and writing skills by suggesting syntactic and grammatical improvements. It can also improve writing style, develop critical thinking skills, and improve reading comprehension by providing students with summaries and explanations of complex texts, making the material more accessible. In a recent study, Han and Cai present a visual storytelling prototype based on generative AI tools, such as ChatGPT, Stable Diffusion, and Midjourney, for children's creative expression, storytelling, and literacy development. It was found that generative AI could significantly enhance reading and writing skills and promote creative storytelling and literacy development in young learners [16]. Another study on the use of GenAI, specifically ChatGPT 3.5 and 4, in primary school education, showed its potential to personalize learning material and cater to students' diverse knowledge and learning abilities. The study involved 110 students and demonstrated that generative AI could support motivated learning and skill development, suggesting a promising future for its use in school education [17].

Generative AI (GenAI) can provide valuable support for middle and high school students in language acquisition and mastering different writing styles in subjects such as language and literature. GenAI can also help students prepare for their exams

and assessments. GenAI tools can generate practice problems and quizzes for subjects like mathematics and physics that help improve the studied material's understanding, contextualization, and retention. They also help to improve problem-solving skills by providing students with detailed explanations, step-by-step solutions, and engaging supplementary questions. This approach clarifies the reasoning behind solutions, promotes analytical thinking, and encourages creative problem-solving strategies. There is also a potential for GenAI, specifically LLMs, to enhance science, technology, engineering, and mathematics (STEM) education with a multimodal analogical reasoning approach. A study by Cao et al. demonstrated how GenAI transforms intricate principles in mathematics, physics, and programming into comprehensible metaphors and converts them into visual form to augment the educational experience further [18]. Khanmigo.ai, for example, powered by GenAI tools, provides a whole bunch of services to support students in improving their writing and critical thinking skills, supporting them in preparation for their maths quizzes, and even helping them with real-time feedback, debate, and collaboration. Similarly, tools.fobizz.com provides a suite of GenAI-powered tools to support both educators and learners.

At the university level, GenAI models such as ChatGPT are recognized for their role in supporting research, completing assignments, and fostering the development of critical thinking and problem-solving skills. These tools can enhance students' research skills by providing access to comprehensive information and relevant resources on specific topics. Students can use these tools to create summaries, organized outlines, and initial sketches of their intended research subject. These tools can also help students efficiently comprehend important concepts and simplify their writing processes. Furthermore, LLMs can be used to find unexplored areas and current research trends, enhancing students' understanding of the subject matter and facilitating analytical analysis [14]. For example, Castillo-Segura et al. demonstrate the potential of generative AI in accelerating the research process, specifically in conducting systematic literature reviews in academia. This research compares six GenAIs (Forefront, GetGPT, ThebAI, Claude, Bard, and H2O) with their respective large language models (LLMs) when classifying 596 articles in the screening phase of a systematic review in the field of medical education. It has been observed that Generative AI tools can significantly reduce the time and effort required for systematic literature reviews (SLRs) by facilitating article identification and classification, demonstrating the practical benefits of AI in academic research [19]. Jonsson & Tholander present a study of a group of university students using generative machine learning to translate from natural language to computer code. The study explores how AI can be understood in terms of co-creation, focusing on how AI may serve as a resource for understanding and learning and, on the other hand, it affects the creative processes [20].

### *3.1.2 Support in professional education*

The integration of AI into daily life and the workplace is increasing, making it crucial to prepare students for future technological demands. According to the World Economic Forum, AI integration will result in a mixed job outlook by 2027, with 25% of companies anticipating job losses and 50% expecting job growth. This trend highlights the significance of providing students with skills in emerging technologies [21]. Familiarity with AI and chatbots may become essential for entering the workforce. Furthermore, technology companies like Google and Microsoft have already announced plans to integrate AI into their products, indicating the increasing

prevalence of AI in various products and services [22, 23]. Given these developments, the use of AI technologies in education prepares students for future job markets and offers opportunities to enhance learning beyond traditional methods.

Large language models (LLMs) have the potential to enhance professional training in a wide range of fields by providing tailored support for the development of specific competencies that are critical for different professional environments. By fine-tuning LLMs on domain-specific corpora, these models can generate industry-specific language and help learners acquire the specialized vocabulary and stylistic nuances needed to write technical reports. This extends the capabilities of LLMs beyond general language processing to specialized training tools that can simulate real-world professional writing and communication scenarios. For example, the adaptability of LLMs to specific professional needs, such as programming, report writing, project management, decision-making, etc., underlines their usefulness in enhancing skills critical to modern workplaces. Tools such as GitHub Copilot, powered by OpenAI's Codex, show how AI can assist with real-time coding tasks, suggesting code completions and providing programming insights directly within the coding environment [24]. Such tools can help generate code, understand programming languages, and even offer debugging support, making them invaluable tools for novice and experienced programmers. The role of LLMs in professional training also emphasizes the importance of domain-specific tuning and the integration of professional expertise to maximize their effectiveness [14, 25]. In the medical field, for example, LLMs can simulate patient interactions, help with the generation of medical reports, and even assist in medical research by providing up-to-date information and generating hypotheses based on current medical literature [26, 27]. Pavlik discussed the potential of generative AI platforms such as ChatGPT for journalism and media education, highlighting the importance of understanding the capabilities and limitations of such technologies [28]. However, integrating LLMs into professional education requires a collaborative approach involving educators, industry professionals, and AI developers. This collaboration ensures that LLMs are fine-tuned for technical accuracy, ethical considerations, professionalism, and the nuanced understanding required in specific fields.

### *3.1.3 Support in learning with disabilities*

Generative AI can help people with disabilities or neurodivergent in the context of education, work, and leisure. By developing inclusive learning strategies, GenAI can help create adaptive writing tools, translate complex texts into more accessible formats, and highlight key content across different media, ensuring that educational content is accessible to all students, regardless of their disabilities. For example, GenAI-powered applications such as "goblin.tools" can help children with Attention Deficit Hyperactivity Disorder (ADHD) to simplify tasks they find overwhelming or difficult [29]. LLMs can be seamlessly integrated with speech-to-text and text-to-speech solutions to assist the students with visual impairments. Earlier research into the use of video models to teach generative spellings to a child with autism spectrum disorder also showed a potential of employing GenAI for the generation of such video models [30]. For example, GenAI models can be integrated into virtual reality (VR) and extended reality (XR) technologies and can provide a wide range of innovative use cases and interaction concepts that can help to reduce barriers for people with specific physical or mental needs, e.g., through simulations, gamification, or training scenarios [31, 32].

Because GenAI has the potential to reflect and perpetuate societal biases, including those related to disability, the use of these technologies must be undertaken with careful consideration of the ethical implications, potential biases, and the need for professional oversight to ensure that the benefits of LLMs are shared equitably among all learners, including those with disabilities [33]. There is also a need to work with therapists, educators, and other professionals to meet the specific needs of learners. The interactions of people with disabilities with LLMs also highlight the need to involve those with lived experience of disability in the development and training of LLMs to ensure that these models serve as empowering tools rather than sources of further marginalization [34].

### **3.2 Teacher-supporting applications**

Teachers use GenAI to enhance their pedagogical activities and ensure students develop the desired learning outcomes. GenAI helps them create tailored learning materials, generate assignments and quizzes, provide feedback, and assist in developing or assessing student exams [14].

#### *3.2.1 Support in creation of learning material*

Generative AI (GenAI), specifically LLMs, can be used to create learning content, exercises, quizzes, presentation slides, etc., for a wide range of subjects and educational levels that can be adapted to meet the diverse needs of students [35]. For example, LLMs can support curriculum development, teaching methodologies, personalized study plans and learning materials, student assessment, and more in medical education [36]. Similarly, Rüdian & Pinkwart presented the use of LLMs (ChatGPT 3.5) in generating learning content for a concrete micro-learning template in German language teaching. Teachers provide a topic as input, and the approach then elicits the required information with instructional prompts and combines responses into a language learning unit. The quality of the generated learning units was assessed for correctness and appropriateness. The results showed the best performance, but the need for “teacher-in-the-loop” is suggested [37]. Based on some existing ideas, teachers can also use GenAI to create innovative discussion topics, animations, and short stories to enhance student engagement or group discussion. Considering the example of creating model texts, LLMs can be asked to “create a discussion about the use of AI in school” and the generated texts can then be adapted by the teacher according to the didactic goal of the learning content [12].

#### *3.2.2 Support in teaching activities*

Generative AI (GenAI) can help teachers provide personalized learning experiences for students by analyzing their responses to specific learning tasks. GenAI can give feedback, hints, or suggestions for learning tasks or generate materials matching the student’s learning needs or skills. For example, LLMs can support teachers in creating inclusive learning activities, questions, and assessment exercises or quizzes targeted to students at different levels of knowledge, ability, and learning styles. Phung et al. present a study on programming showing how GenAI can improve STEM education. Their research highlights the broader capabilities of GenAI to support learning and human tutors in different programming education scenarios. It does so by providing personalized digital tutoring, generating hints, and creating tasks and

explanations [38]. Such support can save teachers time and effort in creating personalized materials and allow them to concentrate on other aspects of teaching.

### *3.2.3 Support in grading of assignments*

Generative AI (GenAI) can support teachers by automating the grading of assignments or exams and providing immediate feedback to students. For instance, LLMs can be used to identify potential strengths or weaknesses in written essays or other writing assignments and provide individualized feedback to students [39, 40]. It speeds up the individual evaluation process and allows for more consistent and objective grading [41]. Furthermore, LLMs can also be used to detect plagiarism, which can help to prevent cheating on submitted writing assignments. Additional AI tools can also be used to analyze assessment data to identify trends, such as common areas where students struggle, enabling targeted interventions to support learning.

## **3.3 System-supporting applications**

### *3.3.1 Support in administration activities*

Large language models (LLMs) can support educational institutions through chatbots to provide instant answers to questions on various administrative topics. For example, LLMs can be used to respond to queries from potential applicants and provide them with up-to-date information. These models can help existing students register for courses and provide administrative information, such as courses, exams, schedules, etc. Students can also use LLMs-based chatbots to find news or other information. LLMs-based chatbots can also be set up for international students and staff to provide multilingual information to students. In addition, LLMs can generate offers or advertisements of learning opportunities based on various factors, such as target audience, age group, gender, location, etc.

Another potential application is the automated tagging of learning resources to provide metadata for effective management and efficient discovery of learning resources [42]. LLMs can be used to develop solutions for automated or semiautomated generation of metadata fields from learning resources using explicitly defined metadata standards. It will significantly facilitate the implementation of personalized learning or intelligent tutoring systems by making it easier to find appropriate learning content without human intervention.

### *3.3.2 Support in tutoring and mentoring*

Generative AI (GenAI) can power intelligent tutoring systems that provide personalized guidance and support to students. These systems can analyze student responses, identify misconceptions, and generate customized explanations or additional practice materials to address individual learning needs. AI tutors can adapt their teaching strategies based on student progress and learning styles, creating a more effective and tailored learning environment. The integration of LLMs into existing learning management systems (LMS) can provide tutoring or mentoring support to students as an educational chatbot. One such example is the “tech4compKI,” a Federal Ministry of Education and Research (BMBF)-funded project of the Educational Technology Lab, DFKI Berlin, where students ask questions and LLM-supported chatbot “BiWi AI Tutor” retrieves information from material (structured

knowledge of the module, learning material from lectures and seminars as well as organized information) and analyzes it to answer questions.

### *3.3.3 Support in collaborative and remote learning*

Generative AI (GenAI) can simulate a collaborative learning environment by acting as a peer to provide support in various collaborative learning tasks, such as peer discussion, to explore a research question or a discussion topic. These models can give immediate feedback on writing artifacts or generate new ideas through peer discussion. One example is PEER (Plan, Edit, Explain, Repeat), a collaborative language model trained to imitate the entire writing process. The model can draft, make suggestions, propose edits, and explain its actions. The model also uses self-learning techniques to adapt to new areas of learning while demonstrating strong performance in different domains and editing tasks [43]. The use of GenAI models in online education systems has the potential to transform remote and group learning by providing interactive, responsive, and tailored responses to each student. In group and remote learning environments, GenAI models can provide a structure for discussion, offer real-time feedback, and give personalized guidance to students, thereby increasing student engagement and participation while adapting to the dynamic nature of group discussions and debates. For example, LLMs can be used to manage conversations and balance the preferences of group members in collective decision-making tasks (such as scheduling meetings) with fair consideration for all participants by extracting individual preferences and suggesting options that satisfy most group members [44].

## **4. Integration of generative AI in educational systems**

### **4.1 Teacher's journey from awareness to creation**

Integrating GenAI tools into educational settings is not just an emerging trend; it's rapidly becoming an essential part of modern teaching methodologies across multiple disciplines. However, teachers' perspectives towards the adoption of these tools vary significantly, predominantly based on their awareness, understanding, and experience with GenAI technologies [45, 46]. This discussion explores educators' perceptions regarding integrating GenAI in education, focusing on transitioning from awareness to classroom creation. Possible stages of adoption and integration are as follows.

*Awareness:* The initial phase involves teachers becoming aware of GenAI's potential educational applications. At this stage, the primary emotion is curiosity mixed with a hint of skepticism, especially among those with limited background in technology. The challenge lies in transforming this curiosity into a genuine interest capable of driving further exploration. As GenAI continues to evolve, the argument for its inevitability in education strengthens; this phase is crucial for setting the groundwork for future engagement.

*Learning:* The learning phase is marked by teachers actively seeking knowledge about GenAI, its capabilities, and how it might be leveraged to enhance teaching and learning experiences. This stage is often accompanied by a range of emotions, from excitement at the possibilities to frustration over the learning curve of new technology. Professional development opportunities, workshops, and online resources support educators through this phase. Here, the divide between tech-savvy educators

and those from non-IT backgrounds becomes most apparent, necessitating tailored learning paths to ensure inclusivity.

*Familiarity:* As educators gain hands-on experience with GenAI tools, their comfort level increases. This familiarity phase is characterized by growing confidence in using these technologies for specific, often limited, tasks within the educational context. For many, this is the stage where the potential of GenAI to transform aspects of teaching and research becomes tangible. Experiences shared among teachers through forums, collaborations, and professional networks further nurture this growing familiarity, turning apprehension into acceptance.

*Creation:* The final phase sees teachers actively integrating GenAI tools into their curriculum as an adjunct technology and a central component of their instructional strategies. This creation phase is where the full potential of GenAI integration is realized, with educators innovating new ways to engage students, personalize learning experiences, and streamline administrative tasks. Here, the emphasis shifts from understanding GenAI to leveraging its capabilities to foster more effective, efficient, and exciting educational environments.

## **4.2 Learner's perspectives towards GenAI**

Understanding the evolving landscape of educational technologies, especially with the integration of GenAI, mandates considering learners' perspectives [47, 48]. As they navigate these technological advancements in their educational journey, their attitudes and skills development play a critical role. Here's a focused exploration of the potential learner's perspectives towards GenAI integration in education:

*Enhancing learning efficiency:* At the outset, learners perceive GenAI as a revolutionary tool, much like a "search engine 2.0," which propels the efficiency of study practices to new heights. Unlike traditional search engines that return a vast array of links requiring further analysis, GenAI, such as ChatGPT, provides concise, tailored answers, significantly reducing the effort and time needed for research. Students may foster a positively inclined attitude towards these technologies, recognizing their potential as a study aid and an essential competency for their future careers. They understand that integrating GenAI technologies into their learning strategies can vastly enhance their understanding and retention of information.

*Navigating the accuracy of GenAI:* An essential perspective that learners must adopt is the understanding that GenAI tools are not infallible for all their advancements. The ability to discern and validate the information provided by GenAI becomes crucial. Hence, developing fact-checking skills is imperative for students, ensuring they can distinguish between accurate information and potential inaccuracies generated by these tools. This skill is particularly significant because GenAI sometimes creates plausible but erroneous content. Encouraging a critical approach towards accepting information will enable learners to utilize these technologies effectively, ensuring their reliance on GenAI complements rather than compromises their educational integrity.

*Personalized learning support:* GenAI technologies have the potential to revolutionize the concept of personalized learning through virtual 1:1 coaching. In this vision, GenAI is an ever-present tutor, available to address learners' queries instantaneously, guide them through complex problems, and provide tailored learning experiences. This perspective views GenAI as a tool and a learning partner capable of fostering the self-paced practice of foundational skills in learners. Such 1:1 coaching can fill gaps in understanding, offering explanations and resources customized to each learner's

needs and pace. For this potential to be fully realized, the application of GenAI in education must be guided by ethical standards and pedagogical principles, ensuring that these technologies genuinely support and enhance the learning experience.

### **4.3 Administrative roadmap to integrate GenAI**

*Strategic planning for GenAI integration:* Strategic planning forms the bedrock of successful GenAI integration within educational settings. Administrators must embark on a detailed analysis of the current technological infrastructure, identifying gaps and envisioning a roadmap for incorporating GenAI tools. This includes addressing hardware and software needs, internet bandwidth, and cybersecurity measures. The strategic plan should align with the institution's broader educational goals, ensuring that GenAI adoption enhances, rather than disrupts, the learning experience. It may involve setting up pilot programs to test the effectiveness of GenAI tools in specific subjects or activities and gathering data to inform broader implementation strategies.

*Comprehensive resource allocation:* Beyond the initial enthusiasm for GenAI's potential, administrators face the practical challenge of resource allocation. It goes beyond budget considerations to encompass a holistic approach that addresses equity, access, and sustainability. For instance, ensuring that all students, including those from underprivileged backgrounds or with special needs, have access to these technologies is crucial. Administrators may discuss partnerships with tech companies for donations or discounts, grants, and other financing models to support this equitable access. Moreover, resource allocation is not solely about technology procurement; it also encompasses investing in human capital—recruiting staff adept at blending GenAI tools with teaching methodologies or providing ongoing training for current educators.

*Ethical considerations and digital citizenship:* The ethical deployment of GenAI in education requires administrators to grapple with questions of data privacy, intellectual honesty, and the potential for technology misuse. Establishing a framework that promotes ethical use while encouraging innovation is a balancing act. Discussions may revolve around developing comprehensive policies that govern data use, consent protocols, and transparency measures. Furthermore, fostering a culture of digital citizenship, where students learn to use GenAI responsibly, becomes a shared mission. This could include curriculum updates to cover topics like digital ethics, privacy rights, and the implications of AI on society.

*Professional development tailored to GenAI:* Professional development is a cornerstone of effective GenAI integration, necessitating discussions on equipping teachers with the necessary skills and confidence to use these tools in the classroom. Training programs might need to be overhauled to include GenAI competencies, ranging from technical know-how to pedagogical strategies for integrating AI tools into lesson plans. Moreover, creating a supportive community where teachers can share experiences, challenges, and best practices is vital. Such initiatives could include internal workshops, online forums, or collaboration with external experts and institutions. The goal is to foster an environment where teachers feel empowered to innovate while ensuring that GenAI enhances the educational experience.

*Policy formulation and student preparedness:* Crafting policies that reflect the complexities of GenAI use in education is another pivotal discussion point. These policies must address academic integrity, ensuring students leverage GenAI as a learning aid without compromising their intellectual development. For instance, guidelines

must clearly define how and when GenAI can be used for assignments, projects, and research. Additionally, preparing students for a future where AI is ubiquitous involves adjusting curricula to include critical thinking, problem-solving, and digital literacy skills. Administrators must consider how education can adapt to prepare students to use AI and understand its impact on society and the workforce.

*Engaging the broader educational community:* Ultimately, successful GenAI integration depends on the engagement of the entire educational community—students, parents, teachers, and staff. Administrators should lead efforts to educate these stakeholders on the benefits and challenges of GenAI, setting realistic expectations while addressing concerns and soliciting feedback. This may involve community forums, informational newsletters, and transparent reporting on pilot programs and initiatives. By fostering an inclusive dialog, administrators can build trust and enthusiasm for the transformative potential of GenAI in education.

## **5. Potential risks and challenges**

### **5.1 Imperfection and polluted content**

The proliferation of generative AI has risks and challenges, particularly in the educational context. A primary issue is the quality control of the content generated. While these AI systems can create high-quality educational materials, they can also produce inaccurate or misleading information, especially in scenarios not covered in their training datasets. This problem is related to AI “hallucination,” where the AI produces content that significantly deviates from factual accuracy, leaning more towards the AI’s interpretations rather than an accurate representation of the information. These hallucinations occur because AI systems, in their current form, do not possess proper knowledge or understanding [49, 50]. In practical terms, if an AI model is uncertain about the factual accuracy of a piece of information, e.g., a historical event, it may provide an educated guess rather than an accurate answer. Compared to carefully curated textbooks, AI-generated content, commonly sourced from the vast and varied Internet, often lacks the rigorous vetting necessary for educational purposes. This discrepancy is significant because the Internet, while a treasure trove of information, can also contain discriminatory and unethical language.

Generative AI’s (GenAI’s) ability to alter or fabricate images and videos, creating highly realistic ‘deepfakes,’ poses a unique challenge to educators and students alike. These deepfakes are increasingly indistinguishable from authentic materials, making it easier to produce and disseminate ‘fake news’ and other forms of misleading information. The absence of stringent regulations and robust monitoring systems means potentially biased or erroneous AI-generated materials are becoming more prevalent online, influencing one of the primary knowledge sources for learners globally. This situation mainly concerns young learners, who may need more background knowledge to discern inaccuracies or biases in AI-generated content. Moreover, there’s a legal aspect to consider: using content without proper consent or attribution can lead to copyright issues and undermine the integrity of educational resources. This issue also creates a recursive challenge for future AI models, as they might train on their AI-generated content from the Internet, perpetuating and amplifying existing biases and errors. This cycle underscores the need for more effective oversight and ethical standards in AI-generated content, particularly in educational contexts. This challenge is exacerbated in an educational setting where critical thinking and accurate information are foundational.

Addressing those mentioned challenges requires a multifaceted approach. A potential solution lies in applying reinforcement learning with human feedback (RLHF), a technique where AI models are fine-tuned based on evaluations of their outputs by human experts. This method allows the models to iteratively improve their content generation to align more closely with factual accuracy and ethical standards. Furthermore, developing and utilizing foundation educational datasets for fine-tuning LLMs can ensure that the AI systems have a solid base of verified and unbiased information, specifically tailored for educational purposes. These datasets would consist of meticulously curated and peer-reviewed educational content, encompassing various subjects and perspectives to minimize biases and inaccuracies. Additionally, implementing robust monitoring systems and ethical guidelines for AI-generated content can help safeguard against disseminating misleading information. Educators and developers must collaborate to integrate these solutions, ensuring AI tools enhance learning experiences while maintaining integrity and factual correctness. This approach addresses the immediate concerns of content quality and lays the groundwork for responsible and ethical AI use in education.

## **5.2 Ethical and societal concerns**

Integrating AI into education requires careful consideration of ethical implications, especially in contexts where comprehensive governmental regulations may not fully address the rapid advancements in AI technologies [51, 52]. A pivotal concern is finding a harmonious balance between leveraging the benefits of AI-driven educational tools and safeguarding student privacy. The effectiveness of these tools largely depends on their ability to analyze extensive datasets, which poses significant questions regarding how student information is utilized. Educators, therefore, bear the critical responsibility of rigorously evaluating AI technologies before their implementation. This entails thoroughly examining the ethical frameworks governing AI tools to ensure they are in harmony with the core values of educational institutions. It also involves fostering collaborative efforts with administrators, parents, and other stakeholders to create a unified set of ethical standards. Additionally, educators must implement robust mechanisms for continuous assessment to ensure that AI applications consistently enhance the educational experience without detracting from it. This commitment includes ongoing professional development to stay informed on the evolving challenges and technological progress in AI's role in education.

An ethical approach to integrating AI in education further includes considerations of accessibility and equity. It is imperative to guarantee that AI's incorporation into the classroom does not deepen existing educational inequalities. Effective strategies must be established to ensure equitable access to AI technologies, aiming to reduce the achievement gap and prevent the expansion of the digital divide. This inclusive approach guarantees that students from diverse backgrounds can equally benefit from the innovations in educational technology [53]. Moreover, integrating a human-in-the-loop system is crucial to complement AI's capabilities [54, 55]. This provides a mechanism for human oversight that ensures AI-driven decisions are appropriate and ethical. This human presence facilitates more accurate and context-aware responses and introduces an essential layer of accountability and transparency in AI applications in education.

Artificial intelligence (AI) systems can inherit and amplify biases present in their training data or design. In an educational context, this could lead to unfair treatment of students based on race, gender, socioeconomic status, or other factors.

Incorporating mechanisms for human feedback is vital for identifying and eliminating biases and inaccuracies within AI systems. Educators and users should be empowered to report and correct biased information and errors, thereby improving the reliability and fairness of the system. This feedback loop is essential for cultivating an AI ecosystem that is both reflective and responsive to the diverse needs and values of its user base, promoting an educational environment that is equitable, inclusive, and grounded in ethical principles.

### **5.3 Environmental costs**

Training large-scale generative AI models' computational and environmental costs are considerable [56]. These models require extensive computational resources, leading to significant energy consumption and carbon dioxide (CO<sub>2</sub>) emissions. These models have demonstrated remarkable performance in various natural language processing tasks. Still, their increasing size has posed challenges for deployment and raised concerns about their environmental and economic impact due to high energy consumption. As the field progresses towards more complex and capable models, managing these costs and their environmental impacts is crucial. In the educational sector, this presents an opportunity to integrate discussions about sustainable AI practices into the curriculum, fostering a generation of students who are not only technologically proficient but also environmentally conscious.

Fortunately, scientists have achieved a breakthrough by proposing small language models (SLMs) and recent 1-bit LLMs [57–60]. An SLM refers to a version of a language-processing AI with fewer parameters than larger models. In machine learning and AI, parameters are the parts of the model learned from the training data and determine the model's behavior. Smaller language models are designed to be lighter and more efficient, making them easier to deploy on devices with limited computational resources, such as mobile phones or embedded systems. While they may not achieve the same level of performance or accuracy as larger models on complex language tasks, small language models can still understand and generate human-like text, perform classification tasks, and more.

## **6. Conclusions**

This chapter delves into the technological underpinnings, diverse applications, challenges, and ethical considerations of integrating generative artificial intelligence into educational systems. It comprehensively explores how GenAI can enhance personalized learning, streamline administrative tasks, and offer innovative teaching and assessment tools while highlighting the need for a critical approach to ensure accuracy and equitable access. The chapter emphasizes the transformative potential of GenAI in education, from improving student engagement and learning outcomes to fostering professional development and addressing the digital divide.

In particular, GenAI holds great promise for education through personalized learning, automated content generation, virtual tutoring, language learning, creativity enhancement, and automated assessment. However, it also underscores the importance of addressing the imperfection and environmental impact of GenAI technologies and the necessity of continuous evaluation and adaptation to leverage GenAI responsibly and effectively in educational contexts. Effective implementation requires seamless integration of GenAI into existing curricula, training of teachers,

addressing ethical concerns, design with a focus on student needs, and continuous evaluation of the impact on educational outcomes.

Additionally, it addresses ethical concerns and the necessity for robust policy frameworks to ensure equitable access and prevent misuse of AI technologies in education. The authors emphasize the aim of guiding educators and policymakers in making informed decisions to leverage GenAI to improve educational outcomes and foster a more inclusive, adaptive, and future-ready learning environment.

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## Chapter 3

# Artificial Intelligence for People with Special Educational Needs

*Esmaeil Zaraii Zavaraki*

### Abstract

Artificial intelligence have very high capacities and capabilities in special education and have been strengthened and upgraded compared to the past. Especially in the field of education, teaching and learning, remarkable progress has happened and is happening. There are examples of artificial intelligence based on assistive technologies that can help people with special educational needs access and interact with educational content. In this chapter of the book, the opportunities and capabilities of artificial intelligence for people with special educational needs, particularly in teaching and learning process, have been introduced and analyzed. The types of assistive technologies based on artificial intelligence for disabled people have been explained. Also, in this chapter of the book, considering the importance of approaches and educational design models in the teaching and learning process of people with special educational and learning needs, the blended learning approach and model in special education have been introduced and its basic components and sub-components have been explained. At the end of the chapter of the book, case studies that have been done by author or by author's supervision in this field have been mentioned.

**Keywords:** special education, educational technology, assistive technologies, artificial intelligence, special teaching and learning

### 1. Introduction

Perhaps the following classification of types of education and training can be provided:

- General or regular Education
- Special Education
- Organizational Education/Training
- Adult Education
- Lifelong learning and continuous professional development

What is meant from the types of education and training mentioned in this chapter of the book is special education. Special education is the study and practice of educating students in a way that adapts their individual differences, disabilities, and special needs. In other word, Special education is the study and ethical application of best practices to improve learning and performance of people with special educational and learning needs through the special strategic of analysis, designing, developing, production, implementation, management, support, assessment and evaluation of learning and instruction processes and resources [1]. Special education aim is to provide adapted education for people with special educational needs such as mental retardation, visual impairment, hearing impairment, physical-motor impairment, learning difficulties, emotional-behavioral impairment, speech-communication impairment, special diseases, multi handi-capped and talented and gifted [2]. Some scholars of education may categorize gifted education under the umbrella of “special education”. Although there are still differences of opinion in this field. People with special educational needs include a wide variety of people with different cognitive, physical, emotional and behavioral learning needs.

New learning approaches such as blended learning approach and new technologies such as artificial intelligence have changed the fundamental nature of teaching - learning process particularly in special education areas. They have made possible learning activities that were not previously practical or feasible. A blended learning environment provides opportunities for the students with special educational needs to interact with their teachers and content. Various researchers have noted that there are limited studies investigating learning through blended learning approach among students with special educational needs [1, 3–12]. According to Allahi [13], Jangizehi [14], Mathews [15], Stamer [16], Toofaninejad [17], Moradi [18], Zaraii Zavaraki & Schneider [11], Zaraii Zavaraki [1], and Linda [12], blended learning approach and new technologies have some potential for special education teachers and their students.

## **2. Artificial intelligence in education**

Artificial intelligence is the theory and development of computer systems capable of performing tasks that historically required human intelligence, such as recognizing speech, making decisions, and identifying patterns.

Some of Artificial intelligence applications are:

- Advanced web search engines
- Recommendation systems
- Understanding human speech
- Generative or creative tools
- Competing at the highest level in strategic games

The traits described below have received the most attention and cover the scope of AI research:

Reasoning, problem-solving, Knowledge representation, Planning and decision making, Learning, Natural language processing, Perception, Robotics, Social intelligence, General intelligence.

Artificial Intelligence technology is used in most of the essential applications, including:

- Search engines
- Targeting online advertisements, recommendation systems
- Driving internet traffic, targeted advertising
- Virtual assistants
- Autonomous vehicles
- Automatic language translation
- Facial recognition
- Image labeling

The rapid development of Artificial Intelligence is having a major impact on all of areas of educational systems. Advances in AI-powered solutions carry enormous potential for the achievement of the sustainable development goals. Artificial Intelligence has the potential to address some of the biggest challenges in education today, innovate teaching and learning practices, and ultimately accelerate the progress towards sustainable development goal 4, quality education. Sustainable Development Goal 4 aims at ensuring inclusive and equitable quality education and promote lifelong learning opportunities for all [19]. Over the past decade, the use of AI tools to support or enhance learning has grown exponentially [20]. This has only increased following the COVID-19 school closures. However, evidence remains scarce on how AI can improve learning outcomes and whether it can help learning scientists and practitioners to better understand how effective learning happens [21]. AI applications designed for education have been divided into three main categories: system-facing, student-facing and teacher-facing [19]. However, for policy-makers, UNESCO propose a set of four needs-based categories of emerging and potential applications:

- Education management and delivery
- Learning and assessment
- Empowering teachers and enhancing teaching
- Lifelong learning [19].

Educational chatbots, OU Analyze, Swift, The ALP, The UniTime, Intelligent tutoring system, Dialog-based tutoring systems, Exploratory learning environments, Automated writing evaluation, AI-supported reading and language

learning, Smart robots, Teachable agents, Educational virtual and augmented reality, Learning network orchestrators, AI-enabled collaborative learning, AI-driven discussion forum monitoring, AI-human ‘dual teacher’ model, AI-powered teaching assistants, AI-driven lifelong learning companion, AI-enabled continuous assessment, AI-enabled record of lifelong learning achievements, and opportunities for AI to advance inclusion and equity in education are some of applications of AI in education [19].

## **2.1 Artificial intelligence in special education**

Artificial intelligence and its applications in the process of education, teaching and learning of people with special educational needs have been proposed at the global level under the two keywords of inclusive education and assistive technologies. In the continuation of this chapter, the inclusive education and then the assistive technologies have been introduced and explained.

### *2.1.1 Opportunities for artificial intelligence to advance inclusion and equity in education*

In addition to focusing on equitable access to Artificial Intelligence technologies for all, we also need to consider the potential of Artificial Intelligence to help achieve SDG 4, to help ‘ensure inclusive and equitable quality education and promote lifelong learning opportunities for all’ [22].

In this challenging context, many Artificial Intelligence technologies might be used, or further developed, to help improve education – especially for older people, refugees, marginalized or isolated communities, and people with special educational and learning needs. To begin with, the UNESCO’s ROAM framework (‘Rights, Openness, Access and Multi-stakeholder Governance’) should be applied, to ensure that the application of Artificial Intelligence in education addresses broader human rights and emerging ethical issues in a holistic manner [23].

For example, and in particular, Artificial Intelligence in education should be made accessible to all citizens, especially for vulnerable groups such as students with learning disabilities), without exacerbating existing inequalities.

Some of examples of Artificial intelligence applications for inclusion and equity in education are:

- The Global Digital Library.
- Dydetective, an AI-powered screening tools.
- AI-powered artificial voices.
- AI and augmented reality applications.
- AI-enabled ‘smart’ robots,
- Telepresence robots.
- AI-powered intelligent tutoring systems.

### *2.1.2 Assistive technologies based on artificial intelligence*

Assistive technologies are tools, devices and services that help people with special educational needs to achieve better functioning and independence at home, school and community. Assistive technologies have high capacities due to the potentials of artificial intelligence and have been strengthened and upgraded compared to the past. Especially in the field of special education, teaching and learning, remarkable progress has happened and is happening.

There are examples of AI-based assistive technology that can help people with special educational needs access and interact with educational content. Some of these examples are:

- **Speech recognition software:** This technology uses artificial intelligence to convert spoken words into written text. This can be especially helpful for students with physical–motor impairment who may have difficulty typing or writing by hand.
- **Text-to-speech software:** This technology uses artificial intelligence to convert written text into spoken words, making digital content easier to access and understand for students with visual impairments or learning disabilities.
- **Augmentative and alternative communication devices:** These devices use artificial intelligence to help students with communication disorders to express themselves. They may include features such as speech synthesis, predictive text, and eye tracking to help students communicate more effectively.
- **Virtual assistants:** Artificial intelligence-based virtual assistants such as Google Assistant can be used to help students with special educational needs access information, complete tasks, and interact with digital devices using voice commands. Chat GPT as an assistant is another example that has been in use in recent months.
- **Adaptive learning software:** This technology uses artificial intelligence to personalize learning experiences for students, adapting content and activities to their unique needs and abilities. This can be particularly useful for students with learning disabilities or other special needs who may need different types of support to learn effectively.
- **Computer vision technology:** This technology uses artificial intelligence to interpret the visual input from the camera. It can be used to help visually impaired students navigate their surroundings, recognize objects, and read printed materials. For example, a computer vision system can be used to read text aloud to a visually impaired student or to identify and describe objects in the student's environment. The Horus system is an example of this technology. The Horus system has integrated capabilities such as routing and independent movement during game activities, being aware of the location of friends in class and school, text recognition and reading, face recognition and object recognition. This technology has the ability to navigate and identify obstacles in 3D, which helps the safe movement of a visually impaired person, and it also has the ability

to read written text and Braille, which can help a person independently in their education and learning activities.

- **Predictive analytics:** This technology uses artificial intelligence to analyze data and predict future outcomes. In education, it can be used to identify students who are at risk of falling behind or dropping out and provide targeted interventions to help them succeed. For students with special needs, predictive analytics can help educators and caregivers identify patterns and trends in their behavior and performance and develop more effective strategies to support them.
- **Brain-computer interfaces:** These devices use artificial intelligence to convert brain signals into computer commands, allowing users to interact with digital devices using their thoughts. They can be especially useful for students with physical –motor impairment who may not be able to use traditional input devices such as keyboards. For example, a brain-computer interface might allow a student with cerebral palsy to control a computer using their brain signals.
- **Social robots:** These robots use artificial intelligence to interact with humans in social and emotional ways, providing companionship and support. They can be especially helpful for students with autism spectrum disorder, who may have difficulty with social interactions and communication. Social robots can be programmed to respond to facial expressions, body language and other social cues, helping students with autism spectrum disorder develop social skills and build relationships.
- **Virtual Reality (VR), Augmented Reality (AR), Mixed Reality (MR) and Extended Reality (ER):** These technologies use artificial intelligence to create immersive and interactive digital environments. They can be used to provide students with special educational needs hands-on learning experiences that may not be possible in the physical world. For example, a virtual reality simulation can allow a student with physical –motor impairment to explore a historical site or laboratory, while an augmented reality application can provide visual and auditory feedback to a student with autism spectrum disorder educate during a session social skills.

Overall, AI-based assistive technology has the capacity to change the way students with special needs are supported. Using the power of machine learning and other artificial intelligence techniques, we can create more effective and personalized tools and interventions to help these students learn, communicate, and thrive.

Elon Musk's company has obtained the license to implant a chip in the human brain. Neuralink announced that it has received approval from the US Food and Drug Administration to conduct the first human trials of its chip. The company says it wants to help restore sight and mobility to the disabled by connecting the brain to a computer.

One of the important missions of educational technologists and learning specialists is to identify emerging technologies and introduce their strengths, weaknesses, opportunities and threats in the process of education, teaching and learning. In the meantime, it is very important to discover the platforms and how to use these technologies intelligently and effectively to improve education and learning. One of the emerging technologies that has emerged in recent years is Metaverse technology,

which may be called Farajehan technology in Persian. It seems that this technology has considerable capacities and platforms in improving the teaching and learning process. Whether it is normal education, special education, organizational internship, adult education, continuous learning, lifelong learning, and professional development, which requires extensive research. Metaverse is a multi-user environment that integrates physical and virtual reality. Virtual reality, augmented reality, mixed reality, extended reality, recording of daily activities of a person using a digital device<sup>1</sup> and mirror world can be considered among the Metaverse technologies that have wide applications in the process of education, teaching and learning, especially for people with special educational needs. Computer, network, game console, headset and virtual reality glasses, mixed and augmented, virtual reality gloves are some of the necessary tools to use this technology. Some of the advantages that Metaverse technology has in the teaching and learning process are: establishing educational justice, experiencing comprehensive interaction, visualization, increasing participation, reducing costs, continuous improvement, unlimited time and space, fast sharing, personalization and strengthen communication. It seems that we need more researches at the national and international level to discover more of this emerging technology [24].

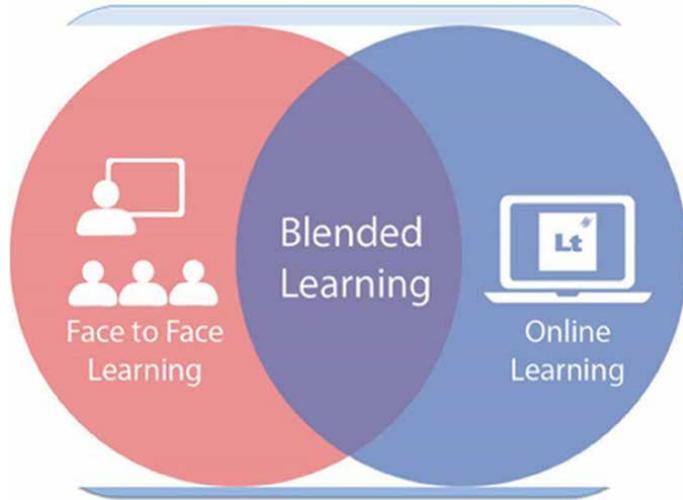
## 2.2 Blended learning approach and models

In the process of education, teaching and learning, we need pedagogy, andragogy and heutagogy to take advantage of the capacities of any type of technology, including artificial intelligence technology. Therefore, choosing the right approach and models in this field is very necessary and vital. Without having a suitable approach and model, we will not be able to make the most of the capacities of technology, especially new and emerging technologies in education, especially in the education of people with special educational needs. Therefore, in the rest of this chapter, we will discuss the blended learning approach and its conceptual and procedural models.

Blended learning refers to the systematic integration of online and face-to-face engagement to support and enhance meaningful interaction between students, teachers and resources [25]. Blended learning gives students with special educational needs the benefits of both online learning and in-person instruction. According to Christensen, Horn, and Staker ([26], p. 9), blended learning is defined as: “a formal education program in which a student learns at least in part through online learning with some element of student control over time, place, path, and/or pace and at least in part at a supervised brick-and-mortar location away from home. The modalities along each student’s learning path within a course or subject are connected to provide an integrated learning experience.” Students in formal blended learning educational programs learn online part of the time, yet have the benefit of face-to-face instruction and supervision to maximize their learning and to best fit their own needs ([27], p. 5).

Blended learning may also allow teachers to spend less time giving whole-class lessons, and more time meeting and interacting with students with special educational needs individually or in small groups to help them with specific concepts, skills, questions, or learning problems (**Figure 1**, [1]). In blended-learning situations, students with special educational needs are required to use digital and online technologies and they naturally acquire more technological literacy and greater confidence using new technologies, which is very essential in twenty-first century life and in future [11].

The author of the chapter, made extensive efforts to design and develop the educational model based on blended learning approach for students with special



**Figure 1.**  
*The conceptual learning model based on blended learning approach for students with special educational needs [11, 28].*

educational needs. According to **Table 1**, 6 main components and 49 sub-components were found. These components underneath the umbrella of two other infrastructure components were considered as face-to-face learning and computer and network-based learning. First, a conceptual model that included all of the main components was designed and then the procedural model was designed and developed by the investigator. The conceptual model and the procedural model showed in the **Figures 2** and **3**.

According to the **Figure 2**, 6 main components of the educational model based on blended learning approach for students with special educational needs are: analysis, designing, production, implementation, management and support, assessment and evaluation and revision and modification were obtained. These six main components underneath the umbrella of two other infrastructure components were considered as face-to-face learning and computer and network-based learning.

According to the **Figure 3**, 49 sub-components of the educational model based on blended learning approach for students with special educational needs are:

goal, learner, teacher, the content, media, message, environment and learning space, educational resources and learning resources, technology, the context, the combination of learning theories, purpose, environment and learning space, methods, strategies, media, message, technology, principles of universal design, presence, learning activities, measurement techniques, technology, media, training, material, guides, enrichment, interaction, participation, access, engagement, facilitate, coordination, presence, cooperation, learner support, teacher support, course support, portfolios, self-assessment, peer-assessment, teacher-assessment, intelligent assessment, diagnostic evaluation, formative evaluation, summative evaluation, follow up evaluation, evaluation of learners' interaction.

As showed in **Table 1** and **Figure 3**, each of the sub-component including several minor sub-components. For example, the sub-component of learner including minor sub-components of mental retardation, visual impairment, hearing impairment, physical-motor impairment, learning difficulties, emotional-behavioral impairment,

| Row | Components                             | Sub-components   |
|-----|--|--|
| 1   | Analysis                               | Goal, Learner (mental retardation, visual impairment, hearing impairment, physical-motor impairment, learning difficulties, emotional-behavioral impairment, speech-communication impairment, special diseases, talent and gift), Teacher, The content, Media (interactive, non-interactive), Message, Environment and learning space, Educational resources and learning resources, Technology (print, visual, audio, audio-visual, computer-based, network-based, technology integration), The Context (social, cultural, economic, political).  |
| 2   | Designing                              | The combination of learning theories (Behaviorism, Cognitivism, Constructivism, and Connectivism), Purpose (general, partial and behavioral), Environment and learning space, Methods (based on class, computer-based, multimedia-based, social media -based, web-based), Strategies (educational, learning), Media (interactive, non- interactive), Message, Technology (print, visual, audio, audio-visual, computer-based, network-based, technology integration), Principles of universal design (fair use, flexibility of learning activities in use, simple and direct, comprehensible information, Tolerance against errors, Low physical effort, Space and size for use, community of learners, educational atmosphere), Presence (cognitive, teaching, social, emotional), Learning activities (based on information and communications technology, without information and communications technology, based on artistic, individual and group activities), Measurement techniques (self-assessment, peer evaluation, teacher assessment, portfolio, intelligent evaluation). |
| 3   | Production                             | Technology (print, visual, audio, audio-visual, computer-based, network-based, gaming, simulation, augmented reality, virtual reality, technology integration), Media (interactive, non- interactive), Content (textbook, tuition, announcement, newsletter), Training, material, Guides (Teacher's guide, Learner's guide, Parent's guide, Tutorial assistant guide).   |
| 4   | Implementation, Management and Support | Enrichment, Interaction (learner - teacher, learner-learner, learner-content)<br>Participation (learner, teacher, parent, assistant, manager, therapist, counselor, social worker), Access (limited to the classroom, limited to school, unlimited, throughout the day), Engagement (question and answer, discussion, activity, observe, report presentation), Facilitate, Coordination, Presence (cognitive, teaching, social, emotional), Cooperation, Learner support (administrative, service, advisory, medical, therapeutic, educational, technical), Teacher support (educational, administrative, service, professional, specialized), Course support (educational, technical).  |
| 5   | Assessment and Evaluation              | Portfolios (traditional, electronic), Self-assessment, Peer-assessment, Teacher-assessment, Intelligent assessment, Diagnostic evaluation, Formative evaluation, Summative evaluation, Follow up evaluation, Evaluation of learners' interaction (in the learning environment, in the learning Space. (  |
| 6   | Revision and Modification              | Revision and Modification of the teaching – learning process.  |

**Table 1.**  
*Component and sub-components of educational model based on blended learning approach for students with special educational needs [1].*

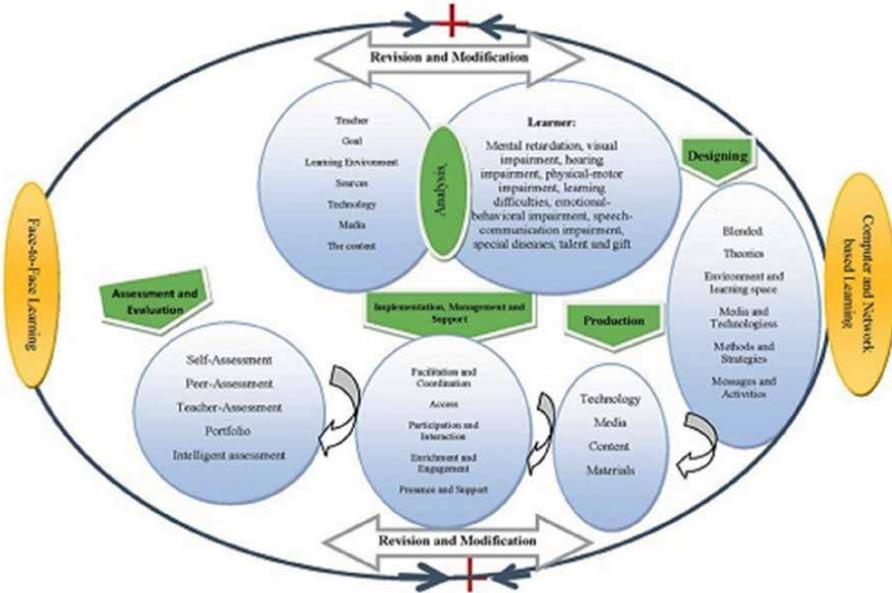


Figure 2. The conceptual learning model based on blended learning approach for students with special educational needs [1, 28].

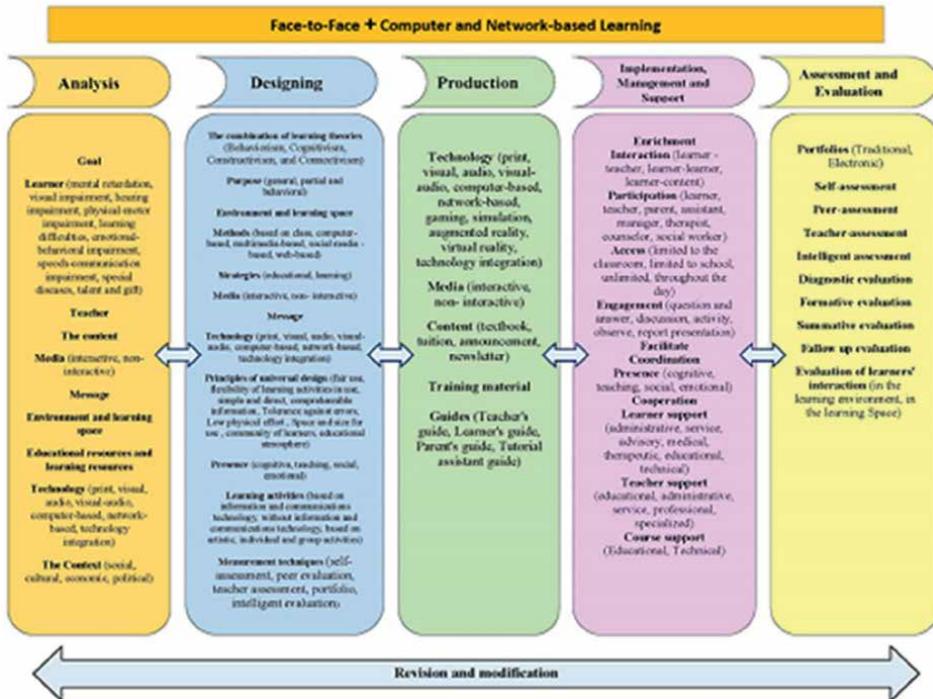


Figure 3. The procedural learning model based on blended learning approach for students with special educational needs [1].

speech-communication impairment, special diseases, talent and gift, and the sub-component of learner support including minor sub-components of administrative, service, advisory, medical, therapeutic, educational and technical support [1].

### **2.3 Case studies**

To check the validity of the blended learning approach and its models in special education, several researches were designed and implemented by the author of the current chapter of the book or with his supervisor in the last years. In the rest of this chapter of the book, some of these researches are mentioned.

Allahi [13] conducted a research entitled “design and validation of a mobile phone learning pattern for visually impaired students”. The aim of his study was to design an educational model of using a mobile phone and its effects on academic achievement motivation, learning and participation ratio of blind students in English courses. He developed an educational conceptual model of using the mobile phone for blind people with 4 components of human, training, technology and support factors as well as a procedural model with 4 stages of preparation, design, implementation and evaluation.

Toofaninejad [17] conducted a research entitled “designing instructional pattern of the learning environment enriched by virtual social network and its impact on learning rate and the social skills of the students with hearing impairment in science course”. He discovered 7 final categories including engagement, interaction, feedback, content, sources, evaluation, and support. He also were extracted 24 sub categories. Based upon discovered categories, a conceptual model was designed that is encompassed all mentioned categories. Next, procedural model, which it is a practical model, was designed and developed. The investigator also showed that the instructional pattern of the learning environment enriched by the virtual social network by 99% of confidence interval has a positive effect on learning and social skills of DHH students.

Zareei [29] conducted a research entitled “design and validation of virtual social networks of Iran’s schools”. He discovered four main components of the model including network learning, network facilitation, network management, network technology, and the following sixteen sub-components: information valuation, content co-creation and reproduction, interaction, self-assessment and peer-assessment, excitement, learning support, process evaluation, empowerment, learning analytic, network information, network content, network interaction, network evaluation.

Moradi [30] conducted a research entitled “design and validate an educational model based on assistive technology and its effect on the amount of motivation for academic achievement, learning and academic satisfaction of students with physical-motor impairment in English language lesson”. He discovered five important components of analysis, design, production, implementation, support and evaluation. Also, 34 sub-components were extracted for the main components. The researcher designed and developed a conceptual model and the procedural pattern. Also, the results showed that the educational model based on assistive technology for teaching English language lesson for students with physical-motor impairment is effective.

Zaraii Zavaraki and Schneider [11] conducted a research entitled “blended learning approach for students with special educational needs: a systematic review”. The analysis revealed that approach, environment, learner, tools, support and evaluation are categories of extracted in blended learning approach for students with special educational needs. The elements of each category are introduced and explained in

the article. However besides presenting the evidence found in literature, our analysis highlights that researching the effect of blended learning approach on special educational needs students remains an under-explored area of study. Further well-designed research into the use of blended learning approach in special education is therefore needed.

Zaraii Zavarakhi [1] conducted a research entitled “designing and validating of blended learning model with emphasis on digital technologies for students with special educational needs”. The purpose of this study was to design and validate an educational model based on blended learning approach for students with Special Educational Needs. A mixed method in a type of the exploratory was used. To obtain the components of the model, an inductive content analysis was performed and for internal validity of the model, descriptive survey method was used. First, a conceptual model that included all of the main components was designed and then the procedural model was designed and developed. Findings of internal validation from the viewpoint of experts showed that the conceptual and procedural models were considered to be comprehensive, suitable, applicable, enriching, appropriate, promote new educational approaches, can help in the development of educational strategies, suitable and can improve the quality of teaching and learning processes of students with special educational needs at the international level. Therefore, it is suggested to use these models as innovative strategies for students with special educational needs.

Delavaryan [31] conducted a research entitled “designing a technology-based instructional program for teaching English to mentally retarded students and its impact on academic achievement motivation, learning and retention”. The collected data were analyzed in multi-variable MANCOVA method. The results of statistics analysis showed that the technology-based instruction has caused a meaningful increase in academic achievement motivation of experiment group students and also the development and improvement of their learning and retention in English Language Lesson.

Khateri [32] conducted a research entitled “the impact of augmented reality technology on academic achievement motivation and learning of second-grade dyslexic students”. In this study, the sample size was 20 students divided into experimental and control groups. At first, a pre-test learning and academic achievement motivation is taken from both groups and then an Augmented Reality Program was used for the experimental group. The results show that augmented reality utilization improve learning and academic achievement motivation the students with dyslexia disorder.

Ghasemi Sameni [33] conducted a research entitled “designing and validating of instructional model in computer game environment and its effect on cooperative learning of high-functioning autism students”. Once content analysis and code extraction had been completed, the components and sub-components were provided in the form of a model. A conceptual model was constructed accordingly. Then, a procedural model was developed. It was found that the difference between the experimental group and control group in cooperative learning and its components (positive interdependence, individual accountability, group processing, social skills, and interaction) was significant after weighting the pre-test scores. Therefore, it can be said that the instructional model in computer game environment had a significant effect on the cooperative learning of high-functioning autistic students.

Masnavi [34] conducted a research entitled “Design and validation of a model of mobile multimedia learning environment and its effect on learning and learning transfer of social skills of students with high-performance autism spectrum disorder”.

Quantitative and qualitative research methods were used to conduct the research. The results showed that the program designed based on the model of mobile multimedia learning environment was effective on learning and learning transfer of 3 subjects and had an effect on one subject learning but on his learning transfer did not have. Using these results, it can be said that the use of the proposed mobile multimedia learning environment model was effective on learning and transfer of learning, learners with autism spectrum disorder with high performance.

Bakhtiarvand [35] conducted a research entitled “designing and validating an instructional model of picture exchange communication system based on technology and investigating its effectiveness on social and communication skills and behavioral problems in children with high-functioning autism disorder”. Mixed research method was used to conduct the research. Using these results, it can be said that the use of the proposed educational model of technology-based PECS is effective on social and communication skills and reducing the behavioral problems of high-functioning autistic children.

Kabiri [36] conducted a research entitled “designing and validating of educational model for applying technology in philosophy program for children and its impact on the critical thinking of gifted students in the second period of elementary school”. In order to achieve the goal of the research, a mixed method of sequential exploratory type was used. The results obtained from the data analysis related to the research hypothesis showed that after removing the pre-test effect, there was a significant difference between the average critical thinking scores of the two groups in the post-test stage. The results showed that this educational intervention had a positive impact on all the components of critical thinking. According to the results of the research, it can be said that the educational model for applying technology in the philosophy program for children is effective on the development of critical thinking of gifted students in the second period of elementary school.

Ghanat [37] conducted a research entitled “the effect of computer game on the recognition of facial emotions in students with hearing impairment in the elementary school of Arak city”. In this study, the experimental group received 12 sessions of the Emotion Sorting computer game, which was designed for this group of children with the aim of improving facial emotion recognition skills and in accordance with the pattern and principles of game design. On the other hand, in the control group, it was done in the usual way. The results of this study showed that the emotion matching computer game with the aim of recognizing facial emotions in the four levels of discrimination, naming, selection and matching was effective in children with hearing impairment and improved this skill, the most impact being on the emotion matching component with 71% was. The results of this study can provide important information about the effectiveness of computer games as a tool to improve cognition and emotional understanding in children with hearing loss. This information can be used to guide the development of interventions and programs to improve the social and emotional well-being of children with hearing loss.

Abbas Zadeh Rogoshui [38] conducted a research entitled “the effect of digital educational game on the visual perception of dyslexic first grade students”. The findings showed that the digital educational game has an effect on improving the subjects’ visual perception and all five students were able to identify and write Farsi signs independently after participating in the project. Therefore, it can be concluded that the digital educational game is a new tool with the combination of images, sound and interactive activities in the game environment of the subject, which creates and maintains the focus of learning and the continuity of the signs compared to the

traditional model, and it can be used to improve and learn better Farsi signs benefit students with dyslexia.

Zaraii Zavaraki and Alimardani [28] conducted a research entitled “the role of blended learning approach on interaction process of students with special educational needs”. The purpose of this study was to determine the role of blended learning approach on interaction process of students with special educational needs. The data gathering tool was a questionnaire of 52 items that 51 questions was created according to 7 point Likert scale and 1 question was created according to open-ended question. Three items of this questionnaire were related to the interaction variable and the other items included other variables such as learning enrichment, engagement, participation, facilitation, coordination, sense of presence, cooperation, support, motivation, academic achievement and learning rate. The validity of the questionnaire was evaluated by teachers and its reliability was 0.98 with Cronbach’s alpha. Findings from the viewpoint of teachers showed that the blended learning approach has a great role on interaction process of students with special educational needs.

Faizi [39] study is in progress) Conducting a research titled “designing and validating of learning program using artificial intelligence and its impact on problem solving skills of students with math learning disorder”.

Ahmadi [40] study is in progress) Conducting a research titled “designing an educational program based on social robot technology and its impact on social skills and academic achievement motivation of high-functioning autism spectrum disorder students”.

### **3. Conclusions**

In this chapter of the book, the author tried to introduce the capacities and capabilities of artificial intelligence in education, especially special education, and share its common uses in the process of education, teaching and learning of people with special educational needs with the esteemed readers. Also, to introduce various assistive technologies based on artificial intelligence in special education. Considering the importance of the approach and model in the education process, the blended learning approach and related models were introduced. The case studies that have been done and are being done in the field of artificial intelligence and its applications in special education were also discussed by the author and his research team. It seems that we need more researches at the national and international level to discover more of this emerging technology.

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## Chapter 4

# Impact of Artificial Intelligence in Achieving Quality Education

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### Abstract

This chapter highlighted the impact of artificial intelligence (AI) in achieving quality education. The purpose of this chapter was clearly articulated by investigating the intersection of AI and education by considering its role in educational technology through AI-powered learning management system, personalized learning, virtual and augmented reality among others. The various ways of enhancing teaching methods using AI-driven tutoring systems, adaptive learning platforms, intelligent classroom assistants were constructively considered. Literature review showed the various ways that artificial intelligence have been used in addressing inequality in education by helping to mitigate learning disparities in diverse student populations, overcoming language barriers through AI translation and bridging the digital divide. The challenges and ethical considerations in educational AI system were identified as Bias in AI algorithms and privacy concerns. The various strategies mitigating these challenges relating to AI use in education to achieve quality education were also captured. However, the policy implications and governance regarding AI use in education including international collaboration for standardization to assist in enhancing responsible AI implementation to achieve quality education were also properly presented. The outcome of the investigations showed that with the active collaboration of the major stakeholders in education in its implementation, artificial intelligence has improved the quality of education globally.

**Keywords:** quality education, artificial intelligence, AI-translation, learners, educators

### 1. Introduction

Artificial intelligence has been a topic of interest and has raised curiosity in various disciplines of which education is one of the prime spaces of its applications. Artificial intelligence (AI) is described as the designing and building of intelligent agents which depend on recognition by the senses from the environment and acts in a way that affects the environment. It is a branch of computer science that use algorithms and machine learning techniques to replicate or simulate human intelligence [1]. The Oxford dictionary of phrase and fable further defined artificial intelligence as the theory and development of computer systems which has the ability to carry out tasks that normally require human intelligence, decision making as well as language translations. There are three types of artificial intelligence namely: Narrow AI, General AI and Artificial superintelligence. Narrow AI is the most common and realized form of

artificial intelligence. It is goal-oriented and employs machine learning techniques to actualize a task. General AI is also known as deep AI, it is one that is deemed on par with human capabilities which can discern the needs or emotions of other intelligent beings. While the Artificial Super intelligent is AI which is more capable than humans [2]. AI is considered the most admirable among all other technological revolutions in the world. Quality education describes a holistic educational approach which provides learners with academic knowledge, critical thinking, skills for solving daily problems, creativity and provide them with a sense of social responsibility. Any form of education which is considered quality must be all inclusive, equitable and accessible to all learners, must promote lifelong learning and should be able to prepare its recipients for active participation in the society. Quality education is the basis for individual growth and societal development globally. It provides knowledge for individuals empowering them with critical thinking skills and creativity, encouraging personal developments and learning throughout the individual's life. It helps to create economic opportunities and employment for individuals thereby promoting their income potentials. Quality education speeds up societal progress by promoting social integration, bringing down societal inequality while enhancing the creation of an informed citizenry who are properly engaged. Nations whose citizens have received quality education are better prepared and equipped to address the challenges of poverty, health and environment. Such nations have been known to develop better innovations and adapted favorably to the demands of a rapidly evolving global economy. Quality education has served as the driving force for sustainable development and progress in the society while it shapes and empowers individuals as informed citizens. UNESCO [3] emphasized the global significance of quality education for individual and societal development using the SDG4—Education 2030, Incheon Declaration (ID) and framework for action which states that “For the implementation of sustainable Development Goal 4, ensure inclusive and Equitable Quality Education and Promote Lifelong Learning Opportunities for All”. Hence, the purpose of this chapter, is to explore the impact of artificial intelligence (AI) in achieving quality education.

## **2. Main body**

### **2.1 Impact of artificial intelligence in achieving quality education**

Artificial intelligence has transformed the entire globe, it is important that this chapter provides a brief discussion of the many applications of artificial intelligence across various industries and domains that showcase its versatility in improving efficiency and decisions before giving a detailed description of its impact in achieving quality education. The domains are as briefly discussed below:

- a. *Education*: artificial intelligence has been employed in the education sector to support personalized learning, instructional system, educational analytics, among others.
- b. *Health care*: AI has been found very assistive in disease diagnosis, personalized medicine and drug delivery.
- c. *Finance*: AI is used by financial institutions for detection of fraud, algorithmic trading as well as enhancing services rendered to customers in banks.

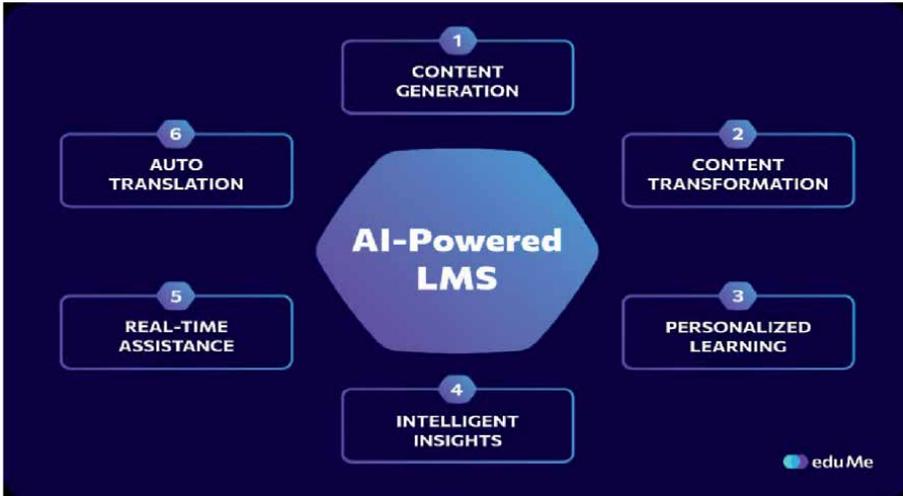
- d. *Retail services*: AI has improved retail services by its ability to enable recommendation systems, demand forecasting and supply chain optimization.
- e. *Autonomous vehicles*: the emergence of self-driving cars and drones for navigation and decision making has been traced back to Artificial Intelligence which powers them.
- f. *Manufacturing*: AI is used in manufacturing for predictive maintenance procedures, quality control as well as process optimization.
- g. *Customer services*: customer support interactions have been greatly improved by the use of Chatbots and virtual assistants.
- h. *Marketing*: AI has improved marketing strategies by assisting in targeted advertising, social media analysis and in customer segmentation.
- i. *Cyber security*: AI is used to detect threats, anomaly detection and to secure digital systems.
- j. *Human resources*: AI helps employers in engaging employees, talent acquisition and workforce analytics.
- k. *Natural language processing*: AI has been used in chatbots, language translations and in sentiment analysis.
- l. *Entertainment*: AI has been employed in games, virtual reality experiences and content recommendation.
- m. *Agriculture*: precision farming, monitoring of crops and prediction of yields has been improved by Artificial intelligence.
- n. *Energy*: AI is employed for smart grid management, preventive maintenance and optimization for energy consumption.
- o. *Legal*: AI assist legal practitioners to review documents, analyze contracts and carry out legal research.

However, in exploring the impact of AI in achieving quality education. It is necessary to look at various areas where AI and education intersect by considering the following subsections:

## **2.2 The role of AI in educational technology**

### *2.2.1 AI powered learning management system*

According to [4], learning analytics can substantially increase the way the field of learning science understands learning both theoretically and practically. Hence artificial intelligence in learning management system through data analysis can optimize content delivery by personalizing learning paths, access learner's performance and improve engagement with adaptive learning techniques.



**Figure 1.**  
*Roles of AI-powered LMS.*

The significant roles played by AI-powered LMS centers around the improvement of content generation and transformation, personalized learning, intelligent insights, real-time assistance, and auto translation as shown in **Figure 1**. Artificial intelligence easily adapts to learners needs and provides contents and feedbacks which are tailored to actualize learning outcomes in the best possible ways. With AI, the teachers are assisted to create more effective lesson plans and assessments.

Artificial intelligence can become a student companion and assistant. This is so because AI understands the strength and weakness of an individual learner. AI has the capacity of analyzing learner's pace and can identify the latent skills in learners which can be used to guide them during the teaching and learning process.

On the part of the teacher, AI can assist the teacher to properly guide the learners, to know the right time for evaluation of their teaching, the type of questions to be chosen for evaluation on a particular topic, the rate of lecture delivery and the choice of topic that will benefit redundant learners. With AI, teachers can quickly outsource their targets and actualize the outcomes set for each learner's performance. There are many examples of AI-powered LMS but a few of them has been described in this chapter.

- *Zavvy*: this is an AI powered LMS which provides features that can be used to create engaging training courses in a very short duration. It assists in course creation, launches workshops and on-demand courses faster than traditional learning platforms. It can handle repetitive basics while allowing more time for the improvement of course content. *Zavvy* platform is used in translating training contents into multiple languages and can help its users manage their courses into one centralized location there by enhancing a course library management, thus bridging knowledge gaps.
- *Paradiso*: this is an AI-powered authoring tool which creates e-learning courses. Its templates help learners generate content, videos, images and presentations to be transformed into training materials. This technology help learners manage instruction design, graphic design, voice-overs, videos and assessments which can be customized for individual learners to enhance their specific development goals.

- *Docebo*: this provides a variety of efficient and customized learning programs with special features which permits learners to create audience specific pages using drag and drop functionality. Docebo encourages customized learning experiences with virtual coaching, content suggestion as well as auto-tagging thereby encouraging personalized learning. This LMS offers gamification, auto assignment of training depending on the required skills of the learners. It also helps learners to streamline non-formal learning and automates learning management. With this platform, various business systems are brought within one learning environment using its over four hundred integrations with the inclusion of web conferencing, payment gateways among others.
- *Cipher learning*: this AI-LMS helps learners create courses and assessments. It encourages personalized learning. Learners can build course outlines, descriptions and content in very many languages. Learner's progress can easily be tracked.
- *Moodle*: this is an online learning management system built on an open-source platform. This is best suited for organizing distance learning in which the learner is privileged to independently choose the sequence and schedule of learning.
- *EdAPP*: this is a mobile learning platform with efficient AI features that can be used for training. With this platform users have their personalized course content, course creation and generation of whole lesson highly simplified. Learners can easily analyze online resources and obtain relevant information within a possible short time frame. Schools and organization employers can use EdAPP to manage training of their employees anytime and from various locations.
- *Absorb LMS*: this is designed for universal learning. With this system, organizations are empowered to train their staff with modern skills to keep them updated and relevant in modern societies. It enables organizations maximize staff efficiency by inspiring learning and increasing business productivity. It is a cloud based LMS which engages learners, enhances content retention and increases training programs.

### 2.2.2 Examples of AI-powered intelligent classroom assistants

- *Squirrel AI*: this is an adaptive learning platform that uses AI algorithms to personalize learning for each learner. It provides tailored recommendations and feedback to improve learners understanding.
- *Edmodo*: this uses AI to provide learners with personalized learning experiences. It offers features such as quizzes, assignments and collaborative tools to enhance student engagement and performance.
- *Brainy*: this is a community-driven assistant that can help learners ask and answer academic question. It uses AI to match questions with relevant answers helping them find solutions quickly and efficiently.
- *Cognii*: this is a virtual learning assistant that relies on conversational technology to assist learners from open resource format. They are designed to provide instant feedback with written responses. It utilizes Natural Language Processing

algorithm to evaluate essays, giving personalized feedback thereby improving learners writing skills.

- *IBM Watson Education*: this assistant provides AI powered solutions for classrooms. Its tools leverage AI to enhance individualized learning experiences, enhancing learning outcomes and optimizing teaching techniques. It provides virtual tutors, adaptive learning systems as well as analytic tools.

### *2.2.3 AI enhances individualized or personalized learning*

This is so because AI can adapt to individual learner's related requirements there by reducing the unproductive works of the teachers and help to increase the quality of teaching and learning.

AI has also improved the grading system used in the educational sector. This has been possible by automating the grading system in multiple choice questions. This has reduced to a great extent time wastage and stress on the part of the teachers.

AI promotes global access to quality education by providing global classroom for learners in every part of the world. The gap of communication between learners and instructors can be comfortably filled by the use of artificial intelligence. Real time subtitles in AI can help blind learners with sight, hearing difficulties and those with different languages to understand and assimilate the learning process effectively. Moreover, AI assists learners from all over the world to connect themselves for brainstorming and further interaction thereby increasing knowledge spread among the students. Vanlehn [5], in an experiment to compare the effectiveness of human tutoring and intelligent tutoring system with other tutoring systems, observed that intelligent tutoring system possess step-based form of interaction while other tutoring systems have answer-based user interfaces. The experiment concluded that the effective size of intelligent tutoring system was as nearly as effective as that of the human tutoring. Hence AI algorithms can be used to customized educational content and learning paths thereby enhancing personalized learning which in turn improves the quality of learning.

AI algorithms analyze large amounts of data to ensure that learning experiences are learner centered and are tailored to the learners needs and preferences.

However, personalization in education using artificial intelligent are reflected in the following aspects which are described below:

- *Adaptive learning platforms*: this provides opportunity for the learner's strengths and weaknesses to be assessed by AI algorithms and the content delivery are adapted to focus on the areas that need to be improved. This ensures that learning pace and style proceeds based on individual learner. Dam [6] showed from his work that the integration of AI methods into adaptive learning system enables it to dynamically adapt feedback, pacing, content and teaching methods to the learners need. According to him, advances in multimodal learning analytics, Natural Language Processing (NLP) and affective computing can improve personalization and adaptability of AI powered learning system. The adaptation is achieved in AI system by analyzing learner's performance, preferences and behavior to dynamically adjust the experience in order to promote an effective learning path. AI performs an important role in adaptive navigation support within educational hypermedia systems. These systems utilize AI algorithms to individualize the learning experience in the following specific ways:

1. *User modeling*: by analyzing learners' preferences, behavior and style of learning, AI creates accurate user models. The knowledge obtained from such models will then be learning used to tailor the navigation suggestions to the learners need.
2. *Adaptive content delivery*: AI helps to evaluate learner's proficiency and adaptive learners' content at a level where the learner finds difficult and makes sure that the instructional materials suit the current understanding of the learner; this ensures the optimization of learning outcome.
3. *Use of AI-powered recommendation system*: this ensures the provision of personalized suggestions for learning paths. This in turn assist learners to navigate through the entire learning content more efficiently thereby improving learning comprehension and engagement of the learning process.
4. *Natural Language Processing (NLP)*: using its NPL ability, AI is able to understand and answer learner's questions correctly. This provides learners with an effective interactive and conversational learning experience.
5. *Provision of instant feedback*: AI provides real-time feedback on the progress of the learner pointing out the learner's area of strength and weakness. Such feedbacks affect the adaptive navigation by moving the learner to the needed instructional content which will address the identified gaps in learning.
6. *Dynamic pathways*: AI has the ability to dynamically adjust the learning path according to the learner's performances. The system can suggest a more challenging material if the learner's performance becomes excellent in a particular area while providing additional support in areas where help is needed.
7. *Continuous learning improvement*: the continuous interaction of the learner with AI system makes it possible for the system to identify the learner and to continuously refine his model, making specific recommendations for him. This creates opportunities for interactive learning which ensures accuracy of adaptive navigation support that is tailored specifically to individual learner.
8. *Intelligent classroom assistants*: AI assistants are used by teachers for routine administrative tasks and classroom management. AI intelligent assistants help by automating administrative tasks, streamlining workflows and enhancing efficiency. These assistants can manage data entry, schedule appointments and routine communications thus allowing human professionals to focus their attention on more complex roles. Thus, saving meaningful time and minimizing human errors associated with manual tasks. In classroom management, AI assistants provide educators with teaching tools to improve their teaching strategies. They can assist with grading and analysis of the learners thereby providing the instructor with the proper insight into the learner's performance. However, it is important to strike a balance in order to prevent over reliance on AI assistance as this may diminish the human touch in education and administration which is extremely needed in order to produce learners with exceptional outcomes.

- *Learning analytics*: artificial intelligence has been used to track the learner's progress. This helps to provide insights as to the learning pattern of each student. This knowledge can be used by instructors to pinpoint learner's challenges, refine the instructional materials/contents and hence can provide adequate and timely help where it is needed to improve the entire learning experience.
- *Automated feedback*: AI algorithms help to generate immediate and automated feedbacks on assignments, quizzes and examinations to enable the learners see and understand where they have made mistakes and correct them. This in turn reinforces the learning objectives.
- *Accessibility and inclusivity*: the various learning needs of the students can be taken care of easily by artificial intelligence which can customize the learning content. The diverse group of learners are considered including disabled learners and those with learning challenges. This enhances inclusivity of all learners in the learning process.
- *Adjustments of learning paths*: artificial intelligence helps to adjust the learning path of the learner depending on his/her progress. This helps to prevent boredom and improves learner's ability to learn.
- *Prediction of learners needs*: based on the historical data of the learner, AI has the ability to predict the future learning needs of the student. This helps the instructor to be very proactive in addressing the learning challenges. This approach helps to fill the gaps in learning and enhances quality education.
- *Cognitive tutoring system*: AI tutoring system encourages individualized interaction with learners. This enables tutors to adapt their teaching strategies to fit individual learning styles. The cognitive tutoring system powered by AI provides real-time assistance and better comprehension and retention by the learners.

#### *2.2.4 Virtual and augmented reality in education*

In describing the role of virtual and augmented reality in creating immersive learning experiences, Dede [7] pointed out that interactive media enable various degrees of digital immersion and that the more a virtual immersive experience is based on design strategies that combine actional symbolic and sensory factors, the greater the participants suspension of disbelief of being inside an enhanced digital setting. He emphasized that immersion in a digital environment enhances quality education by allowing multiple perspectives situated in learning and transfer. Virtual and augmented reality contribute in developing quality education by making available immersive individualized and accessible learning experiences. This is made possible by enabling remote learning and removal of geographical barriers. The availability of virtual classrooms makes possible for experiences to be shared among learners as well as encourage collaborative projects among them. This in effect fosters a sense of global connection among students. Augmented reality offers contextual insights in education by overlaying digital information onto the real world. It has the immense ability of fostering deeper understanding of learners by enriching textbooks with 3D models, audiovisual aids and supplementary information. Virtual reality uses simulated environments to immerse learners into a world of experimental learning. This is

a powerful tool used in producing quality and realistic learning in science subjects or in exploring historical events.

### *2.2.5 Enhancement of teaching methods by artificial intelligence*

Teaching methods have been greatly enhanced by using AI-driven tutoring systems. The effectiveness of AI tutors in providing personalized assistance to learners cannot be over emphasized. Anderson et al. [8] observed from their experiments using a computer based instructional technology called Cognitive Tutor that the best tutorial interaction style for learners was the one in which the tutor provided immediate feedback with short and direct error messages. They pointed out that tutors worked better when presented as non-human tools. Hence, AI-driven tutor system through the provision of personalized assistance to learners is playing a pivotal role in achieving quality education.

### *2.2.6 Addressing educational inequality with artificial intelligence*

AI has been employed to mitigate learning disparities in diverse student populations. Warschaver and Matuchniak [9] showed that new technologies and digital world can be powerful tools for transforming learning and can be used in several ways to promote equality and justice in the society by providing access to knowledge and improved communication to every one irrespective of their geographical location and socio-economic status. AI has been classified as one of the latest technologies and the most admired among them which can be used to address educational inequality globally. By providing personalized and adaptive learning experiences which are tailored to individual learners, by analyzing diverse learner's data, discovering learning gaps and offering targeted exercises, assisting instructors in creating inclusive learning contents that takes care of varied learning styles, diverse cultures and languages, AI provides an equitable educational environment for learners which in turn helps to achieve quality education.

### *2.2.7 Overcoming language barriers through AI translation*

AI has played vital roles in breaking language barriers and promoting inclusivity in an attempt to improve the quality of education. For instance, AI-driven translation tools facilitate multilingual communication, empowering both teachers and students to easily access teaching and learning resources in their native languages. AI powered language learning platform personalize instructions adapting to the learner's proficiency levels and styles thereby contributing to a more inclusive and effective educational experiences. AI-driven language translation tools enable learners and instructors from diverse nations of the world and languages to collaborate on different projects and learn from each other. Agbonika [10], in his findings, reaffirmed that by harnessing the power of AI, the status quo of Northern Nigeria can be disrupted and her educational system transformed, empowering her students to reach their full potential thereby contributing to a more equitable and prosperous future for the region.

### *2.2.8 Bridging the digital divide with artificial intelligence*

AI initiatives are used to improve digital accessibility in underserved communities. The AI-driven mobile apps are used to provide educational resources, bridging the digital divide by offering learning materials to learners who have limited access to traditional

schooling. For areas with limited medical resources, AI-powered Chatbots have been used to make available healthcare information and support. All these initiatives aim at leveraging AI technology to address inequality and improve access to essential services.

### **2.3 Real-world applications and case study success stories of AI in achieving quality of education**

There have been notable instances showing how AI has impacted positively and improved the quality of educational outcomes. Seo et al. [11] conducted a study to determine the impact of artificial intelligence on learner-instructor interaction in online learning by using speed Dating with storyboards to analyze the authentic voices of 12 students and 11 instructors on diverse use of possible AI systems in online learning. Their findings showed that participants envisioned that adopting AI system in online learning can enable personalized learner-instructor interaction at scale though at the risk of violating social boundaries. Their findings have implications for the design of AI systems to ensure explainability, human-in-the-loop, careful data collection and presentation.

Chen et al. [12] conducted a study to assess the impact of AI on education with the scope limited to AI application and effects on administration, instruction and learning, leveraging the use of literature review as a research design. Their study discovered that using AI, instructors were able to review and grade students more effectively and efficiently and achieved higher quality in their teaching activities. The curriculum and learning contents became customized and adapted to the learners needs which improved their learning experiences and overall quality of learning.

In an attempt to explore some real-life examples of how AI was used to improve the quality of education and how students' successes were achieved, [13], described how an AI program developed by a Stanford researcher was used to provide students with assistance when they get stuck in self-paced digital learning. The study tested a machine-learning program that would predict when a student was likely to get stuck and start wheel-spinning as well as the point it would recommend a relevant solution. The training was done by analyzing the performance data from over a hundred school children who had used tablets to learn English reading skills using videos and mini-games. The result showed that the program clearly predicted when a learner would fall into wheel-spinning before the start of a new lesson. His conclusion showed that AI can be used to identify learner's problems and make it easier for a limited number of human instructors to assist a large number of learners.

Hwang et al. [14] proposed an intelligent tutoring system to assist fifth-grade students learn multiplication and division of mathematical units. They found out that students mathematical learning performance and learning motivation was greatly improved by the intelligent tutoring system (ITS) and that AI improved students grades by 30% while reducing their anxiety by 20%.

According to Verma [13], an AI-powered Chatbot called Jill Watson developed by IBM's Watson at the Georgia institute of technology which was employed as a teaching assistant for a course with 300 students produced a 97% success rate in answering ten thousand students' inquiries each semester with a very remarkable human-like efficiency.

The result of the study conducted by [15], with the objective of analyzing the impact of AI components and computational sciences on student performance using web of science (WOS) and Scopus databases showed the positive impact that AI and computational sciences have on student performance. They found a rise in the

students' attitude towards learning and their motivation especially in the Science, Technology, Engineering and Mathematics.

Camesaria et al. [16] conducted a systematic review of literature which focused on the analysis of the application of AI in the assessment of primary and secondary school students through collections of published articles in the most popular databases from 2010 onwards. They concluded that despite the complexity of AI, the potential of AI-related tools to improve the quality of teaching particularly student assessment at lower levels is very high.

## **2.4 Challenges and ethical considerations facing use of AI in achieving quality education**

### *2.4.1 Bias in AI algorithms*

Bias in AI algorithm can stem from biased training data or the algorithm design itself. It is important to identify and address these to ensure that AI applications produce fair and equitable outcomes.

However, the essential factors for mitigating this challenge include the following factors

- Ethical considerations
- Regular audits
- Diverse dataset representation

Bias in educational artificial intelligence algorithms can lead to several challenges. If there is any form of bias in the training data employed in developing the AI algorithm, then it is certain that it will perpetuate and increase the existing inequality in education. This may affect certain groups and lead to unfair advantages and disadvantages. Biased AI algorithms can limit opportunities for certain groups preventing their access to quality education. This can lead to a lack of diversity in educational resources and content. Biased AI algorithms is related to transparency and accountability. However, to mitigate this challenge, a thorough understanding of how AI algorithms make decisions and efforts to ensure that they are fair and unbiased will help to build trust in this educational technology. Moreover, collaborative efforts from educators, policymakers, and developers to mitigate this challenge remains very essential to creating inclusive and equitable educational technologies.

### *2.4.2 Privacy concerns in educational AI*

As AI technology expands across the diverse industries, it opens up a great many privacy concerns thereby putting the traditional norms of personal data protection to many challenges. AI privacy dilemma involves the following main issues:

- The insatiable appetite of AI for extensive personal data to supply its machine learning algorithm has brought about serious concerns regarding data storage, usage and access. These have raised questions regarding data sources, storage and accessibility which the traditional data protection cannot provide answers to. The remarkable ability of AI to analyze and make complex analysis within the received

data poses privacy concerns. AI's potential to infer sensitive information relating to an individual's location, habits and personal preferences, poses risks of unauthorized data dissemination. The fact that AI also has the potential for identity theft and unwarranted surveillance poses a set of worries and challenges that requires proactive attentions. AI developments have given rise to ethical guidelines and best practices to reduce privacy risks and several leaders in industries have risen to address these concerns. Several esteemed bodies have proposed ethical benchmark to which the partnerships on AI (PAI) which is a coalition of leading companies, organizations and persons impacted by AI stand out a cornerstone. By bringing different stakeholders from tech-giants to AI users together, PAI creates a platform that share collaboration between entities that might not typically interact. The aim is to establish a common ground with PAI as a unifying agent for positive change among AI users. Collecting student's data with artificial intelligence has raised several ethical concerns related to privacy, consent and potential misuse of information. Therefore, it is necessary to ensure transparent communication regarding data collection purposes, obtain users consent and implement robust sensitive measures to protect sensitive information. Addressing the challenges of biases in AI algorithms is important to mitigate unfair treatment or discrimination based on student data. Therefore, a balance should be maintained between leveraging on AI for educational advantages while respecting the user's privacy.

## **2.5 Ensuring fair access to AI-enhanced education**

To ensure fair access to AI-enhanced education, the following strategies must be considered in combination:

*Digital inclusion:* access to the necessary hardware and internet connectivity must be provided for all learners.

*Integration into educational content:* AI educational tools must be integrated into the curriculum of the learners in order to expose them to the modern educational technology.

*Training educators:* the educators must be trained on AI tools and methods of use to ensure efficient and effective implementation.

*Equitable distribution of AI tools:* AI tools and resources must be distributed evenly among schools and communities.

*Accessibility features:* AI applications and tools must be developed with accessibility features that can accommodate and sustain the different learning needs of the students.

*Community engagement:* communities must be carried along and included in decision-making to help in addressing local needs and ensure inclusivity.

*Regular assessment:* the need for regular monitoring and evaluation of the impact of AI enhanced education on both the teachers and learners within different geographical locations will help to identify and address disparities.

*Addressing privacy and security concerns:* there must be measures put in place to respect the learner's privacy and security when using AI tools.

## **2.6 Future trends and innovation in educational AI**

### *2.6.1 Emerging technologies in educational AI*

There are many cutting-edge technologies likely to shape the future of AI in education. These cutting-edge technologies possess the potentials of reshaping education by making a more personalized, efficient and adaptive learning experiences. This in turn

enhances a highly advanced era in AI education. The following technologies described below hold the potential to significantly shape the educational AI.

*Brain-computer interface*: commonly abbreviated as (BCIs), can enable direct thought-based interaction with the educational curriculum which in turn could revolutionize learning when there is constant direct communication between the brain and computers.

*Edge AI*: this involves bringing AI processing nearer to the source of data enabling real-time and localized AI applications which is advantageous in constrained environments.

*Neuro-informed learning systems*: this educational approach draws insight from neuroscience to inform the design and implementation of learning experiences. It leverages an understanding of the brain's ability to learn and process data to optimize educational strategies and techniques to enhance individualize instruction, cognitive load management, feedback mechanism, metacognition development among other key elements. AI system could incorporate neuroscientific principles to understand and care for learner's cognitive processes in a much better way.

*Explainable AI (XAI)*: this is the capability of an AI system to provide explanations that are understandable and clear regarding its decisions and actions. The aim of XAI is to make AI systems more accessible and interpretable enabling users to comprehend reasons behind its specific outputs. This applies more in the domains of healthcare and finance where trust is highly needed.

*Block chain for credential verification*: this is an emerging technology in educational AI which can secure and streamline the verification of academic credentials to enhance the authenticity of educational records and to prevent frauds.

*Emotion recognition*: this can be incorporated in the AI systems to help recognize and respond to learners' emotions. This will enhance the learning experience by adapting the curriculum based on the learner's emotional state and provide support when needed.

*Computer vision*: when computer vision is integrated into education, remote learning experiences are encouraged and enhanced. This can be achieved by enabling the AI systems to analyze learners' facial expressions and engagement levels, while providing necessary feedback to the teachers.

*Educational robots*: robots which are designed with AI has the potentials of providing interactive learning experiences and they can help with important learning tasks such as language learning, coding and problem solving.

*Federated learning*: this is a decentralized educational approach which allows AI models to be trained across multiple servers or devices without the exchange of raw data. This helps to improve security and privacy by localizing student's sensitive data.

*Quantum Computing*: this computing system has the potential of solving complex problems in machine learning and optimization. It is believed that the quantum computing technology can revolutionize the AI application in education.

*AI wearable technologies*: incorporating AI with human wearable devices or other technologies can improve human capacity. This can produce tools or devices that can provide assistants to handicapped or disabled learners and provide additional support in education.

## 2.6.2 Potential disruptions and transformations by artificial intelligence

AI may disrupt traditional educational models and foster innovative approaches. AI has the potential of revolutionizing education by personalizing learning,

automating educational administrative tasks and enhancing innovative pedagogical techniques. AI powered adaptive learning platforms can tailor educational curriculum to individual learners needs promoting better learning. It can automate grading, creating more free time for instructors to concentrate on personal mentorship. AI-driven simulation environments and virtual reality provides immersive learning environments for improving practical skills. However, the challenges associated with AI use relating to ethical considerations, privacy of data and digital divide must be adequately managed to ensure equal accessibility and responsible implementation. Christenson et al. [17] explored the concept of destructive innovation in education. They emphasized the potential of technology instruction to transform traditional educational models. They argued that customizable student-centric approaches can meet diverse learning needs better and challenge established norms. They also described the impact of disruptive technologies on K-12 education and suggested that accepting innovations is the key to addressing the limitations of conventional education.

## **2.7 Anticipated challenges of educational AI and preparation for the future**

Future AI developments may pose several challenges such as described in this chapter. However, addressing these challenges will entail collaborative efforts from researchers, government, leaders in industries and the entire society to ensure that AI technologies are deployed beneficially and responsibly. Some of the anticipated challenges of AI developments for educational use include the following:

1. *Ethical concerns*: AI usage ethical concerns are usually related to bias, transparency and accountability. Experience has shown that ensuring fairness and avoidance of discrimination in AI systems has remained critical challenges.
2. *Redundancy*: AI has the potential of automating the grading system and other administrative tasks in education. However, AI-driven automation could replace and displace jobs leading to unemployment in certain sectors thereby preparing the workforce for new skill requirements which is not very convenient.
3. *Lack of standards and regulations*: the rapid pace of AI development can outstrip regulatory frameworks leading to gap creation in oversight. Therefore, it is important to establish global standards for AI deployment to ensure responsible practices.
4. *Privacy and security risks*: as the vast amount of personal data handled by AI system increases, an equal increase in risk of privacy breaches arises. With this, the possibility of safeguarding sensitive information and preventing unauthorized access becomes an increasing risk.
5. *Dependency and bias*: prolonged and continuous usage of AI system can lead to over reliance and dependency on the system. This factor alongside the bias embedded in AI system can bring about errors in decision making as well as reinforce already existing social inequalities. Nevertheless, there have been ongoing efforts to manage these challenges.
6. *Unintended consequences*: AI systems produces unintended behaviors resulting in consequences that are unintended especially in complex and dynamic

environments. Anticipating and preventing these unintended outcomes has posed significant challenges.

7. *Human-AI collaboration*: it has been a huge challenge to create an effective collaboration between humans and the AI system. This is because all the efforts to do so have resulted in diminishing human autonomy and creating over-dependence on the AI-system. Hence, careful design and implementation is required in order to mitigate this challenge.
8. *Energy consumption*: developing energy efficient AI solutions has been a very big challenge and this has impacted negatively on the environment. This is so because substantial computing power require large amount of energy in training sophisticated AI models. This can be prevented by developing energy efficient AI solutions which are yet to be achieved.
9. *Public understanding and perception of AI*: there has been widespread fear and resistance to AI implementation by the public due to their perceptions and misunderstanding regarding AI and its usage. This has affected the responsible adoption of AI both in education and other sectors. Hence enhancing public perception through proper public awareness campaigns and education regarding AI capabilities and limitations can increase its adoption by the public.
10. *International cooperation*: the global nature of AI development requires that international standards and norm be established to manage all its challenges which are related to ethical standards, data sharing and security issues.

## **2.8 Strategies for addressing potential challenges arising from future AI developments**

In view of the anticipated potential challenges arising from future AI developments; the following strategies have been suggested for educators in order to prepare themselves ahead of these challenges

*Ethical frameworks and guidelines*: ethical guidelines should be developed and enforced in order to address challenges of bias, transparency and accountability. The industrial sector should be encouraged to embrace self-regulation and adhere to ethical standards.

*Training and education of the workforce*: public education awareness campaigns should be launched to enlighten the public on AI technologies and thereby impact on the society. Misconceptions regarding AI should also be cleared by fostering open dialogs with the public.

Educational and training programs should be organized regularly in order to equip the workforce with the required skills relevant to face the AI driven future labor market.

- *Privacy and security measures*: the use of privacy-preserving technologies and encryption in AI applications should be strengthened with strict privacy measures properly enforced.
- *Regulatory policies*: it is important to form clear regulatory policies that can adapt to the rapid pace of AI advancements. Harmonized standards for

AI developments and implementations should be created by international cooperation.

- *Transparency*: transparency in AI algorithms should be advocated and standards for providing explanations for AI driven decisions should also be put in place especially in the critical domains such as in the health care and finance sectors where trust is highly needed
- *Diversity and inclusion*: this can be used to reduce bias in AI algorithms when diversity is promoted among the AI development teams. When proper representations from different and varied backgrounds are included in decision making, then the challenge related to decision-making processes in AI will be addressed.
- *Energy efficiency*: researches geared towards the development of energy efficient AI models and algorithms should be encouraged and developed to address the challenge of energy consumption and its consequent environmental impact. The use of renewable sources of energy in AI data centers should also be promoted.
- *International collaborations*: by fostering international collaboration and global cooperation in the policies and standards of AI, the challenges can be properly managed. Establishing forums or platforms that are internationally coordinated will help to share ideas on the best practices globally.

## **2.9 Need for regulatory frameworks for artificial intelligence in education**

There is a critical need for establishing regulatory frameworks for AI in education to ensure its responsible and ethical use in education in order to achieve quality education. These frameworks provide protection against misuse. This is because regulatory frameworks establish guidelines for ethical development of AI algorithms, usage and data handling. Thus, they foster responsible learning environments and help to prevent bias in education AI.

According to European commission [18], “a framework for trustworthy AI provide guidelines which articulates a framework for achieving trustworthy AI based on fundamental right as enshrined in the charter of fundamental Rights of the European union (EU charter) and in relevant international human rights law”. The commission emphasized that any trustworthy AI is composed of three components which include the following:

1. It should be lawful, complying with all laws and regulations which are applicable.
2. It should be ethical, ensuring adherence to all ethical principles and values.
3. It should be robust both from a technical and social perspective. Indicating that such AI systems should perform in a safe, secure and reliable manner and safeguards should be foreseen to avoid unintended adverse effects.

The following guidelines and best practices among others have been Suggested for maintaining standards in AI applications:

1. *Ethical committee formation*: establishment of ethical review boards or committees is a good practice which will assess the impact of AI and its ethical implications before applying in teaching and learning.
2. *Regular monitoring and evaluation*: regularly monitoring and evaluating of the effects of AI applications on the learners, instructors and the entire educational system will help to predict and identify possible unintended consequences and enable stakeholders to effect corrective measures.
3. *Involvement of stakeholders*: all the major stakeholders in education such as students, parents, educators and the community must be actively involved in the decision-making process in AI education application as this will foster collaborative cooperation and decision making.
4. *Continuous training of stakeholders*: educators and administrators should be provided with continuous training and upgrading to remind them of the ethical considerations, responsible use of AI and potential biases associated with its applications.
5. *Regular audit*: auditing of the AI system should be performed at regular intervals to identify and correct any challenges and concerns. Such regular auditing process will promote any ongoing improvement in AI technology.
6. *Improving accessibility*: there is need to design AI system with more accessibility to learners. This will provide an AI system that is adapted to the personalized needs and ability of the learner.
7. *Incorporation of human oversight*: this will ensure that decisions are made in line with the required ethical standards thus enhancing interventions when needed.
8. *Transparency and explainability*: the AI system when designed and made explainable, enable stakeholders to understand how decisions are made. This in turn promotes accountability and trust.
9. *Informed consent*: it is very important that user's consent be sorted especially regarding sensitive data. It is also very necessary to let the users know and understand how data obtained from them will be handled. This is important for building trust in the AI system.

## **2.10 Stakeholders perspectives on the impact of AI in achieving quality education**

Byers [19] reported on some interviews conducted among educators on their embrace of the usefulness of AI in achieving quality education and its potential problems when used in the classroom. He quoted a high school principal saying that the focus is driven towards how to use AI to elicit better educational experience for the students. The report further described the use of AI in education as an evolving phenomenon at every level of the academia which has made educators and administrators to seek ways of determining program's potential use in the classroom and whether its use could lead to possible forms of cheating, plagiarism or other forms of academic misconducts which are detrimental to students.

The U.S department of Educator's AI main focus has been on how AI permits the educators and their students to experience new forms of interaction, loops of feedback enhancement and how the technology has been making easier the work of the teachers [19]. Commenting further on the positive impacts of AI use in the classroom, the high school principal acknowledged that learning software embedded in AI such as Grammarly, provides help for writing and that other programs such as Magic eraser for image alteration and Tetra can assist in note taking during virtual meetings. He stated that the technology is making people more efficient especially as it applies to teachers creating lesson plans and scoring tests leading to more time to focus on students' school experience.

An interview with a professor of humanities reported by the same author, exposed the fear and notion nurtured by some educators regarding AI technology. The professor questioned information gathered by AI system and who has access to them. He used the phrase "garbage in, garbage out" implying that if the source material for AI is not quality, then the content will not yield quality, and that the education system is running the risk of over trusting in the AI system. Another educator expressed his concern on students use of AI programs such as Chat GPT to complete an assignment, emphasizing that such works often lack the personal touch and author's voice which makes the work original, and that disciplinary measures are not yet in place on how to manage AI use in assignments. He concluded that the inclusion of AI in education may cause him to rethink some of his assignments to ensure the originality of the work.

Ryu and Han [20] studied Korean school teachers' perception of AI education and reported that teachers with experience in leadership recognized that AI would help to improve creativity.

The study carried out by Marrone et al. [21], highlighted an analysis on the students view on the relationship between AI and creativity as four key concepts captured as social, affective, technological and learning factors. According to them, the students with a higher understanding of AI gave more positive thoughts about integrating AI into their classrooms, while those with low understanding of the system expressed fear of AI technology inclusion in education and hence explained that AI could never match human creativity. Nevertheless, the majority of the learners expressed satisfaction for the benefits they enjoyed from AI enhanced and quality education through personalized learning, adaptive assessments and real-time feedback. AI system also facilitated collaborative learning among learners from varied geographical locations, promoted critical thinking and offered diverse educational resources which contributed to a better engagement and holistic environment.

Parental and community involvement in AI educational initiative ensures that AI education is made relevant and accessible to a wide range of learners. Parental involvement plays a crucial role in a child's academic achievement and overall well-being. Parental involvement is a powerful force which shapes the student's academic success, social development and the entire well-being. It creates a supportive and enriching educational environment which empowers the students to reach their full potentials. Recent reports from Tech novation on family interest on artificial intelligence revealed that 86% of parents want new ways to learn critical computing skills outside the traditional classroom in order to provide their children with more guidance on at-home education. With immersive AI curriculum for children and their families, parents learn with their children and help to create AI-based products that solve problems in their communities. Hence, involving parents in the AI education

initiatives helps to create a holistic learning environment for the learners. It also helps in bridging the generational gap in understanding technology as well as fosters parental support for their children. Community involvement in AI education initiatives encourages collaboration, knowledge sharing, diversity and supportive network for the learners. Diverse perceptions from members of the community provides grounds for more initiatives and helps to identify and address local challenges associated with AI initiatives.

### **2.11 Use of AI in addressing language barriers in education**

AI has been a vital tool for addressing language barriers in education by making available the following relevant language resources and services available to both learners and educators.

- *Provision of language translation services:* AI translation tools can assist language translators to point out and correct mistakes, make suggestions, recommend alternatives and provide translation in real-time. AI provides enabling environment for communication among people with diverse languages to understand each other. AI translation tools can augment human translators by providing instant translations of spoken or written content. AI translators work by ensuring that contents are broken down into smaller segments and algorithms are then applied to each segment. This analyzes the content to generate a translation depending on patterns and set rules. AI translators can also improve future translations accuracy and consistency by learning from previous translations. Example of AI translators include: Google Translate, Microsoft Translator and DeepL.
- *Provision of Natural Language Processing resources:* AI provides natural language tools such as google Cloud Natural Language API, Gensim, SpaCy, IBM Watson, Natural language Toolkit, chatbots, search engines among others to help resolve ambiguities in language. The language APP provided by AI can help learners with diverse languages with list of vocabularies, listening exercises, grammar lessons, explanations and interactive language exercises.
- *Language teaching:* AI language Apps are used by teachers to translate texts, generate summaries at various levels. Multilingual learners also use AI tools and platforms to interpret words, construct sentences, write essays, generate communications and learn different language skills. AI enhance language evaluation by providing automated grading and feedback. AI language processing tools and Chatbots provide enhanced immersive language practice. Learners' speech can be evaluated and real-time feedbacks on punctuation, intonation and rhythm can be provided for him/her and the feedback in turn gives the learner the opportunity to improve the speaking skills accurately within the shortest time.

### **2.12 Current policies and regulations regarding the use of AI in education**

Policies and regulations of AI in education differ from country to country and regions, however, irrespective of how these policies differ, some common considerations have been identified which play vital roles in teaching and learning. They are as follows:

*Policies on ethical considerations:* all stakeholders in education must be educated on the ethical use of AI in education. This is important because maintaining student privacy must be considered a primary ethical issue. This is supported by the fact that AI requires data to function and educational AI collects and analyzes sensitive data related to the learner's personal information which must be kept confidential and must not be shared without their consent. Even with consent, it is not right to prompt public models with data which can be traced to the learner.

*Policies on bias and fairness:* all stakeholders in education must be trained to identify and respond to bias associated with AI algorithms appropriately. This is because AI is usually trained using existing database which can lead to bias. Hence educators and learners must be prepared to recognize inaccurate information and racism as well as how to manage them.

*Accessibility and equity:* AI technology must be universal and accessible to all categories of educators and learners irrespective of their location, culture, ability, disability and social-economic status.

*Instructor-learner relationship:* AI technology must not be allowed to replace the human emotional, social and moral components which cannot be exhibited by AI. This relationship is very essential to enhance improve quality of learning in education.

*Policy on balance use of AI:* all stakeholders in education must be trained on the responsible use of AI in teaching and learning. This is because AI technologies use over time can pose the risk of dependency which can lead to hindered critical thinking skills which will affect the cognitive ability of the learners. This will also affect their problem-solving ability which can hinder learning. Hence the policy on maintenance of balance in use of educational AI.

### **2.13 Impact of generative AI on the quality of education**

Generative AI includes all AI systems which has the potential of generating new contents such as written text, images and videos. Examples of Generative AIs include GPT, Pix 2 Pix, Cycle GAN, Style GAN, Text to image synthesis among others. Generative AI has significantly impacted the quality of education in the following ways.

*Analyzing data:* AI algorithms has the potential of analyzing large amount of educational data to point out areas that require improvement, identify patterns and various trends thereby educating stakeholders in education to reach useful decisions and help educators refine their pedagogical strategies.

*Easy accessibility:* generative AI makes it easy for learners to access learning resources irrespective of the category they belong. They help learners with various disabilities with alternative formats in form of text-to-speech features-, audio- and audio-visual descriptors for enhanced quality of learning, this on the other hand makes teaching and learning more inclusive.

*Bridging language barriers:* generative AI provides immersive experiences, language translation and language acquisition for all learners globally. These has helped in bridging the language gap in teaching and learning thereby making teaching and learning experience more qualitative.

*Provision of automated feedbacks:* generative AI provides a tutoring system that enable instant or automated feedback for learners. This in effect provide corrections for errors and provide guidance and support. These tutoring has the potential of augmenting the conventional pedagogy technologies and providing a better understanding of the learning process.

Individualized learning/instruction: generative AI enhances education quality by helping the learners learn at their own pace, according to their specific needs and circumstance, preferences and learning style. This helps to encourage engagement and better comprehension.

*Task management:* generative AI platforms can help instructors to manage their administrative tasks by automating assignment and quiz gradings, managing learners records thereby permitting the teachers to concentrate more on teaching and mentoring of the learners.

*Creation of educational content:* generative AI helps educators and instructors in generating assignments, quizzes, exercises and lesson content preparations and textbooks. This in turn helps him/her to present a very high-quality content to the learners.

### **3. Conclusion**

The emergence and inclusion of artificial intelligence in education has contributed immensely in the achievement of quality education globally and this has benefited all the stakeholders. With AI system integration in teaching and learning content, the learners are better equipped mentally and psychologically with material resources to face learning challenges. The educators are assisted with administrative tasks which affords them the opportunity to attend to other important pedagogical activities. AI in education has given rise to automated grading system, real-time feedback, personalized learning, intelligent classroom assistants, intelligent Tutoring system among other advantages and these have enhanced the quality of education. However, AI system, has posed several challenges related to biases in AI algorithms, privacy concerns, redundancy, over dependency among others. These challenges have been addressed and strategies are being put in place to prepare for future challenges. Hence, AI in education has impacted positively in achieving quality education on a global scale.

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# An Approach to Assist Learners to Build Their Own Curriculum in Personal Learning Environment Context, Based on the AI Concepts

*Belhassen Guettat, Ramzi Farhat and Syrine Karoui*

## Abstract

With the emergence of information technologies and the proliferation and diversification of learning tools, educational institutions have diversified their approaches and resources in order to improve learners' performance and education quality. Thus, they have invested in the learning environments which offer learners' personalization learning possibilities. But this option depends generally on institutional constraints. Considering this limit, personal learning environments (PLEs) have come to allow learners to individually develop their learning environment by selecting the right curriculum, resources, and appropriate activities. This concept is in vogue, especially in the lifelong learning context. Mostly, the setting up of such an environment is not based on educational concepts (choice of objectives, selection of appropriate programs and activities). As a result, we are faced with undesirable situations: learning is not aligned with learner prerequisites; training layout does not align with the content and learner expectations. The question arises: how can learners define their learning objectives, set up their own activities, and follow their training? In this context, we propose an approach to assist learners to build their own curriculum, which is supported by an assisted PLE developed on the basis of artificial intelligence (AI) concepts and using a dynamic questionnaire.

**Keywords:** learning curriculum, personalization, personal learning environment (PLE), lifelong learning, machine learning algorithms

## 1. Introduction

Our contribution consists of defining an approach to assist engineering learners to build their own curriculum without pedagogy prior knowledge and to take autonomous control of their learning. It promotes lifelong learning, which aligns perfectly with the goals of sustainable development (SDGs). Three phases characterize our approach: the first concerns assistance in the identification of learning objectives and the recommend appropriate curriculum, the second will be assistance in the search for appropriate activities to the objectives already set, and the last will be responsible

for maintaining and managing the learner's profile. In this paper, we will only focus on the first phase; the purpose is to build a learner's own curriculum. To do this, a consistent environment must be able to provide assistance to engineering learners to identify and choose their learning objectives. It is based on a dynamic questionnaire that takes into consideration the profiles and feedback learners' information. An educational learning objective according to IMS-LD standard [1] is represented by a couple formed by a concept (C) and a learning level (N): C being a concept belonging to a domain ontology  $\theta$  and N is one among the taxonomic levels in pedagogy [2]. Once the couple is identified, our environment will be able to offer one or more curricula from a curricula corpus issue from different sources: educational and training institutions and other resources (Cloud, OER, Moocs). A classification strategy using unsupervised machine learning algorithms (ascending hierarchical classification also called clustering) will then be applied to recommend appropriate curricula. Before going into the details, it would be appropriate to review the basic PLE theoretical foundations and the related work carried out in this area. We will first start by explaining the PLE concept, the PLE-related work, and then we will present our assistance approach, and subsequently our recommender system. We will end by presenting our experiment, and the results are obtained.

## **2. Theoretical foundations of a PLE**

Personal learning environment can be considered as a concept related to the use of learning technologies emphasizing learner ownership of tools and resources. The questions discussed are how does the learner use technology to manage his/her learning? How is individual activity captured? What are the distinctive characteristics of personal learning environment? This study supports the idea that PLE can be considered as a complex activity system using the activity theory (AT) framework [3].

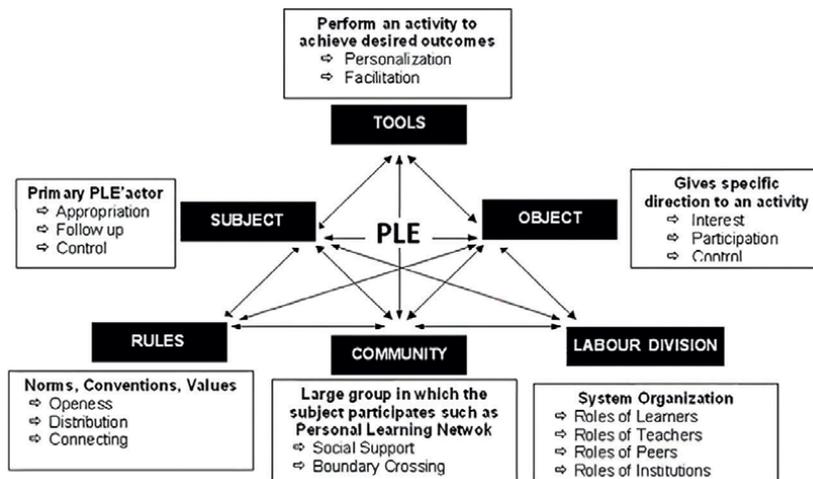
### **2.1 Activity theory (AT) as an integrated framework**

The PLE concept emphasizes the appropriation of tools and resources by learners. The view of learning as a mediation tool or collective activity is the basic principle of activity [4, 5]. Activity theory (AT) has been used as a framework for exploring pedagogical innovations and as a conceptual framework for analyzing and designing support systems for collaborative learning [6–10], mobile learning [4], and learning technologies evaluation [11, 12].

The study conducted by Buchem on a wide range of PLE publications supports the idea that a PLE can be considered as a complex system of activities and can be analyzed using the framework of activity theory in order to describe its main components [3, 9] (**Figure 1**).

### **2.2 PLE definitions**

Several works have been carried out to bring a certain maturity to the PLE concept and above all a definition; we mainly cite the works of Buchem [3, 13–15]. From this review of the literature, we have identified several definitions of the term PLE: some have an educational vocation and others a technological vocation (**Tables 1 and 2**).



**Figure 1.**  
 Summary of the PLE elements and its main dimensions.

This diversification in the definitions led us to analyze them more closely and to propose our own definition which has a techno-pedagogical vocation: “A PLE is a learner-centered approach, based on web technologies and allowing support, control and appropriation of learning independently of technical and institutional constraints” [15].

### 2.3 PLE characteristics

Based on the views of Chatti and et al. [14], Martindale et al. [31], Drachler et al. [32], Jafari et al. [33], Johnson et al. [21], Lubensky [17], and Guettat et al. [15], PLEs should have the following characteristics:

- PLEs are open systems controlled by learners independent of the educational establishment.
- PLEs are customizable by learners.
- PLEs concentrate all the tools useful for the learner in a single environment.
- PLEs promote informal learning and lifelong learning.

As a result, it becomes clear that PLEs represent a turning point, from a model where learners simply consume information to one where learners become autonomous and create connections with a variety of resources that they select and curate themselves.

### 2.4 PLE objectives

Although some of the fundamental needs of users of PLEs have not yet been clearly defined, two major objectives have nonetheless emerged in the literature: a PLE must be centered on learners and should enable lifelong learning [3]. These two goals align with the Sustainable Development Goals (SDGs).

| Year | Author(s)   | Definition   |
|------|---|--|
| 2006 | Van Harmelen [16]   | “A PLE is a system that helps learners to take charge of their own learning: set their own learning goals, manage their learning (content and process), communicate with others and thus achieve their learning goals.”  |
| 2006 | Lubensky [17]   | “A PLE is the ease for an individual to access, aggregate, configure and manipulate digital objects during his/her learning.”  |
| 2006 | Milligan, Johnson, Sharples, Wilson, Liber [18]           | “A PLE facilitates choice and control for a learner and enables the selection and combination of formal and informal learning opportunities issue from various sources.”   |
| 2007 | Attwell [19]  | “A PLE should not be considered a software application, but a new approach in the use of new technologies in learning.”  |
| 2007 | Chen, Huang, Li [20]                                      | “A PLE is a learning-oriented strategy that promotes each learner’s learning ability in a web-based learning environment.”   |
| 2007 | Downes [13]   | “A PLE is recognition that the “one size fits all” approach which characterizes LMSs will no longer be sufficient to meet the varied needs of the learners. It is not a software application in itself, but rather a characterization of an e-Learning approach.”                    |
| 2008 | Johnson, Liber [21]                                       | “A PLE is the desire to create learning centered on the learner; who is seen as the provider of his/her learning and that personal learning is fundamentally a learner-driven model of education where the traditional role centered on institutions is contested.”                  |
| 2008 | Wilson, Liber, Johnson, Beauvoir, Sharples, Milligan [22] | “A PLE can be considered as a concept related to the use of technology for learning with an emphasis on learner appropriation of tools and resources.”   |
| 2008 | Schaffert, Hilzensauer [23]                               | “A PLE is the idea of a user-centered approach to learning, using social tools and software.”  |
| 2008 | Aviram, Ronen, Somekh, Winer, Sarid [24]                  | “A PLE is an educational model used for the self-regulated development of learners who are able to make informed, considered and strategic choices and plan their own learning as well as adapt the learning process according to their own needs, interests and their preferences.” |
| 2010 | Buchem [3]  | “A PLE can be considered as a concept related to the use of technology for learning with an emphasis on learner appropriation of tools and resources.”   |
| 2010 | McLoughlin, Lee [25]                                      | “A PLE is a concept adopting web 2.0 to promote continuous learning, informal learning and self-directed learning. It is an approach and not an application that allows the learner to take control of own learning environment.”  |
| 2011 | Chatti, Jarke, Specht, Schroeder [14]                     | “A PLE is a model for learner-centered learning that takes small, loosely-glued instructional chunks, characterized by their free-form use by a set of learner-controlled learning tools.”   |
| 2022 | Sarah, Serhan, Noraffandy [26]                            | “A PLE can be identified as a lifelong learning environment.”  |

**Table 1.**  
*PLE definitions from an educational point of view.*

## 2.5 PLE needs

With the trend in PLE being clearly visible today, questions continue to arise [14]: Who would need a PLE? Is there any feedback on PLEs? We need PLEs for lifelong

| Year | Author(s)   | Definition   |
|------|---|--|
| 2001 | Olivier, Liber [27]                                       | “A PLE is a single-user e-Learning system that provides access to a variety of learning resources, and which may provide access to learners and teachers who use other PLEs and/or other VLE (Virtual Learning Environments).” |
| 2007 | Wilson, Liber, Johnson, Beauvoir, Sharples, Milligan [22] | “A PLE is not a piece of software. It is an environment where people, tools, communities and resources interact flexibly.”   |
| 2007 | Anderson [28]   | “A PLE is a web interface in the owners’ digital environment.”   |
| 2007 | Siemens [29]  | “A PLE is a collection of tools brought together under the conceptual notion of openness, interoperability and learner control.”   |
| 2008 | Attwell, Costa [19]                                       | “A PLE provides both the framework and technologies to integrate personal learning and the work.”  |
| 2009 | Educause [30]   | “A PLE describes the tools, communities and services that constitute the different educational platforms learners use to direct their own learning and to achieve educational goals.”  |
| 2010 | Martindale, Dowdy [31]                                    | “A PLE is a specific tool or collection of defined tools used by the learner to organize and control their own learning.”  |
| 2011 | Chatti, Jarke, Specht, Schroeder [14]                     | “A PLE is a way of creating new web applications by combining (by aggregation and/or integration) existing data and services from different sources.”  |
| 2022 | Sarah, Serhan, Noraffandy [26]                            | “A PLE is open access online learning with learner-based guidance, self-direction and self-regulation.”  |

**Table 2.**  
*PLE definitions from a technological point of view.*

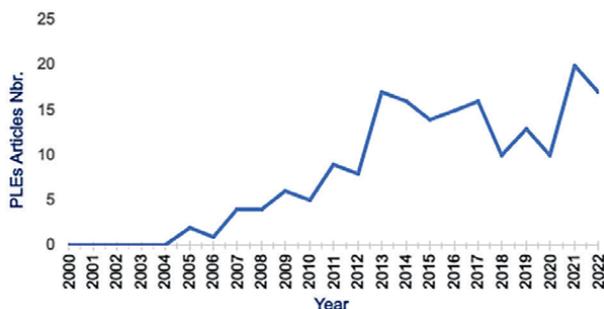
learning. The need is also the response to approaches requiring that the learning environment be under the control of the learner and that activities can be carried out offline. These needs have encouraged certain educational establishments to raise awareness among learners and teachers of the interest and contribution of PLEs, by instilling in them this PLENK 2010 culture [13].

## 2.6 PLE statistics

A study carried out by Sarah et al. [26] and published in 2022 in the “International Journal of Information and Education Technology,” presented statistics and graphs showing the keen interest shown in this concept by researchers (**Figure 2**).

## 2.7 PLE limits

Following this brief overview of PLEs, we noted the lack of consensus on the terminology and even on the definition, hence the need for a more stable theoretical framework. In addition, the tools making up a PLE are heterogeneous; the need to orchestrate them is therefore desired. We also noted the limited number of methods and approaches that respond to the various issues raised [15]. We believe that, with the emergence of information technologies, PLEs work will progress further to compensate for the scientific deficiencies observed.



**Figure 2.**  
*Number of PLE article publications per year.*

## 2.8 Synthesis

After analyzing publications made on PLEs, and reviewing the studies and work carried out by many researchers [3, 15, 26], we deduce the learner could obtain his/her educational and technological independence toward institution, by having the possibility of building his/her own learning environment and choosing his/her own resources and activities in order to achieve learning and personal objectives. However, several questions arise: how will the learner identify his/her objectives and therefore his/her learning curriculum?

Two answers can be considered: either the teacher guides the learner in his/her choices, in that case, we return to institutional learning environments with tutors and curricula dependency, or the learner, through the use of an intelligent system, could compose his/her personal curriculum. This second alternative, which has not been the subject of previous work, will be the subject of our research [15].

## 3. Lifelong learning concepts

Faced with the new landscape of educational technologies, learners continually face challenges in their learning. The speed of change as well as the growth of needs motivate learners to maintain the direction and extent of their lifelong learning. PLEs can be the appropriate solution to these situations. These environments give learners the freedom to learn beyond course boundaries and institutional constraints and customize their own learning environments before and during training. Additionally, e-portfolios used by learners as a tool to trace their learning provide future employers an overview of the individual's learning history and results, skills, and achievements. With PLEs, they allow learners to demonstrate their professional abilities in a continuous learning framework [34].

### 3.1 Lifelong learning vision

Lifelong learning is the “Ongoing, voluntary, and self-motivated pursuit of knowledge for either personal or professional reasons. Therefore, it not only enhances social inclusion, active citizenship, and personal development, but also competitiveness and employability” [13, 35, 36]. The diffusing of the lifelong learning vision signals the need for more personal, social, and participatory approaches that support learners in becoming active users and coproducers of his/her learning resources [35, 37]. The

emphasis on the shift from formal to informal e-learning through knowledge management and sharing has been placed, with particular attention on the PLE as a learner-centered space. Nevertheless, the investigations are motivated by the many educational theories, implications, and challenges that PLE concept has posed [25].

### **3.2 Learner-centered learning**

In a landscape marked by the evolution and emergence of educational technologies, and innovation in learning modes, models, and methods, the learner is obliged to assume his/her tool choices to use and contributions intended to make in learning. Therefore, we need a learning model centered on learner, adaptable, flexible, and specific, depending on the context, such that the learner will be able to control his/her individual choices in terms of the technologies to use by aligning them with his/her personal needs, interests, learning style, preferences, and context. In this way, learners will know how to build and manage a personal and self-reflective learning environment rather than operating an environment constructed, managed, and imposed by the teacher and/or institution [19].

### **3.3 PLEs roles in the lifelong learning**

The PLEs give students the freedom to learn beyond course boundaries and to personalize their own learning environment. They allow learners to learn anytime and anywhere. E-portfolios are currently used by learners in many education institutions as a tool to document and reflect on their learning. They provide future employers with a snapshot of the learner's learning history, learning achievements, and reflective practice [38].

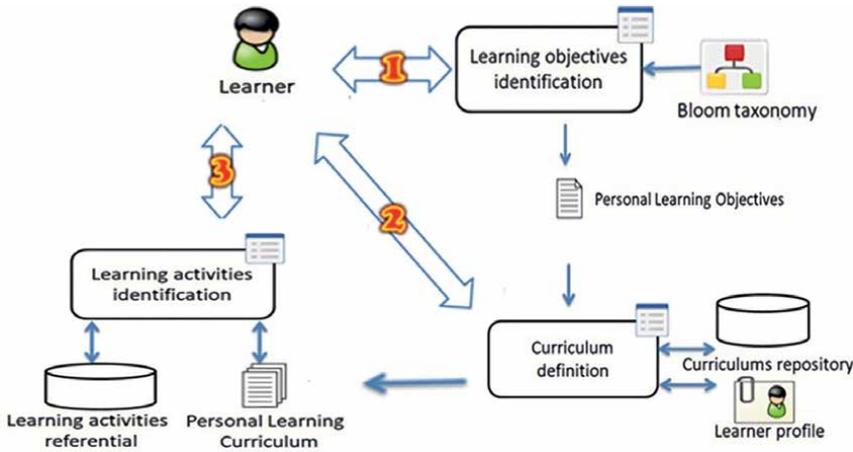
### **3.4 Our critical analysis**

Today's learning systems should break away from traditional learning methods because they can no longer satisfy everyone, especially with the perpetual evolution of technology. Other measures should be found to motivate learners to learn not only when they are in academic training but also when they are independent. In our context, we are interested in lifelong engineering learners whose appropriation of learning can constitute a challenge for them. The solution that seems to be most appropriate is PLE. However, putting up personal learning environments requires solving a number of problems: how can the learner build his own personal curriculum? How does the learner profile will be maintained?

## **4. Our assistance approach**

### **4.1 Overview**

As part of our research in the field of PLE started in 2008, we have developed an innovative approach [15, 36], allowing learners to build their personal learning environment, by building their own curriculums and choosing their appropriate learning activities. Such an approach will promote lifelong learning. To do this, we defined architecture with three components: the "Curriculum builder," the "Learning activities recommender," and the "Profile manager" (**Figure 3**).



**Figure 3.**  
Overview of our assistance approach.

## 4.2 Modeling learner

Nowadays, there are several specifications that aim to describe the learner in learning environments: IEEE PAPI [39], IMS-GLC-LIP [40], IMS-LTI [41], IMS-GLC-RDCEO [42], and IMS-GLC-LIS [43]. However, no study has been conducted to assess whether any of those specifications are appropriate to the PLEs.

So, we are concerned with finding a specification useful in the case of PLE in general and for our approach in particular. We have identified a requirement set of the learner model:

- Personal information (used to identify the learner and to interact with tools and learning environments),
- Previous knowledge (used to build his personal curriculum),
- Learning traces (used to manage the learning process),
- Learning objectives (used to store personal curriculum), and
- Preferences of the learner (used to select appropriate learning activities).

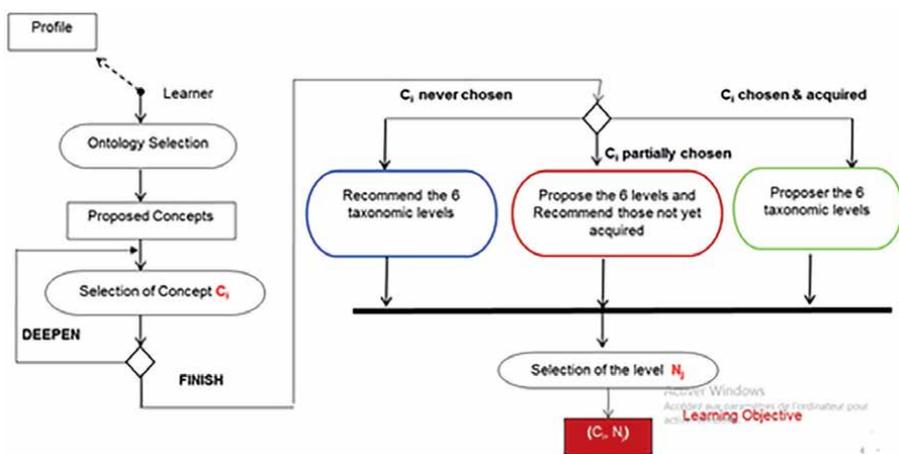
Based on our study, we demonstrate how the IEEE PAPI is suitable for the case of our approach and in general for the PLEs (Table 3) [44].

## 4.3 Assistance for identifying learning objectives

This component helps learners to choose their learning objectives. We start by offering them a list of concepts so they can choose one, for example, mechanics, computer science, management, mathematics, or medicine. Each concept has a sub-concepts list. For the “Computer Science” concept we propose “Algorithmics,” “Office Automation,” “Programming,” “Databases,” “Computer Architecture,” “Operating Systems,” and “Computer Networks.” The choice of objectives will be based on an interactive dialogue with the learner using a dynamic and user-friendly questionnaire (Figure 4).

| PAPI Category PLE requirements | PAPI contact | PAPI relations | PAPI security | PAPI preferences | PAPI performance | PAPI portfolio |
|--------------------------------|--------------|----------------|---------------|------------------|------------------|----------------|
| Learner informations           | ☑            |                | ☑             |                  |                  |                |
| Previous knowledge             |              |                |               |                  |                  | ☑              |
| Learning traces                |              | ☑              |               |                  | ☑                |                |
| Learning objectives            |              |                |               |                  | ☑                |                |
| Learner preferences            |              |                |               | ☑                |                  |                |

**Table 3.**  
 Adequacy of IEEE-PAPI for PLE.



**Figure 4.**  
 Objective identification process.

#### 4.4 Assistance for curriculum selection

Once the choice is made (concept  $C_i$ , taxonomic level  $N_j$ ), the next step will consist of finding adapted curriculums. Two possible situations: In the first, an exact match is found between the curriculum’s general objective and the learner learning objective, and in the second situation, we cannot find the right curriculum associated with the concept  $C_i$ .

##### 4.4.1 First situation: exact match found

The selected curriculum will be used to identify the learning activities that must be accomplished by the learner. For example, we are looking for a course in “Computer Science” with a taxonomic level equals 2 (“Comprehension”); we found a bachelor’s degree curriculum in computer science that matches. But in such a situation, several equivalent curricula may be found. Faced with such a situation, we will use concepts from Artificial Intelligence (AI) to apply one of the classification algorithms either to aggregate pieces of curriculums found or to make a classification to recommend curricula to the learner [45]. Based on our contribution which improved the IEEE-PAPI learner model in a PLE context, we are detecting significant and useful variables (features) for unsupervised machine learning algorithms—ascending hierarchical classification also called clustering (**Table 4**).

| Variable | Codification | Description   |
|----------|--------------|---|
| V1       | LANG         | Learner’s preferred Language: Fr, Ang, Ar, All, Esp.        |
| V2       | TYPF         | Desired type of training: quick, medium, long.              |
| V3       | NBUC         | Uses number of a given curriculum.                          |
| V4       | NBAC         | Number of completions on a given curriculum.                |
| V5       | RACC         | Completion ratio on a given curriculum (RACC = NBAC/NBUC)   |
| V6       | NBOB         | Number of objectives in a given curriculum.                 |
| V7       | NATC         | Average of marks awarded by learners on a given curriculum. |

**Table 4.**  
Sample of variables (features).

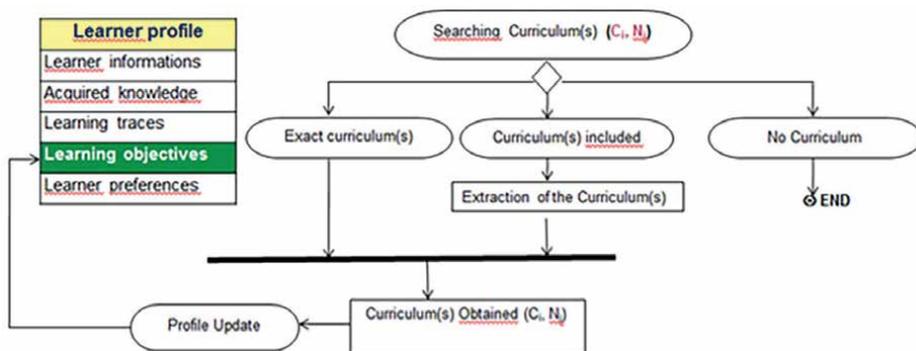
In **Figure 5**, we present a diagram describing the process of obtaining a personal curriculum.

In **Figure 5**, we can see how the learner profile will be updated once the curriculum is selected. We know the curriculum is a couple formed by an objective (Ontology Concept C) and a taxonomic level of learning N. According to our learner model based on IEEE-Papi learner, we will access the “Learning Objectives” class to update it, either by adding this objective if it is not part of the learner’s profile or by updating this objective if the learner has evolved in learning by moving from one taxonomic level to another.

Previously, the classes representing the learner profile (**Table 4**) will also be updated according to the data provided by the learner, which is associated with the features involved in the ascending hierarchical classification algorithm (machine learning algorithm).

#### 4.4.2 Second situation: right curriculum not found

For example, we are looking for training in BCNF (Boyce Codd Normal Form), but our system found nothing in the corpus. In this case, we need to go down the ontology and go to the “Normalization” node. It would then be necessary to work on the content of each curriculum concerning this node using its XML file and see if the associated block with the BCNF concept exists. The same thing here, we can find several equivalent blocks corresponding to our concept  $C_i$  and we must choose the most appropriate according to a classification strategy with always the same sample of variables.



**Figure 5.**  
Curriculum selection process.

To update the learner profile, we will use the same algorithm presented in the first situation.

## 5. Experimentation and results

In this section, we will experiment with a part of our approach (identification of personal learning objectives and curriculum recommendation). We have developed an assistant system, which allows any learner to use services offered without any technical or institutional constraints.

### 5.1 Web architecture

This is web architecture with a client using a browser (e.g., Chrome) containing our system, which will allow the learner to compose a personal curriculum and obtain the list of appropriate activities (Figure 6).

### 5.2 Web interface

In our system, which is based on our approach, we have a thin client which, through a Windows browser, offers the services planned and mentioned by our assistance system (Figure 7).



Figure 6.  
Web architecture of our assistance system.



Figure 7.  
Web interface of our assistance system.

By clicking on the “PLE” assistant, the learner could benefit from the offered services system: identifying learning objectives assistant, curriculums recommender, and activities recommender (**Figure 8**).

### 5.3 Assistance in identifying learning objectives

#### 5.3.1 Input data set

To experiment with this component, we had the following data sets:

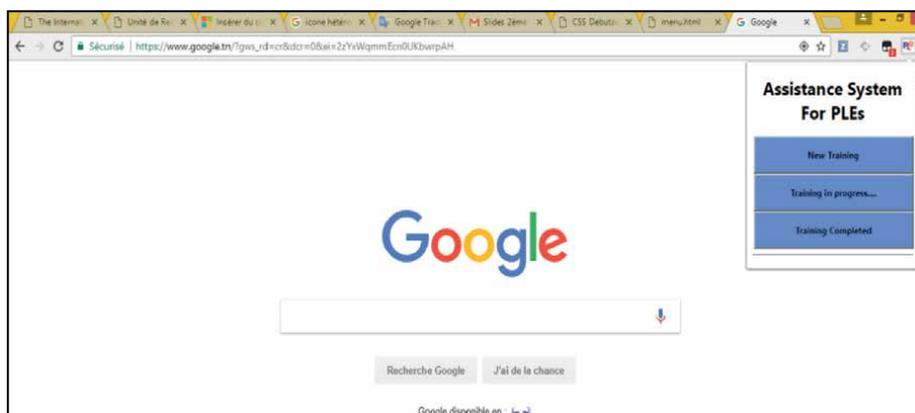
- Set of learner profiles with different scenarios: learner has never completed learning in a given concept, or has partially completed learning at given taxonomic levels, or has completely completed learning in a concept.
- Sample of learners requesting new learning curricula.
- A corpus of curriculums: each curriculum concerns a well-defined concept.

#### 5.3.2 First situation: learner wants to learn “databases” level 1

Our system will offer him all the curriculums (“DB,” 1) from our corpus. Which one will we recommend to him? Firstly, our system will make a filter by taking into consideration the learner’s requirements and his/her profile. After that, our system will execute the unsupervised machine learning algorithm (ascending hierarchical classification also called clustering). After notification of the variables, we obtained a curriculum list from our curriculum corpus, including those dealing with “Databases” concept and the taxonomic levels. Given that the learner is interested in learning (“DB,” 1), the system extracts from our corpus all the “DB” curriculums with taxonomic level equals 1 (**Table 5**).

Which curriculum our system will recommend to learner? The ML algorithm will calculate the similarity distances; before, it converts all the values in the interval [0...1], and sorts the curricula in ascending order according to d2 rubric (**Table 6**).

As we noted, the curriculum with the lowest distance will be recommended, and in our case, it is the curriculum (“DB,” 1) with distance  $d^2 = 0.979$ .



**Figure 8.**  
Services offered by our assistance system.

| Concept | Level | LANG | TYPF | NBOB | NBUC | NBAC | RACC  | NATC  |
|---------|-------|------|------|------|------|------|-------|-------|
| DB      | 1     | 1    | 1    | 2    | 1855 | 1000 | 0.539 | 06.20 |
| DB      | 1     | 1    | 1    | 2    | 2500 | 1500 | 0.600 | 08.00 |
| DB      | 1     | 0.66 | 0.66 | 3    | 1985 | 600  | 0.302 | 05.40 |
| DB      | 1     | 0.5  | 1    | 2    | 750  | 300  | 0.400 | 04.80 |
| DB      | 1     | 1    | 0.66 | 3    | 2265 | 1265 | 0.558 | 06.10 |
| DB      | 1     | 1    | 0.33 | 5    | 4578 | 4000 | 0.874 | 08.70 |

**Table 5.**  
 Extraction of curriculums related to (“DB,” 1).

| Concept | Level | LANG | TYPF | NBOB | NBUC | NBAC | RACC  | NATC | Distance ( $d^2$ ) |
|---------|-------|------|------|------|------|------|-------|------|--------------------|
| DB      | N1    | 1    | 0.33 | 5    | 4578 | 4000 | 0.874 | 0.98 | 00.979             |
| DB      | N1    | 1    | 0.66 | 3    | 2265 | 1265 | 0.558 | 0.69 | 02.060             |
| DB      | N1    | 1    | 1    | 2    | 2500 | 1500 | 0.600 | 0.90 | 02.296             |
| DB      | N1    | 0.66 | 0.66 | 3    | 1985 | 600  | 0.302 | 0.61 | 02.720             |
| DB      | N1    | 0.5  | 1    | 2    | 750  | 300  | 0.400 | 0.54 | 03.507             |
| DB      | N1    | 1    | 1    | 2    | 1855 | 1000 | 0.539 | 0.70 | 02.632             |

**Table 6.**  
 ( $d^2$ ) sorted in ascending order by ML algorithm. Green color indicates the recommended curriculum(s).

### 5.3.3 Second situation: learner having “DB” levels 1 & 2 wants a “BCNF” level 1 curriculum

Our system searched in the corpus but found nothing. He turned back to his domain ontology to go back to one level. There, we found the concept “Normalization.” We know well that the BCNF concept is one of the normal forms encountered in database courses, containing the “Normalization” chapter. We will therefore search all the normalization curricula and detect the presence of the specific objective relating to the Boyce and Codd normal form. This means the system will work on the curriculum content (XML file) and its metadata is made up of the following sections: Concept, level, language, training type, objective number, description, and list of specific objectives.

To find the concept, the system will process the list of specific objectives contained in the XML files. As soon as we find concept\_objs = “BCNF,” it will select the corresponding curriculum. After processing the already selected curriculums, we marked those which contain the concept “BCNF.”

An example of an XML block containing the concept “BCNF” is shown as follows:

```
<Curriculum>
<id>BD25879 </id>
<Concept>NORM</Concept>
<Title>Normalization</Title>
<Level>1</ Level>
<Description> Basic Concepts of Normalization</Description>
<Duration>2h00</Duration>
<Nb_Objectives>3</Nb_Objectives>
```

```

<li>
<id_objs>1</id_objs>
<concept_objs>DF</concept_objs>
<Title>Functional Dependence</Title >
< Level_objs>1</ Level_objs>
<id_objs>2</id_objs>
<concept_objs>3NF</concept_objs>
< Title >Normal Forms</ Title >
< Level_objs>1</ Level_objs>
<id_objs>3</id_objs>
<concept_objs>BCNF</concept_objs>
< Title > Boyce Codd Normal Form</Title >
< Level_objs>1</ Level_objs>
</li>

```

</Curriculum>

To find the concept, the system will process the list of specific objectives contained in the XML files. As soon as we find concept\_objs = “BCNF,” it will select the corresponding curriculum. After processing the already selected curriculums, we marked those which contain the concept “BCNF.” Following this processing, we obtain the following four curricula (Table 7).

The learner is looking for a BCNF curriculum with level = 1; our system recommends two, but the one with  $d^2 = 0.2433$  will be best recommended.

### 5.4 Experimentation results

Nearly, a hundred learners enrolled in the first year of IT engineering took part in the experiment. At first, they passed a pretest to divide them into two similar groups according to their level. After that, the two groups were invited for a test (on the same day: 2 hours). We asked the learners to solve the same exercise (about relational databases normalization) by creating their own PLE. Each learner in the control group has to build his/her own PLE and therefore to solve the given exercise. However, learners in the experimental group have access to our assistance system installed in their web browser. To evaluate the effectiveness of our approach, we measured the time and scores obtained by the group that used an unassisted PLE and the one that used an assisted PLE. We observed firstly the time of realization for the same activity to the two groups (control and experimental) (Table 8).

| Concept       | Level | LANG | TYPF | NBOB | NBUC | NBAC | RACC  | NATC | Distance ( $d^2$ ) |
|---------------|-------|------|------|------|------|------|-------|------|--------------------|
| Normalization | N3    | 0,66 | 0,66 | 0,33 | 0,47 | 0,19 | 0,396 | 0,98 | 01,978             |
| Normalization | N1    | 0,5  | 0,66 | 0,33 | 0,15 | 0,13 | 0,821 | 0,67 | 02,433             |
| Normalization | N1    | 1    | 1    | 0,00 | 0,13 | 0,13 | 0,977 | 0,46 | 02,818             |
| Normalization | N4    | 0,66 | 0,66 | 0,33 | 0,00 | 0,00 | 0,000 | 0,00 | 04,676             |

**Table 7.** List of obtained curricula. Green color indicates the recommended curriculum(s).

|      | Group        | Number of participants | Average (mn) | Standard deviation |
|------|--------------|------------------------|--------------|--------------------|
| Time | Control      | 50                     | 108,4000     | 10,20022           |
|      | Experimental | 50                     | 20,8333      | 2,00144            |

**Table 8.**  
*Average of times activity.*

|        | Group        | Number of participants | Average (mn) | Standard deviation |
|--------|--------------|------------------------|--------------|--------------------|
| Scores | Control      | 50                     | 7,85         | 5,71086            |
|        | Experimental | 50                     | 14,64        | 1,64485            |

**Table 9.**  
*Average of scores activity.*

The results confirm what we observed on the premises: the learner in the control group wasted a lot of time to find the appropriate resources to carry out the activity. We conclude that with an assisted PLE there is a gain in required learning time. On the other hand, we obtained the scores obtained by the two groups (**Table 9**).

We find that the mean of the control group is 7.9 with a standard deviation of 5.7. On the other hand, the results obtained in the experimental group are much better. Indeed, the average score is 14.6 (almost double) with a small standard deviation compared to that observed in the control group. This clearly shows that the use of an assisted PLE improves the learners' performance.

## 6. Conclusion

Nowadays, with the emergence of information and communication technologies, learners have access to different learning systems: ranging from simple resources such as tutorials, e-Books, Moocs, and OER, to learning environments, which are generally led by an institutional framework whose teaching strategies are defined in advance: curricula, predefined teaching scenarios and methods, teaching tools and logistics, trainers, etc. In such a context, the learner only exploits these environments at the request of the teacher or the institution without being involved in the structuring of courses and pedagogical choices. The only possibility offered to them during their training is to personalize their environment during learning according to their profile and preferences. Such a strategy cannot surely satisfy all learners: Demotivation during learning, poor perception of certain modules included in the curriculum, and risk of repeating certain modules already validated elsewhere. All these are because of the design and implementation of training strategies that were developed based on teaching centered on the teacher. Such systems, which suffer from several failures: lack of harmonization between education systems and the professional environment and gaps in the design of training curricula, can no longer create value within training institutions.

In certain countries where learning strategies are frequently reviewed in the direction of continuous improvement and learner satisfaction, there is a trend toward a break with traditional systems centered on the teacher. We want learning centered on the learner where the latter would be involved at all levels of training: from pedagogical choices to the choice of resources in the learning environment. Such a system aims to be

flexible at all times: learning without time constraints, learning anywhere, learning with any equipment, and total autonomy of learners in the choice of curriculum elements and even in the choice of their activities learning. This break is essentially justified by a better quality of learning with better motivation of the learner, who will move from the traditional passive mode to another comfort with the appropriation of his learning, from the choice of the objectives of his curriculum until the completion of the related activities. This would be ideal for working individuals who wish to acquire scientific and professional skills as part of lifelong learning. A question arises in this case: in practice, are there learning environments can offer this type of service to these learners?

This last decade has seen the emergence of a new concept, which is currently attracting the attention of several research teams. These are personal learning environments (PLE): do not confuse them with customizable learning environments. In our chapter, we have removed this ambiguity in order to clarify the PLE concept for researchers working on it. This concept, despite the efforts made by researchers, fails to reach a maturity threshold in terms of the stability of the concept, given the different educational and technological points of view presented in several works. Most mention the learning resource needs of learners but never the method of identifying objectives and selecting training programs. As if the learner is initiated into the creation of his curriculum, it is able to choose the appropriate objectives according to his profile and able to select the appropriate learning activities. In practice, only those who have teaching skills (trainers) are capable of doing all this. At this level, we asked ourselves several questions: Is the learner capable of identifying his or her own learning objectives? Do they need to introduce them to certain educational concepts to do so? Should it depend on an institutional structure to carry out this work? In other words, could the learner, without being an expert in pedagogy, identify his objectives and build his personal curriculum? All these reflections have been detailed in this chapter thanks to a new assistance for learners in a personal learning environment context and in a lifelong learning framework and which mainly based on artificial intelligence concepts for recommending appropriate curricula and activities.

In this chapter, we presented a brief overview of the state of the art on personal learning environments: we reviewed the basic concepts; the research carried out and the fit between PLEs and lifelong learning. Then, we detailed the different phases of our assistance approach in a personal learning environment: definition and identification of learning objectives, selection of a learning curriculum, and management of the learner profile. For the learner model, we adapted the IEEE-PAPI learner standard for PLEs in general and particularly for our approach (standards adopted have until now not dealt with the case of PLEs). In the different phases of our approach, we used artificial intelligence (AI) concepts and more precisely machine learning algorithms (ascending hierarchical classification) to offer learners appropriate curricula and activities. Our approach was implemented, and the system was developed and tested on a representative sample of learners. The experimentation results are analyzed and interpreted. It was carried out on two groups of learners, a first group working freely on their own PLE to solve a given exercise, with learning tools of their choice, without guidelines, method or approach, and another group, which had the privilege of using our support system while solving the same exercise.

Obviously, this contribution remains open to other actions, either in terms of potential for improvement or in terms of extension. The first action consists of activating the assistance phase which consists of offering appropriate educational activities to the learner after choosing their curriculum; knowing that on the same curriculum, activities can vary from one learner to another depending on their

preferences, profile, etc.. The same machine learning process will be applied but this time on activities and no longer on curricula.

As for perspectives, the first will concern the learner profile manager, who is responsible for storing the learner's information in a consistent manner so that his profile is up to date. A learner's activities can come from several learning environments, and to update a learner's profile, we must use a generic model to convert their data not necessarily from the same model. The goal is to prevent the learner from repeating activities already carried out in other environments.

The second perspective is an extension of our approach in terms of learning situations. We recall that we worked on two situations (finding exactly curricula aligned with learning objective and taxonomic level and finding objective and level including in others curricula).

A third situation not developed could be subject to an extension of our approach: it concerns the first approach phase of identifying objectives and the search for a curriculum: it is a situation where the learner introduces a concept  $C_i$  relating to a domain ontology and a taxonomic level  $N$  to our system, the latter will check in the corpus of curricula, but does not find a curriculum associated with the concept  $C_i$  and the taxonomic level  $N$ . However, in certain curricula, we find some pieces of curriculum ( $m_k$ ), which, by aggregating them, can give rise to a curriculum approaching the desired one. Proposing a solution to this situation seems easy on the surface, but in reality, it is not going to be easy. How could our system assist a learner so that the latter can affirm whether such a piece  $m_k$  is part of his concept  $C_i$ ? Generally, this is the mission of a teaching expert. In its absence, it would then be necessary to add an intelligent component (AI concepts) capable of detecting these pieces and recommending them to the learner.

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## Chapter 6

# AI-Based Edutech for Adaptive Teaching and Learning

*Hwang Eunkyung*

### Abstract

The artificial intelligence (AI)-based problem learning system quickly and accurately performs problem setting and scoring using algorithm. In this process, the learner's level of prior learning is identified, the subject and quantity to be learned are determined and problem learning is provided for each learner. The basic use of AI-based problem learning enhances ease and fairness in performing assignment and evaluation and provides data that can strengthen interactions between instructors and students. Above all, the biggest advantage is the possibility of helping individual learners with different levels of prior learning to strengthen basic learning. To this end, instructors need to understand the technical aspects of the system, check the content system as an educational goal set by the instructor, and make efforts to supplement the necessary parts. When AI-based problem learning is used in connection with classes, a technical understanding of a system that can utilize various functions of the AI system more efficiently is required. In addition, instructional design is needed to expand thinking and strengthen capabilities through the process of structuring and understanding the contextual relationship between concepts based on the learned knowledge of students using AI-based problem learning systems.

**Keywords:** artificial intelligence, problem learning system, adaptive learning, adaptive class, instructional design

### 1. Introduction

Edutech is used in various ways to enhance the quantitative and qualitative effectiveness of the teaching and learning process based on the rapid development of the hardware of information devices and the software technology necessary for the operation and management of these devices. In particular, the use of artificial intelligence as edutech, which has recently attracted attention, is being used in various forms depending on the level of technology, such as customized education tailored to the characteristics of learners, interactive systems, learning and inquiry support, student writing analysis, and intelligent agents [1, 2].

These changes also affect the university curriculum, expanding to the use of customized learning and adaptive teaching methods in consideration of students' learning situations [3–5]. This is being attempted as an alternative to teaching and learning to meet the needs of the teaching and learning process, such as bridging the learning gap and improving basic academic ability, in the lecture field, where students who

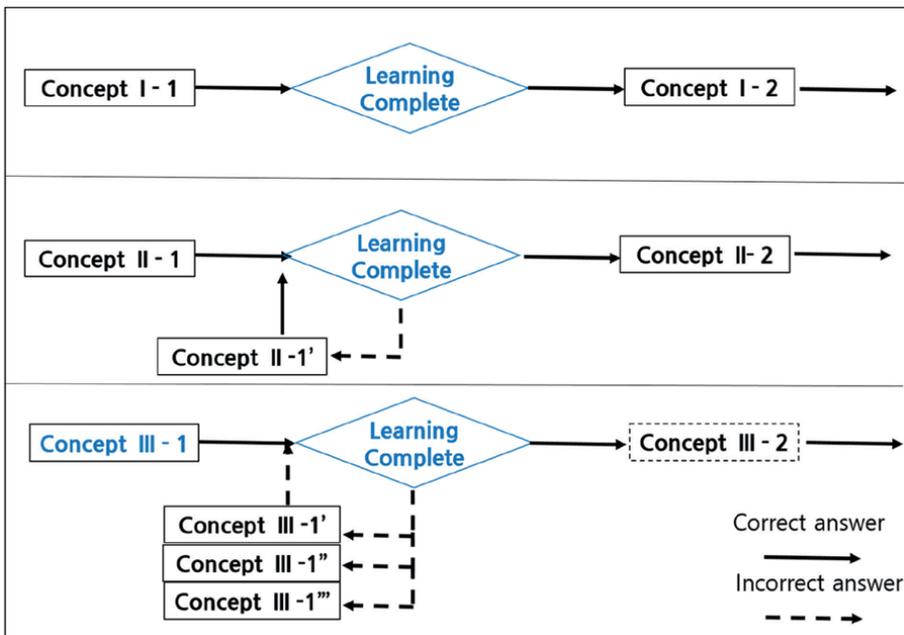
take these subjects have various majors and the difference in their prior learning and learning competencies is based on the same subject content.

## 2. AI-based edutech for adaptive teaching and learning

### 2.1 Characteristics of AI-based edutech

From Alan Turing’s Turing test in 1950, the Expert system used in Dendral and MYCIN in the 1970s, and deep learning, a type of machine learning in the 2000s, to Generative AI, the rapid development of artificial intelligence, which can be seen at several symbolic stages, is expanding its role to its use as edutech. However, algorithms in which artificial intelligence (AI) learned through deep learning analyzes data on the amount of individual students and learning outcomes to present individual learning paths are one of the important features of AI-based edutech, thanks to the improved performance of parallel computers capable of processing big data at high speed [2, 3]. These algorithms are related to the Rule Base Algorithm, which sets priorities based on rules, organizes, proceeds, and verifies decision trees, and the Item Response Theory, which analyzes data in response to questions to calculate the degree of learning completion of respondents and the difficulty of individual questions [6, 7]. The flowchart in **Figure 1** briefly illustrates the principle of problem generation that plays an important role in customized or adaptive teaching and learning based on these algorithms.

First, taking Concept I as an example, if a student presents the correct answer to a given problem (Concept I-1) dealing with Concept I in the learning path, the learning of Concept I-2 proceeds, followed by the learning of Concept I-3 and Concept I-4, and



**Figure 1.**  
Problem generation process.

learning related to Concept II can also begin. If the student gives an incorrect answer to the problem (Concept II-1), as shown in the schematic diagram related to Concept II, the algorithm will allow further learning of the content with the accompanying supplementary explanation and then make the student solve the problem of Concept II-1' similar to Concept II-1. If, as in concept III, a similar problem-solving is retried, the correct answer is not presented immediately, and the wrong answer is repeatedly submitted, the learning proceeds by continuously solving the similar problem until it is recognized as complete learning. As shown in concept III-1 in **Figure 1**, if learning completion is not achieved even through repeated attempts, the system recognizes the level of learning by the 'Learning' step, which is a lower level than 'Learning Completion', then the next learning proceeds. In the learning path shown in **Figure 1**, this problem generation method proceeds up to the main concepts I, II, and III, and learning-related information is collected by checking the number of consecutive correct answers, the number of correct answers and incorrect answers. This is used as direct data for AI algorithms to determine whether individual learners' understanding of concepts is completed or not. For example, in a system that has set three consecutive correct answers to a single concept as 'Learning Completed', if a student submits three consecutive correct answers to a question about Concept I, the system recognizes it as 'Learning Completed' and proceeds the learning path with the next concept, concept I-2. Whereas, if the incorrect answer is submitted between the submitted answers even though the correct answers have been submitted three times in this process, the learning path is conducted to solve additional problems, determine 'complete learning' using a separate scoring method, and solve the next step, concept I-2. For other topics selected in consideration of teaching and learning objectives, this principle is also basically used to generate problems that reflect priorities in the rule-based algorithm to proceed with learning. These AI problem learning systems were initially provided as independent adaptive problem learning, but recently, their scope of use has been expanded in a way that is used to implement adaptive teaching methods using problem learning in classes [8, 9].

## 2.2 Learning diagnostics

The evaluation method conducted by the instructor for learning diagnosis and analysis can be classified based on the factors of problem generation, scoring, and scoring result analysis as expressed in **Table 1**.

First, In the case of the traditional paper test conducted using paper prints, a professor directly creates, distributes, scores, and analyzes problems. Although the assistant supports it, the professor is involved and participates in a series of processes related to the evaluation of learning. Next, In the CBT system using screens and keyboards on computers connected to the Internet, a professor develops, creates,

|                            | Question creation | Question distribution | Scoring             | Result analysis     |
|----------------------------|-------------------|-----------------------|---------------------|---------------------|
| Paper based test system    | Professor         | Professor/Assistant   | Professor/Assistant | Professor/Assistant |
| Computer-based test system | Professor         | System                | System              | System              |
| AI-based test system       | System            | System                | System              | System              |

**Table 1.**  
*Evaluation for learning diagnosis and analysis.*

and enters a problem into the system through a professor or other inputter. Problem Distribution, scoring, and analysis are a method of receiving help from a computer connected to the Internet of systems. Recently, in conjunction with the comprehensive learning system, it also supports overall matters related to learning, such as learning materials, information, and announcements provided to students. Finally, in an AI-based test system, an AI algorithm is involved in the distribution of the generated problem and management of information about learning in an integrated manner in computer-based test systems. A subsequent learning path through analysis of the automatically scored result is determined and proposed by the AI algorithm.

The AI system identifies topics and concepts that each student needs to learn through initial diagnostic tests, generates related problems to be initially distributed based on the percentage of correct answers, and starts individual learning paths. The student's problem-solving scoring results in the learning process according to this learning path are stored as data. Basic results such as the completion rate of problem learning for each topic and concept and data such as the time required to solve problems by concept, access time, and end time are stored as diagnostic information about the learning progress of individual students and then are sometimes shared to professors and students. The information is provided to the professor as a sum and average information about all students. Additionally, diagnostic information related to students' conceptual understanding is provided by providing information such as questions with high incorrect answer rates, questions with many correct answers, and time required in order to analyze questions. These materials are converted into a relative understanding of specific topics among individual learners' entire subjects and used as basic data to determine the learner's level of prior learning, helping to determine the content and quantity of instructors' teaching and learning activities. These learning result analyses and diagnostic data are organized and shared on a dashboard for easy use by instructors. This is also possible when the CBT evaluation system itself or the CBT system is operated in conjunction with the comprehensive learning management system, but the functions are much more diverse and rich in AI-based testing systems.

In particular, it provides both instructors and individual students with comprehensive and integrated information on learning based on individual learning paths. Based on this, question-and-answer required for learning can be made more effective between students and professors, which seems to contribute to enhancing interaction. In addition, in the case of a problem learning system that provides the ability for instructors to view the student's learning screen the same, it allows one to understand the more specific request for learning.

For example, in the case of ALEKS, which is frequently used for AI-based adaptive problem learning, 'ALEKS Pie', which allows you to intuitively check the level and level of learning of each subject, and 'Progress Report', which provides information that details the learning situations are provided to professor and individual students. This information can be used to identify the level of learning through relative comparison with other students by providing average information for all students.

Also, since the AI-based problem learning system creates and distributes similar types of different problems on the same subject to students, it helps to manage and supervise large-scale or non-face-to-face test takers and to secure and strengthen fairness.

However, the questions loaded on the AI-based platform mainly deal with multiple-choice question types, and in the case of subjective questions, they mainly deal with short-answer questions that involve writing calculation results using expressions

with implied concepts or writing down simple words, so professors are responsible for solving concept-related problems. To check the interpretation and understanding process or to evaluate comprehensive thinking during the problem-solving process, the professor may need to conduct an additional separate evaluation.

### 2.3 Self-directed learning

In addition to being used for evaluation to diagnose the learning level of students from the instructor’s perspective, AI-based adaptive learning appears to play an important role as self-directed, individualized problem-solving learning from the learner’s perspective. In this context, the paper-and-pencil tests, computer-based tests, and artificial intelligence-based tests as examined in **Table 1** are classified according to the scoring and analysis results that can help students learn, and the method of providing supplementary explanations can be shown in **Table 2**.

In the case of the paper test system, students usually solve test questions printed on paper, and the answers written on this questionnaire are scored by the instructor or assistant and the analysis of the scoring results. After that, the solution learning is conducted through the process of additional support such as announcing the correct answer, providing face-to-face or non-face questions and answers to necessary parts, and providing related recorded videos. In the case of CBT, if the problem generated by the instructor is loaded into the system with the correct answer, it is automatically scored, and the scoring and analysis results can be shared and announced. However, it is difficult for students to comprehensively examine information related to learning, and solutions provided in the problem-learning process are mainly presented to the extent that the solutions correspond to simple explanations. Also, Because the information that students can see is limited, in conjunction with the Learning Management System (LMS), through additional data editing steps, the problems mounted by the instructor are scored, the results are shared, and the analysis is provided through additional data editing steps. In this respect, in the case of an AI-based problem learning system, compared to a Computer Adaptive Test, which is known as an evaluation that considers learners’ learning levels among CBTs, AI-based tests provide more sophisticated learning diagnostics due to deep learning of artificial intelligence and provide a customized set of problems that further reflect learners’ learning levels and situations, allowing students to learn self-directed concepts using “solvable” and “to solve.” Additionally, individual students can obtain and use their learning-related information in a relatively diverse and sophisticated manner through the use of dashboards in a similar manner to instructors, and they can judge

|                            | <b>Scoring results announcement</b> | <b>Analysis results announcement</b> | <b>Review</b>                                      |
|----------------------------|-------------------------------------|--------------------------------------|--|
| Paper based test system    | Professor/Assistant                 | Professor/Assistant                  | Correct answer                                     |
| Computer-based test system | System                              | System                               | Solution   |
| AI-based test system       | System                              | System                               | Solution/supplementary explanation adapted problem |

**Table 2.**  
*Reflective learning in evaluation.*

and use their learning situations and ask for help, such as question-and-answer that fits their learning needs. The supplementary explanation supported in the problem-solving process deals with a relatively detailed and varied amount of content, not just feedback. However, in the case of learning effects obtained from explanations, the degree of understanding and acquisition of knowledge is related to the student's level of understanding of prior learning, so there seems to be a limit to some extent for students to independently grasp the concept's concreteness and connection between concepts [10]. Additionally, for concept problems where incorrect answers are submitted, solving similar problems is repeated to provide additional learning.

### 3. AI-based adaptive learning system

AI-based adaptive problem learning can be used for personalized assignments and regular evaluations within the course operation. To this end, the basic teaching design for the operation of the semester is established based on the characteristics of the subject classification, the characteristics of the subject, the major of the student, and the grade. In addition, after reviewing the content structure of the curriculum to be covered, necessary topics must be selected from the overall content system of the AI-based system and set in the system so that they can be dealt with effectively.

#### 3.1 Content analysis

In order to use the AI learning system as problem learning, it is necessary to grasp the hierarchical structure that deals with the essential knowledge required in the curriculum and the lower level according to the knowledge within the AI system. For example, the hierarchical structure of each piece of knowledge can be dealt with based on the major subject, the sub-subject, and the concept, which is the lower layer of each sub-topic, as shown in **Table 3**. In this regard, most programs of AI-based problem learning systems are introduced mainly by educational companies, and their programs already create problems dealing with the concepts within the system at the launch stage and provide them in input and mounted form. Therefore, the most common method of problem generation is to select and use the entire topic that is automatically presented and mounted in the system, aimed at complete learning proposed by AI. Also, based on the instructional design of the subject, the professor may select and create specific topics in consideration of the amount of problem-solving learning of students that increases as the number of topics selected increases and the completion rate of learning that may be affected accordingly. In the course of learning, the learning deadline for each topic-related problem may be set to provide a learning environment so that problems related to all concepts can be solved freely throughout the semester, or to provide an environment in which concepts related to the topics covered in the lecture can be learned according to the progress of the semester.

| Major subject | Sub subject         | Concept | Summary description                            | Difficulty | Question number |
|---------------|---------------------|---------|--|------------|-----------------|
| Measurement   | Scientific notation | Decimal | use of an exponent to represent a large number | easy       | I-1             |

**Table 3.**  
*An example of a hierarchical analysis of knowledge.*

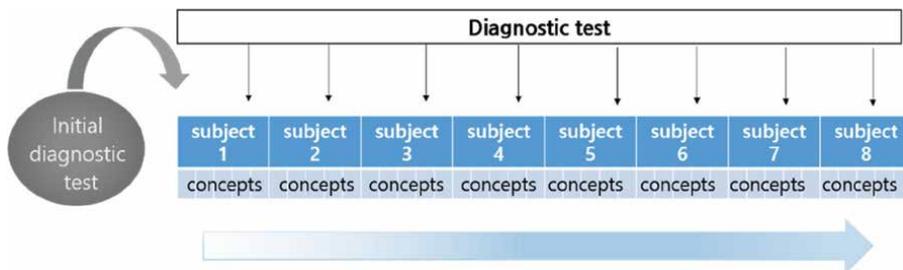
This content analysis strengthens the connection with the content of the knowledge system that must be dealt with to achieve the educational goals and objectives of the subject, helping to more effectively utilize the content provided by the AI-based system. The figures related to the learning progress and learning completion rates of the concepts covered in the content hierarchy of **Table 3** and the results of the formative evaluation conducted to confirm the educational effectiveness through teaching and learning performance are used to confirm whether the content provided by the system matches the educational goals.

### 3.2 Adapted learning system implementation

AI diagnoses the level of prior learning for the core concepts to be covered in the course. To this end, an initial diagnostic test as shown in **Figure 2** is conducted during the orientation or the first lecture for the semester. As an initial diagnostic test, the AI system distributes questions about the subject's essential concepts, analyzes them based on the results of scoring the answers submitted by the student, identifies the topics and concepts that each student needs to learn, decides related problems to be initially distributed for subsequent learning, and initiates individual learning paths. Based on this, AI assigns individual problems to individual students to learn sub-concepts related to the diagnosed subject. After that, students are assigned different concepts and a numbers of questions according to the students' individual learning situations. Students' learning time varies depending on the stage of prior learning or their understanding of learning. In addition, unlike the initial diagnostic evaluation, additional diagnosis, which is another data that determines the student's level of completion of learning for each topic, is conducted within the AI system, and the timing and evaluation of this diagnosis may be controlled by the instructor. The method of reflecting the grades for the assignment after the end of one semester can be given in various ways using the learning-related data provided, and in the case of based on the learning completion rate, the grades for the assignment can be calculated by assigning a grade such as A/B/C according to the ratio.

As a result of comparing the learning completion rate according to the deadline-setting method in relation to adaptive problem learning operation, the learning completion rate was higher when the deadline was set to induce learning than when the learning of all topics could be carried out without a limit on the learning period for one semester. In addition, in most cases, students tended to learn problems on related topics after the instructor's lecture [2].

AI-based adaptive problem-solving learning contributes to diagnosing the understanding of students with different levels of prior learning and strengthening the



**Figure 2.**  
A schematic diagram of system implementation.

learning of basic and core concepts in the subject, but the connection and expansion process between each learned concept seems to be lacking. In particular, additional learning can be achieved by utilizing problem-related concept explanations provided during the problem-learning process, but such learning is mainly limited to fragmentary concepts, so students without much prior knowledge may be more vulnerable to structuring and solving problems. Considering this aspect, it seems that customized problem learning should be supplemented with interactions that allow sharing of various perspectives and interpretations with instructors and other students during the learning process so that it is not biased toward answering repetitive problems or acquiring simple concepts.

## **4. AI-based adaptive class**

### **4.1 Adaptive instruction**

Adaptive instruction can be understood as identifying students' learning situations based on their learning data and providing appropriate teaching and learning [9, 11]. However, adaptive measures for students' learning situations in the teaching and learning field for a large number of students mainly use group learning by learning level in class, but they do not implement completely personalized class management as shown in the operation of supplementary classes to support learning for certain groups of students with low basic learning ability [12]. However, with the development of edutech, adaptive classes so far have recently been linked to AI-based adaptive systems with classes that analyzed the learning status reached in the students' conceptual learning process according to personalized learning paths, set appropriate teaching and learning goals that most students can reach, and construct classes that can deal with the use of content and concepts, and are expanding learner-centered countermeasures using teaching methods such as flipped learning and blended learning methods [3, 13, 14].

### **4.2 Instructional strategy**

To apply AI-based problem learning in connection with adaptive instruction, it is necessary to select and set the topics to be covered in the class after further elaborating on the content systems to be used by comparing and reviewing the results of the content system analysis conducted in the previous problem learning implementation stage with the curriculum content system. In other words, rather than simply acquiring specific concepts from the content system mounted on the AI platform, it is necessary to design a content composition that creates an efficient connection relationship and structure of content systems that can effectively use each concept so that the instructor can create a mutually cooperative synergistic effect with the content system that has been previously dealt with.

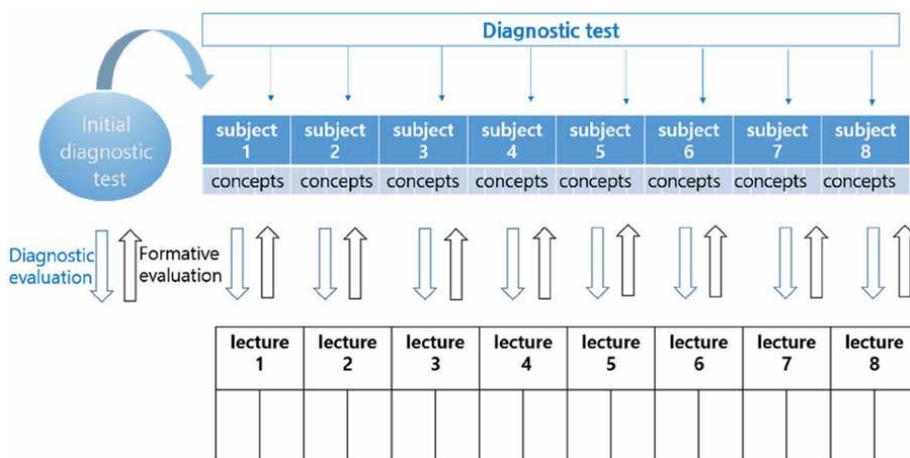
It also requires a system understanding that can flexibly and selectively adjust the various features of AI-based systems needed to implement these designs. In other words, when using the problem learning system in connection with the class, first select whether to use a video or e-textbook that has already been installed in the system, whether to present and submit assignments, the duration of participation in the assignment, the timing of evaluation, and the place of evaluation. The artificial intelligence-based adaptive learning system itself also provides the use of related

videos for learning basic concepts, but the use of videos produced by the participation of instructors helped in terms of class composition applying the instructor’s perspective. In addition, it seems necessary to grasp the system utilization technology in order to more diverse and efficiently utilize the data on students’ learning outcomes provided by the AI system. First, students autonomously learn about the subject through customized problem learning. The level of understanding through such prior learning is confirmed through a diagnostic evaluation of the learning system and the instructor checks through a report to see how much the students have learned the topics necessary for learning before the lecture and conducts the lecture. This diagnostic evaluation data was combined with the evaluation data of other individual learners and used to understand the average learning level and learning orientation of all students and reflected in the composition of the class. It is also possible to check teaching and learning outcomes by using an artificial intelligence-based evaluation system for formative evaluation.

### 4.3 AI-based adaptive system implementation in class

These class operations are reported to be applied in connection with classes based on the flipped learning teaching method, which is a part of blended learning that has been introduced as a teaching method that can use various edutech as a learner-centered teaching method [3, 15]. An example of the use of this adaptive problem-learning system can be represented in the same way as shown in **Figure 3**.

The course of the class is as follows. First, students learn beforehand through basic concept videos for each chapter produced by instructors and customized problem learning. In the case of a diagnostic evaluation linked to the progress of the class, a diagnostic report on the pre-learning activities on the day before class is prepared. The class began by identifying problems with high incorrect answer rates with students, and the topics related to these problems were intensively explained in the lecture. The main concepts of the content system provided by the artificial intelligence-based adaptive learning system were identified in the first class, and a summary lecture was conducted in connection with the instructor’s content composition using the topics provided by the courseware. If most students have not yet progressed



**Figure 3.** Schematic class utilization of adaptive problem learning system.

on a specific topic, the lecture was used in a way that lectures were conducted from the basic contents of the related topic, not just a review. In the second class, information on the progress of students' personalized tasks is calculated in the form of a weekly report and used to encourage students to learn AI problems. In addition, since it is the second half of the chapter, each topic was viewed from a macro perspective by expanding through the system and causal relationships between the basic concepts learned by students, and presentations and group discussions on the approach in problem-solving learning was also addressed to complement the interaction between peer learners. In addition, the formative evaluation was conducted 15 min before the end of the second class, and it was completed at the end of the class.

The implementation of AI problem learning as a teaching tool linked to lectures at universities will require continuous research on teaching design that presents learning outcomes that experience opportunities for the application and expansion of concepts and foster in-depth analysis, thinking, and reasoning skills by utilizing concepts learned in terms of content. In addition, in terms of methodology, the use of learning diagnosis data will become more diverse and the ability to utilize it will increase compared to operating adaptive problem learning individually. In addition, it is common to use the hierarchical structure of concepts related to the content system to be considered and the understanding of the use of the system for individual problem learning, but its strength and importance seem to be higher.

## **5. Conclusions**

Problem learning using AI-based systems in the teaching and learning process at university seems to be one of the good ways to understand and reinforce concepts in terms of knowledge transfer. However, the goal of basic university education is that conceptual learning should not be limited to simple knowledge understanding and problem-solving. The correlation and contextual connection of each concept should be made, and it should be utilized to play a role related to competency cultivation while expanding in various ways. Therefore, it is thought that the direction of active use of AI-based systems in university education is not to fully implement the various functions and learning completeness provided by the system, but to properly implement the knowledge learned through the system to be effectively linked to various educational activities. Finally, the points to consider for the actual operation of the AI-based system are summarized as follows. First, it can be viewed as content analysis (conceptual structure research) for system utilization. In other words, it is necessary to compare and review the content system established by the instructor, focusing on topics deemed necessary to achieve the educational goals of the subject, in connection with the content system of the system. Next, it seems that there is a need for a system adaptation process that can implement basic functions related to system operation. The costs required for purchasing and using the system should also be considered for long-term use. In the early stages of system operation, it seems necessary to cooperate with edutech experts supported at the university level to utilize the system effectively and efficiently reflecting the effort required from the instructor's side and the amount of learning required from the learner's side. In particular, when the amount of problems that must be repeatedly solved to reach the level of learning completeness required by the system is determined, there are only a few areas where the instructor can arbitrarily control the amount of learning the learner can control, so it is necessary to review the system utilization plan in this regard before the start of the

semester, which should consider both learning maintenance and learning effects. In addition, since most of the languages currently used in AI-based systems are English, it is necessary to consider them at the teaching and learning design stage to reduce the additional learning burden related to language that may be felt if English is not the native language or does not use English textbooks.

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## Chapter 7

# The Role of AI in Automating Grading: Enhancing Feedback and Efficiency

*Johnbenetic Gnanaprakasam and Ravi Lourdusamy*

### Abstract

This chapter discusses the different ways in which artificial intelligence (AI) can be used to automate the grading process within the educational systems. The first part gives the background of how we got here, how grading practices have historically changed, and then how AI has progressed in integrating with these systems. The real emphasis is the potential use of AI to reduce the grading backlog (through instant feedback, learning incentives, scalability, and important notes) and more effective large and diverse student/learner management. Furthermore, it also delves into the use of AI on the subjective and creative aspects, quite a new realm of grading from the traditional ways. The chapter also provides a critical discussion about challenges associated with AI in grading (such as potential biases, fairness, and ethics), making an emphasis on the necessity to tailor such challenges in order to efficiently and responsibly deploy AI for educational purposes. Finally, it concludes with a reflection on what the next generation of AI-powered educational assessment experiences could look like and what the potential implications for educators and students may be.

**Keywords:** artificial intelligence (AI), automated grading systems, personalized feedback, educational assessment, natural language processing (NLP), machine learning (ML), bias and fairness in AI, data privacy in education, ethical considerations, future of educational technology

## 1. Introduction

### 1.1 Traditional grading systems

#### *1.1.1 Historical overview of grading systems*

The evolution of grading systems in education represents a complex journey, marked by efforts to balance fair assessment of student success with challenges of subjectivity and practicality. Initially, grading was rudimentary, often utilizing a simple pass/fail method. This approach, while straightforward, provided limited insights into a student's abilities and challenges. As educational systems advanced, so

too did the grading methods, evolving into a more nuanced letter grade system (A, B, C, etc.). These systems offered clearer indications of performance levels but still depended heavily on educators' subjective judgments.

Dating back several centuries, the initial focus in educational settings was on oral examinations and personal evaluations by educators. Smith and Johnson offer an extensive overview of this evolution, highlighting the transition from oral to written examinations and then to a more standardized grading scale [1].

### *1.1.2 Challenges in traditional methods*

Because of their intrinsic subjectivity, traditional grading systems present many difficulties and raise questions regarding consistency and fairness between various teachers and students. Grading takes time, especially for comprehensive assignments like essays, and can be particularly difficult in larger classes when there is a significant amount of work to be done. The assessment process is made more difficult by the consistent approach used by traditional grading techniques, which may not sufficiently take into account different learning styles or variations in student ability. Standardized examinations and scoring rubrics were created to provide more objective indicators of student achievement to solve these problems. Although these techniques address some issues with fairness, they can occasionally be restrictive and miss the distinctive contributions made by each student. Standardized testing has come under fire for prioritizing exam-taking techniques over more comprehensive learning goals [1].

Thomas, O'Brien, Sanguino, and Green draw attention to the subjectivity of these systems, emphasizing how teacher prejudices and subjective views can have a big impact on students' assessments [2]. Li draws attention to how standard grading fails to take into account various learning styles, which frequently results in a generalized approach that might not fairly represent the comprehension or advancement of any one student [3].

## **1.2 Need for innovation in grading**

### *1.2.1 Limitations of conventional grading*

The limitations of traditional grading systems have become increasingly clear. Cain highlights a lack of consistency and probable disparities in grading standards as severe disadvantages, with serious consequences for students' academic careers and future chances [4].

### *1.2.2 Emergence of digital technology in education*

The incorporation of digital technology in education has brought about a significant and profound change. Kim and Lee highlight the significance of technology in facilitating the use of more impartial and thorough evaluation instruments. The emergence of AI-powered grading systems, employing algorithms and machine learning to assess student work, signifies a significant progress in rectifying the limitations of conventional grading approaches [5].

AI-powered systems offer the potential for evaluations that are more impartial and consistent by prioritizing comprehension and methodology rather than simply correct or incorrect responses. Owoc demonstrates the ability of these systems to effectively handle substantial amounts of tests, resulting in a significant decrease in the workload of instructors. This adjustment not only improves the equity of grading

but also provides instructors with additional time for interactive and personalized instruction [6].

To summarize, although traditional grading systems have served as the basis for educational assessments for a long time, their inadequacies are evident. AI-powered grading systems offer a novel solution, utilizing improvements in digital technology to address the limitations of traditional approaches and establish a fairer and more efficient educational evaluation system.

## **2. Evolution of automated grading systems**

The growth of automated grading systems is a fascinating journey, beginning with rudimentary computer-assisted evaluations in the mid-twentieth century and advancing to today's powerful AI-driven solutions. This narrative goes beyond simply documenting technological progress; it represents a change in how education is assessed and teaching methods are approached. Our thorough analysis will uncover the significant advancements that have influenced this transformation, emphasizing the interaction between technological progress and educational principles.

### **2.1 Introduction to computer-assisted assessments**

#### *2.1.1 Early stages and initial developments*

The inception of computer-assisted examinations extends back to the early days of computer technology, first focusing on automating simple tasks like scoring multiple-choice tests. Regan provides a detailed description of these early systems, demonstrating how they utilized fundamental computational methods for tasks such as score tabulation and simple answer key management [7]. Despite their limitations due to the computer power and software capabilities of the time, these systems provided the framework for future advanced automated grading innovations.

### **2.2 Emergence of automated grading systems**

#### *2.2.1 Advancements in the 1980s and 1990s*

The 1980s and 1990s represented a key transition in computerized grading methods. During this era, breakthroughs in computer processing and software design led to the introduction of more complicated grading systems. Garcia and Pearson highlight how these systems began implementing complicated algorithms capable of judging not just objective responses but also subjective ones like short answers and essays [8]. This shift signified a transition from solely quantitative assessment to a blend of quantitative and qualitative evaluation, enabling a broader review of student responses.

### **2.3 Advancements in language processing and AI**

#### *2.3.1 Turning point in AI application for grading*

The adoption of powerful language processing and AI technology constituted a significant milestone in automated grading systems. Baidoo-Anu studies the

combination of natural language processing (NLP) and machine learning methods, noting their significant impact on these systems' capacity to interpret textual answers [9]. This advancement brought about a more refined and sophisticated examination of written content, enabling the grading process to comprehend and evaluate complicated concepts and arguments offered by people.

## **2.4 Integration of pedagogical theories**

### *2.4.1 Blending educational theory with technology*

Incorporating pedagogical theories into automated grading systems has been a key advancement. Lee and Kim underline the necessity of matching automated grading with educational objectives and learning theories [10]. This fusion has resulted in grading systems that not only measure performance but also enhance the learning process by delivering pedagogically sound feedback matched with educational goals, such as increasing critical thinking and problem-solving skills.

## **2.5 The current landscape: AI-driven adaptive learning systems**

### *2.5.1 State-of-the-art AI systems in education*

Today's automated grading landscape is dominated by powerful AI-driven adaptive learning systems. Darvishi discusses the current innovations in this arena, emphasizing how these systems leverage advanced algorithms to offer individualized feedback and adapt to different learning patterns [11]. Capable of identifying learning gaps, personalizing content, and giving tailored interventions, these technologies dramatically increase the learning experience. They reflect the result of years of evolution in educational technology, blending AI breakthroughs, language processing, and educational theory to create a dynamic, responsive learning environment.

## **3. Principles of AI in grading**

This chapter digs into the underlying ideas of artificial intelligence (AI) in grading systems, focusing on the core AI algorithms that have profoundly revolutionized educational assessment. It investigates the strengths and limitations of these algorithms, exploring crucial issues of accuracy and reliability in AI grading and addressing the technological and ethical components of these revolutionary systems.

### **3.1 AI algorithms in education**

#### *3.1.1 Core algorithms and their capabilities*

AI algorithms have transformed student assessments in schools. Key algorithms such as machine learning (ML) and deep learning are pivotal in this change. Crompton, Burke, and Jones note that these algorithms excel in processing and learning from big datasets, allowing for extremely accurate evaluation of student replies [12]. They are capable of evaluating patterns in student answers, delivering personalized feedback, and modifying evaluation criteria based on individual student performance.

## **3.2 Evolution of AI in grading systems**

### *3.2.1 Technological advancements in NLP and ML*

Advancements in natural language processing (NLP) and machine learning (ML) have greatly pushed the advancement of AI in grading systems. Kompa, Hakim, and Palepu describe how NLP enables AI systems to interpret and analyze human language, which is critical for judging written responses [13]. Meanwhile, ML allows these systems to learn from data, improve over time, and make more accurate assessments regarding the quality and content of student work.

## **3.3 Accuracy and reliability of AI grading**

### *3.3.1 Ensuring fairness and consistency*

Ensuring accuracy and reliability is a fundamental priority in AI grading. Patel underlines the necessity for AI systems to be not just efficient but also fair and consistent in their assessments [14]. This involves the constant development of algorithms to decrease errors and biases and validation against broad datasets to assure equitable grading across various student populations.

## **3.4 Ethical considerations in AI grading**

### *3.4.1 Addressing biases and ethical concerns*

The employment of AI in grading brings forward important ethical problems. Goel underlines the significance of facing potential biases in AI systems, which may emerge from biased training data or incorrect algorithm design [15]. It is vital to guarantee AI systems are transparent and their decision-making processes are accessible to educators and students, sustaining trust and fairness in AI-assisted grading.

## **3.5 The future of AI in educational assessment**

### *3.5.1 Projections and potential developments*

Looking forward, AI in educational assessment is predicted to endure considerable breakthroughs. Chiu thinks that future AI systems would not only grade more efficiently but also deliver more detailed and insightful feedback to people [16]. The combination of AI with other developing technologies, such as augmented reality and virtual reality, could further increase interactive learning and tailored education.

## **4. Enhancing feedback with AI**

### **4.1 Personalized feedback through AI**

#### *4.1.1 Customized responses and their impact*

The integration of AI in education has ushered in a new era of individualized feedback, significantly altering student interaction with learning materials. Igbokwe

studies AI systems that assess individual student replies, indicating distinct learning patterns and opportunities for improvement [17]. This individualized method enables feedback to be adapted to each student's distinct learning style and pace, resulting in more effective support for specific educational needs. The impact of this personalization is enormous, leading to higher student performance, enhanced retention of knowledge, and a deeper comprehension of the subject matter.

## **4.2 Immediate feedback and its advantages**

### *4.2.1 Benefits of real-time feedback*

One of the most transformational elements of AI in education is the provision of immediate feedback. AI Ka'bi addresses the advantages of real-time replies in educational environments [18]. Immediate feedback allows students to promptly rectify mistakes and reinforce accurate concepts, encouraging a more efficient and continuous learning process. This immediacy is especially advantageous in areas requiring a strong basic grasp, as it minimizes the building of misconceptions and bolsters confidence in learning.

## **4.3 AI-driven feedback and student engagement**

### *4.3.1 Impact on student motivation and participation*

AI-driven feedback dramatically influences student engagement and motivation. George studies how AI systems, by offering timely and meaningful feedback, might dramatically enhance student participation in the learning process [19]. This greater engagement is linked to the interactive aspect of AI feedback, which tends to be more immediate and tailored compared to older techniques. Such participation not only enhances motivation but also produces a more dynamic and participative learning environment, enabling students to actively engage in their education.

## **4.4 Impact of AI feedback on learning outcomes**

### *4.4.1 Educational benefits of AI feedback*

The effect of AI-generated feedback on learning outcomes is significant. Chen presents many studies indicating how AI feedback can increase academic achievement and expand subject matter understanding [20]. This efficacy is largely owing to AI systems' capacity to deliver precise, specific feedback addressing the complexities of a student's responses. Furthermore, AI feedback generally includes ideas for development and extra learning resources, making it a full educational tool.

## **4.5 Challenges and ethical considerations**

### *4.5.1 Addressing potential hurdles in AI feedback systems*

Despite its many advantages, the deployment of AI in feedback systems offers problems and ethical considerations. Chen covers numerous topics such as potential biases in AI algorithms, the importance of data protection, and the need for transparency in system operations [20]. These problems underline the need for careful design,

continual monitoring, and regular upgrades to guarantee AI feedback systems are egalitarian, fair, and respectful of student privacy. Additionally, they underline the significance of human oversight to complement AI feedback, ensuring the educational process stays sympathetic and student-focused.

## **5. Efficiency and scalability in AI-enabled grading**

### **5.1 Enhanced resource management in education**

#### *5.1.1 The role of AI in optimizing educational resources*

Effective resource management is vital in education, directly impacting the quality and efficacy of teaching and learning. AI technology plays a vital role in this field. Alqahtani analyzes the impact of AI on grading systems, stressing not only the rapidity of the grading process but also a considerable improvement in the efficiency of resource allocation [21].

AI-enabled systems can efficiently process massive volumes of student work, a task that normally demands significant time and effort from educators. This quick processing ability frees up significant time for teachers, allowing them to focus more on direct educational activities such as lesson planning, individual student interactions, and pedagogical research. Furthermore, these tools assist detect specific areas where students require additional support, enabling teachers to adapt their education and interventions with greater precision.

Beyond the classroom, AI increasingly influences resource management at the administrative level. Schools and educational institutions can gain large cost savings by decreasing the need for extra grading staff or outsourced grading services. This efficient deployment of human and financial resources can be channeled toward strengthening many educational facets, including student support services, technological improvements, and professional development opportunities for educators.

### **5.2 AI's role in expanding educational horizons**

#### *5.2.1 Adapting AI systems for large classes and online learning*

The scalability and adaptability of AI systems are especially significant in big classes and online education, where the student-to-teacher ratio might be disproportionately high. Bauer highlights the inherent obstacles in these situations, such as ensuring equitable and uniform evaluation for a diverse and extensive student body and how AI effectively mitigates these issues [22].

In big classroom environments, traditional assessment procedures typically become unworkable due to the excessive volume of assignments needing examination. AI systems, unencumbered by the limits imposed by human graders, may adeptly manage thousands of assignments concurrently, assuring rapid and uniform grading. This scalability is critical for sustaining academic standards and insuring that students receive fast feedback, essential for their academic growth and progression.

In online education, AI systems demonstrate extraordinary versatility. They can adapt to numerous course styles, academic fields, and diverse levels of student academic readiness. This flexibility is crucial in online platforms that usually serve an international and culturally heterogeneous student community. AI grading systems

can interpret and evaluate responses across different languages and dialects and can be adjusted to adapt to specific curriculum standards and cultural situations.

Moreover, in online education environments, AI systems can offer a level of customization that is impossible to attain in traditional classrooms. By evaluating individual student data, these systems can provide individualized feedback and learning ideas, enhancing the educational experience for each learner.

In summary, the efficiency and scalability of AI-enabled grading systems constitute a significant leap in educational technology. They provide solid solutions for managing resources in education, successfully addressing the particular issues provided by big classroom environments and online educational platforms. As these systems improve, they hold the potential to significantly revolutionize the delivery and assessment of education, increasing learning experiences worldwide.

## **6. Beyond traditional testing: AI in creative and subjective assessment**

### **6.1 Evaluating creative work through AI**

#### *6.1.1 Advanced techniques for assessing creativity*

The application of AI in grading has predominantly been linked to objective assessments with clear right-or-wrong answers. However, recent advancements have extended AI's capabilities to include the evaluation of creative work. This shift involves intricate processes wherein AI algorithms are trained to discern and assess elements such as creativity, originality, and artistic expression.

Johnson and Lee have investigated the methods through which AI can appraise creative assignments [19]. These methods often utilize advanced machine learning techniques, including neural networks and deep learning, capable of analyzing patterns, styles, and techniques in various creative works. For instance, in evaluating written creative work, AI systems can analyze aspects like narrative structure, language use, and originality. In visual arts, they can examine color usage, composition, and artistic techniques.

The subjective nature of creativity presents a unique challenge. Creative works, unlike objective tests, are open to various interpretations. Therefore, AI systems in this field aim to provide a structured evaluation, focusing on technical aspects and widely recognized standards of creativity while avoiding subjective judgment. This approach requires a delicate balance, ensuring that AI assessments both nurture and support creative expression, avoiding the imposition of overly rigid standards.

### **6.2 AI's flexibility in meeting diverse educational needs**

#### *6.2.1 Tailoring learning to individual preferences*

The ability of AI to adapt to diverse educational needs is crucial to its effectiveness in contemporary learning environments. This flexibility is particularly evident in AI's capacity to personalize learning experiences for students with varying learning styles, abilities, and interests.

Alier discusses how AI systems can customize educational content and assessments based on individual student profiles [23]. These profiles are constructed from data such as previous academic achievements, learning speeds, preferred learning

methods (visual, auditory, and kinesthetic), and even emotional reactions to specific types of content.

Personalization in AI goes beyond merely adapting to different learning styles. It encompasses accommodating students with special educational needs, like those with dyslexia or autism, by offering tailored resources and assessment approaches that align with their distinct learning requirements. For example, AI can provide more visually oriented content and interactive modules for learners who struggle with traditional text-based education.

Additionally, the adaptability of AI is vital in serving a culturally diverse student body. It can supply learning materials that are culturally sensitive and create assessments that avoid cultural biases. This inclusivity ensures that students from varied backgrounds receive equitable learning opportunities, promoting an inclusive educational atmosphere.

This chapter outlines the advancements and challenges in employing AI for creative and subjective assessments and its flexibility in addressing diverse educational requirements.

## **7. Fairness and bias in AI grading**

### **7.1 Tackling inherent biases in AI systems**

#### *7.1.1 Identifying and reducing biases*

The challenge of inherent biases in AI grading systems is a key issue in educational technology. AI systems inherently reflect the biases existing in their data and algorithmic basis. Zhang investigates the ways biases might penetrate AI systems, such as through prejudiced training data, the subjective opinions of developers, or the simplifying of complicated human actions [24]. Identifying these biases involves a complete investigation of the AI system's training data, algorithmic structure, and outputs. This process demands a multidisciplinary approach, incorporating not only technologists but also educators, sociologists, and students. Regular audits and updates are crucial to ensure in fairness and accuracy. Mitigating these prejudices is a continual undertaking. It needs broadening the training data to span a broad spectrum of student work across varied ethnicities, backgrounds, and learning styles.

Additionally, adding feedback mechanisms where educators and students can review the AI system's performance and fairness is crucial. This inclusive strategy assures the AI system is continually learning and changing, gradually decreasing biases.

### **7.2 Establishing fair and inclusive grading practices**

#### *7.2.1 Guidelines for equitable AI grading*

Creating solutions for fair and inclusive AI grading is vital to guarantee these systems serve all students equitably. Qian recommends various best practices for educational institutions to employ in pursuit of this purpose [25].

A crucial strategy involves maintaining the transparency of AI systems. Such transparency allows educators and students to comprehend the workings of the AI

system, its grading standards, and the logic behind its ratings. This clarity fosters trust and acceptability in AI systems.

Another essential method is the constant enrichment of AI systems with diverse and representative data. This technique enables the AI system to more precisely and fairly assess work from students of varied cultural backgrounds, learning styles, and capabilities.

Human oversight remains vital in this situation. AI grading systems are designed to complement, not displace, educators. Human educators add crucial context, empathy, and insight to the grading process, traits that AI systems cannot perfectly mimic.

Lastly, it is crucial to create continual collaboration and dialog among technologists, educators, and politicians. This partnership assures that AI grading systems are not only technically strong but also in harmony with educational objectives and ethical values.

## **8. Ethical and privacy considerations**

### **8.1 Data privacy in AI systems**

#### *8.1.1 Protecting sensitive student data*

The application of AI in education presents substantial concerns surrounding data privacy, especially considering the sensitivity of student data. These data comprise not only academic records but also personal information that could be subject to misuse if not securely protected. As stated by Kumar, preserving data privacy in AI systems is not simply a technological issue but also a legal and ethical one [26].

Protecting student data in AI systems involves several key strategies:

1. *Encryption and security measures:* Implementing effective encryption and cybersecurity measures is vital to safeguard data from unauthorized access and breaches.
2. *Data anonymization:* When AI systems use student data for learning and improvement, it is vital to anonymize these data. This involves eliminating any personally identifiable information to guarantee that individual students cannot be traced.
3. *Compliance with regulations:* Educational institutions must comply with data protection regulations such as the General Data Protection Regulation (GDPR) in Europe or the Family Educational Rights and Privacy Act (FERPA) in the United States. These regulations offer frameworks for how student data should be handled and protected.
4. *Transparency and consent:* Transparency regarding what data are gathered, how they are used, and obtaining approval from students or their guardians (in the case of minors) is vital.
5. Educational institutions must work closely with technology vendors to verify that the AI systems they utilize adhere to these privacy standards and legislation.

## **8.2 Ethical implications in automated grading**

### *8.2.1 Ensuring fairness, transparency, and consent*

The ethical issues of automated grading systems extend beyond only the accuracy and efficiency of grading. As Thomas notes, there are greater ethical questions that need to be addressed to ensure that these systems are fair and just [27].

1. *Fairness*: AI systems must be built to grade impartially, without prejudices based on race, gender, or socioeconomic background. This entails regular checks for biases and modifications in the AI algorithms.
2. *Transparency*: There should be information about how the AI system operates, the criteria it employs for grading, and how choices are reached. This transparency is vital for gaining the trust of students and educators.
3. *Consent and choice*: Students and educators should have a vote in whether or how AI grading is employed in their educational experience. Additionally, there should always be a possibility for human review of AI grading choices.
4. *Accountability*: There should be clear accountability for the judgments made by AI systems. In circumstances where a grading decision significantly effects a student's academic career, the process for appealing or revisiting the decision should be straightforward and fair.
5. *Ethical development and deployment*: The development and deployment of AI grading systems should adhere to ethical norms, ensuring they are utilized to enhance education rather than replace the human factors that are crucial to learning.

Addressing these ethical and privacy problems is vital for the proper use of AI in education. It not only assists in developing systems that are fair and just but also ensures that these systems are accepted and trusted by the educational community.

## **9. The future of AI in grading**

### **9.1 Emerging trends and technologies**

#### *9.1.1 NLP advancements and integration with learning management systems (LMS)*

The future of AI in grading is directly connected to continuous improvements in natural language processing (NLP) and the integration of AI technologies with learning management systems (LMS). Harry describes the rapid progress of NLP, with new models and algorithms being developed that can more properly read and process human language [28]. This progress is vital for grading systems, particularly in judging more subjective and complex student responses such as essays and open-ended questions.

One major trend is the development of AI models that can not only evaluate grammar and syntax but also examine the coherence, inventiveness, and depth of student responses. These models are being trained on enormous and diverse datasets, enabling them to grasp distinct writing styles and nuances in multiple languages.

Another noteworthy trend is the seamless integration of AI grading systems with LMS platforms. This integration is redefining how instructors and students interact with educational content and assessments. LMS platforms are rapidly adopting AI capabilities that provide real-time feedback on student assignments, suggest resources for improvement, and adapt learning content depending on individual student performance. This integration provides a more tailored and responsive learning experience, making education more flexible to individual learner needs.

## **9.2 Preparing for advanced AI integration in education**

### *9.2.1 Infrastructure, ethical use, and training*

Preparing for the advanced integration of AI in education demands a diverse approach, focused on infrastructure development, ethical application, and extensive training. As Khairi points out, securing the successful application of AI systems in education extends beyond just technological improvements [29].

- 1. Infrastructure development:* Educational institutions must invest in the essential digital infrastructure to support advanced AI systems. This involves powerful internet connectivity, suitable hardware, and secure cloud storage solutions. Additionally, there needs to be a focus on designing interoperable systems that can combine diverse educational resources and platforms effortlessly.
- 2. Ethical use:* The ethical application of AI in education is crucial. Institutions need to develop explicit standards and policies that regulate the usage of AI systems. This includes guaranteeing data protection, eliminating potential biases in AI systems, and assuring openness in AI-driven judgments. Ethical use also requires ensuring that AI does not replace the key human parts of teaching but rather complements and enriches them.
- 3. Training and professional development:* Educators and administrative personnel need to be trained not only on how to use AI systems efficiently but also on understanding their limitations and potential biases. Continuous professional development programs should be created to keep educators current of the newest AI advances and best practices in integrating AI technologies into their teaching.

The future of AI in grading appears optimistic, with technology growing more sophisticated and integrated into educational procedures. However, this future also involves careful planning and deliberation, ensuring that AI tools are used responsibly and efficiently to enhance the educational experience.

## **10. Conclusion**

### **10.1 Recap and future prospects**

#### *10.1.1 Summarizing key themes and looking ahead*

As we conclude our exploration of AI in grading, it is necessary to recall the key aspects and discuss future opportunities. This book has traveled the landscape of AI in education, from its earliest implementation in grading systems to the ethical, privacy, and technical difficulties it raises. We have seen how AI can boost the efficiency and fairness of grading, provide tailored feedback, and adapt to varied educational demands.

The incorporation of advanced AI technologies like NLP and machine learning into educational procedures, particularly in grading, signifies a fundamental shift in how student achievement is judged. The opportunities of AI in this field are immense. As Pedró and Subosa imply, we are likely to see more advanced AI systems that not only evaluate with high accuracy but also provide nuanced feedback that helps lead students in their learning path [30].

Moreover, the incorporation of AI in grading is projected to expand in line with emerging educational technology. This includes the possible convergence of AI with augmented reality (AR) and virtual reality (VR) for more immersive learning experiences, as well as the usage of big data to get deeper insights into learning patterns and outcomes.

However, as AI systems become more incorporated into educational settings, attention about ethical considerations and data protection becomes increasingly crucial. The future of AI in education will be influenced not just by technology breakthroughs but also by the laws and frameworks designed to guide its ethical and fair use.

### **10.2 Embracing change and innovation**

#### *10.2.1 The broader impact of AI in education*

The broader significance of AI in education extends beyond grading. As Rahman and Kodikal emphasize, AI has the ability to alter the entire educational scene [31]. It can lead to more personalized and adaptable learning settings, where instruction is adapted to individual student requirements, talents, and learning styles. This customization could help bridge gaps in education, delivering support where it needs most and challenging people to realize their full potential.

AI's significance in education also necessitates a reevaluation of established teaching methods and curriculum frameworks. The data-driven insights offered by AI can guide more effective teaching practices and curriculum development, leading to a more responsive and dynamic educational system.

However, embracing this transformation demands a coordinated effort from educators, lawmakers, technologists, and students. It includes not only accepting new technologies but also adapting to the cultural and educational shifts they bring. The role of educators, in particular, will shift, with a greater focus on guiding and mentoring students through a technology-enhanced learning journey.

In conclusion, the future of AI in education is not just about technological innovation; it is about utilizing this technology to produce more equal, effective, and inspiring educational experiences. As we welcome these developments, it is vital to handle them intelligently, ensuring that AI is used as a force for good in defining the future of education.

### *10.2.2 AI-driven tools for grading*

Specific AI-driven solutions currently utilized for grading include automated essay scoring systems (like Turnitin's Gradescope), multiple-choice test graders, and platforms that assess coding assignments (such as CodeSignal). These technologies utilize natural language processing, machine learning algorithms, and pattern recognition to analyze student inputs against a set of criteria or answer keys.

### *10.2.3 Addressing bias and fairness*

The difficulties of prejudice and fairness in AI-aided grading can be addressed by the following:

- Continually training AI models on varied datasets that represent a wide range of language, cultural, and educational backgrounds.
- Implementing transparent algorithms that allow instructors to see and understand the foundation for a grade.
- Incorporating human monitoring to validate AI grading conclusions, ensuring that the final grades reflect a fair assessment.

### *10.2.4 Ethical considerations and mitigation*

The ethical considerations of utilizing AI in grading focus around data privacy, the potential for systematic bias, and the impact on student motivation. Mitigation strategies include the following:

- Ensuring rigorous compliance with data protection requirements to preserve student information.
- Engaging multidisciplinary teams in AI development to eliminate prejudice and assure ethical use.
- Communicating clearly with students about how AI is utilized in their evaluations to ensure confidence and integrity in the educational process.

### *10.2.5 Potential negative impacts*

AI-aided grading could potentially:

- Diminish the qualitative feedback that is vital for student learning and progress.
- Increase dependence on technology, resulting to a loss in essential human evaluative abilities among instructors.

- Exacerbate educational inequities if access to advanced AI techniques is inconsistent across different institutions.

### 10.2.6 Future implication

The incorporation of AI in educational assessment could lead to significant upheavals in the job market, notably for educators. While AI can automate certain portions of grading, the role of educators could expand to focus more on curriculum development, personalized instruction, and mentoring. Additionally, there is potential for new occupations based around AI maintenance, development, and ethical monitoring within educational institutions.

Potential drawbacks of using AI for grading include the following:

- The possibility of mistakes in grading, especially for subjective projects like essays, where nuance and inventiveness could be disregarded.
- The potential for technology to produce errors due to biased training data or algorithmic restrictions.
- The requirement for significant upfront investment in technology and training for schools to effectively employ AI grading tools.

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## Chapter 8

# Integrating AI into VET: Insights from AIM@VET's First Training Activity

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### Abstract

This work presents the objectives, methodologies, and preliminary outcomes of the first training activity (TA1) within the AIM@VET project, an EU initiative aimed at integrating artificial intelligence (AI) into vocational education and training (VET) to align with labor market demands. Addressing the noticeable gap in AI education across various educational levels, AIM@VET, involving six partners from Spain, Portugal, and Slovenia, focuses on developing teacher-centered learning modules in key AI application areas: computer vision, robotics, and ambient intelligence. The project's methodology involves universities in content preparation and VET teachers in content delivery to students, with an iterative feedback loop enhancing the curriculum's relevance and effectiveness. TA1 demonstrated a practical approach to applying AI concepts through a mix of theoretical lessons and hands-on tasks, significantly improving students' technical AI skills and readiness for the digital workforce. The activity underscored the importance of standardizing lesson creation protocols to produce a unified curriculum, thereby facilitating improved coordination among partners. This chapter will detail the project's framework, its execution, and an analysis of the results obtained in the project's first steps.

**Keywords:** AI Literacy, artificial intelligence education, artificial intelligence modules (AIM), Erasmus+ program, project-based learning, digital transformation, vocational training, robotics, ambient intelligence, computer vision

### 1. Introduction

The technical revolution behind artificial intelligence (AI) impacts the society in a global way. Consequently, it is mandatory to educate the whole population in the fundamentals of this digital technology, not only to increase their job opportunities but as a fundamental right to be aware of the decisions that are taken by AI-based

systems [1]. In this scope, the development of AI literacy is a key goal for most educational administrations and organizations around the world [2, 3]. It implies the definition of the skills and competencies that learners should acquire in this topic, as well as the procedures to achieve them, mainly through specific curricula and resources [4].

Many approaches to AI curricula development have arisen in the last 5 years, mainly focused on pre-university levels (secondary school). They come from official educational administrations [5], private initiatives [6], or directly from universities and schools [7]. All of them are still under development and testing because the creation of a formal and reliable curriculum in a new discipline takes time, reflection, and improvement. Most of the existing approaches are based on the guidelines of the AI4K12 initiative [8] and the five big ideas they propose (Perception, Representation and Reasoning, Learning, Natural Interaction, and Societal Impact). These ideas make up wide areas where educators should focus on training secondary school students in the fundamentals of AI. Following these guidelines, some remarkable educational resources in topics like perception, representation, and, mainly, machine learning can be found [9]. The majority of them have been developed for compulsory levels, with a general educational perspective. The technical background required to follow the lessons is low, as there is no warranty about the students' digital knowledge and skills in programming, statistics, or logics to be homogeneous in different countries and regions.

The current work is focused on Vocational Education and Training (VET), where the previous considerations must be reformulated [10]. These students have a clear technical focus, mainly practical, and their training must be aligned with the labor market requirements. Therefore, the existing curricula about AI for pre-university levels must be adapted to this scope, or new ones must be created. In addition, the curriculum organization in VET education is not the same as in secondary school, and here the typical teaching units are organized in “learning modules”, which are more specific and shorter. Hence, there are many specific features to consider when developing an AI curriculum for VET. In this realm, some initiatives have arisen, although they are in the early stages of development. From all of them, the TackleAI project must be highlighted, which has been analyzing the particularities of AI education in VET for the last few years. The main conclusions of their final report have been taken here as a guideline for future development [11]. A more detailed description of the AIM@VET project and its objectives can be found in [12].

The authors of this paper were granted an Erasmus+ project in 2022, called AIM@VET, with the aim of developing AI learning modules adapted to VET education in three areas: autonomous robotics, computer vision, and ambient intelligence. The project encompasses one VET school and one university from Spain, Portugal, and Slovenia, leading to a team of six partners. They have been organized into ‘work islands’—a term referring to specialized working groups, each based in a different country and focused on one of the three distinct AI areas mentioned above. These work islands operate collaboratively yet independently, allowing each group to develop specialized teaching units (TUs) and then share insights and outcomes with other groups. This organizational structure promotes specialization and efficiency in the development of educational content tailored to VET education while facilitating broad collaboration among partners across different countries. Each university team creates specific teaching units (TUs) in their particular area, which are revised by the teachers at the corresponding VET school and tested with their students. From these

results, the university team obtains feedback to improve the TUs. At the project's end, the TUs will be organized into three independent learning modules, and they will be published on the project website to make them available to the entire teaching community [13].

A key step in this project was the first Training Activity (TA1), held in Slovenia, as it tested the TUs developed by the different 'work islands' in a novel context. TA1 facilitated a deeper level of evaluation by involving students from various 'work islands', thus enabling the TUs to be tested across a more diverse student body. Specifically, the initial two teaching units, TU1 and TU2, which were developed as part of the project, were shared with and tested by students from mixed nationalities and backgrounds in collaborative groups. This approach is not only aimed at assessing the TUs' effectiveness but also at fostering an environment of cross-cultural learning and exchange.

The methodology and outcomes of TA1 are presented here, with a focus on analyzing the application of the developed TUs and their impact on the students. Specifically, the TU described here introduces students to the application of Q-learning in robotics for navigation and obstacle avoidance, basic principles and techniques of image processing and object detection in computer vision, and the integration and control of sensors and actuators in the context of ambient intelligence.

## 2. Methodology

This section details the first Training Activity (TA1) within the AIM@VET project, focusing on its dual role: assessing the effectiveness of teaching units from each work island and enhancing collaborative learning among diverse AI specialization students. TA1 was fundamental for evaluating lesson functionality, sharing challenges and insights, and introducing lessons to new students. It also proved very useful for refining practical aspects such as coordination, standardization of lesson format, content, and pedagogical philosophy.

### 2.1 Description of the activity

TA1 focused on the core themes of computer vision, robotics, and ambient intelligence, each managed by one of the three work islands. Each island was responsible for creating scenarios and tasks within their respective domain. The activity encompassed 18 hours of teaching for each thematic area, culminating in a 1:30-hour joint session for presentations and feedback exchange among students. This final session allowed students from different work islands to share their results and insights.

### 2.2 Participants

Participants in TA1 included students from each of the work islands, encompassing a range of educational backgrounds and AI expertise levels. This diversity was intentional to foster cross-disciplinary learning and interaction. In line with this approach, the participants were strategically mixed across different thematic areas, with each work island delivering lessons to students from the other islands. This structure, detailed in **Table 1**, was designed to encourage cross-disciplinary learning and foster a collaborative educational environment.

| Teaching Island | Lesson Focus         | Student Groups                      |
|-----------------|----------------------|-------------------------------------|
| Spain           | Robotics             | 6 students (3 Slovenia, 3 Portugal) |
| Slovenia        | Computer Vision      | 6 students (3 Spain, 3 Portugal)    |
| Portugal        | Ambient Intelligence | 6 students (3 Spain, 3 Slovenia)    |

**Table 1.**  
*Distribution of mixed teaching approach in TA1.*

### 2.3 Target age group and prerequisites

This activity is tailored for VET students aged 15–20. To accommodate this broad age range effectively, clear prerequisites are established to ensure students possess the foundational knowledge necessary for the proposed challenges. These prerequisites are:

- *Programming*: A basic level of programming, including an understanding of conditionals, loops, variables, and functions.
- *Python*: Basic familiarity with the Python programming language, suitable for engaging with simple programming tasks.
- *Mathematics*: Knowledge of Cartesian coordinates, angles, and time measurements is important for the mathematical aspects of the challenges.

These prerequisites aim to equip students with the essential skills required to engage with and benefit from the learning modules, ensuring a productive and enriching educational experience.

### 2.4 Feedback mechanisms

In TA1, several feedback mechanisms were employed to evaluate and enhance the effectiveness of the training sessions.

1. *General Lesson Evaluation Templates for Students*: These templates were used by teachers to assess student performance across the entire training activity unit. The evaluation focused on various aspects of the task, with teachers assigning scores based on a detailed rubric. This approach ensured a consistent and reliable method of evaluating student progress across different curriculum units. The criteria used in these templates included adequate selection of information, time management, design and construction of the solution, creativity, testing and debugging, programming and code, and teamwork.
2. *Specific Evaluation - Questionnaires*: Following the completion of each unit, students were required to answer questionnaires that focused on specific aspects of the lesson, including theory and implementation. These questions aimed to gauge the students' understanding and application of the material covered in the TU.
3. *Teacher Feedback*: Teachers filled out templates evaluating each section of the lesson, with a focus on potential improvements. They provided assessments on the

duration of each task, the theoretical content provided, and evaluation indicators for student performance. Teachers were also encouraged to propose new or modified evaluation indicators, contributing to the ongoing refinement of the teaching units.

These feedback mechanisms were integral to the continuous improvement of the teaching units and overall training activity, ensuring that both theoretical and practical components of the curriculum were effectively delivered and assimilated by the students. The evaluation templates presented here can be found in the modules section of the project website, accessible at [13].

### **3. Description of the teaching units**

A cooperative Project-Based Learning (cPBL) approach has been used to implement the TUs that make the AIM@VET modules. Students are organized in teams to face a challenge that must be solved by means of an AI system they program in Python language. According to the PBL methodology, each TU establishes a set of design specifications, including a video displaying the final response the AI system must show, and provides a tentative organization in steps. The approach is based on a “hands-on” learning perspective in which the theoretical concepts are reinforced as they are required to solve a practical issue (learning by doing), and it is key for VET education.

All the materials associated with these TUs are available at [14], including a main file with the teacher’s guide in pdf, the demonstrative video of the expected solution, the code with the Python programs, and other supportive materials.

#### **3.1 Robotics**

The current resource corresponds to the second TU of the robotics module of the AIM@VET project, focused on mobile robotics. The ultimate challenge of this TU is to enable a mobile robot to move autonomously within an industrial-like scenario, avoiding the risks of obstacles and floor level changes, and aiming to solve a patrolling task in an autonomous way. In the following subsections, more details regarding this resource and its scope in AI teaching for VET education are provided.

##### *3.1.1 Temporal organization and required resources*

The robotics unit is structured to be completed over 15 hours and tailored for students who have met the specified prerequisites. The curriculum is segmented into four main tasks, with the following time allocation: 5 hours for Task 1, 3 hours for Task 2, 4 hours for Task 3, and 3 hours for Task 4. This structure is designed to provide an in-depth exploration of each topic.

- In Task 1, students engage in learning how to detect and avoid potential hazards in the environment, with a significant emphasis on practical application and understanding.
- Task 2 introduces the basics of Q-learning, allocating sufficient time for both theoretical discussions and practical exercises.

- Tasks 3 and 4 continue to explore advanced concepts and applications of Q-learning, with time allotted for comprehensive engagement with the content, hands-on activities, and problem-solving.

Each task commences with a theoretical introduction by the teacher, detailing the scope and objectives. Students are provided with specific time frames to work on the challenges, encouraging active engagement and the development of problem-solving skills. Upon completion, collective discussions are held to review possible solutions, facilitating reflective learning and consolidation of knowledge.

The following resources are necessary to facilitate this TU:

1. Each student needs access to a laptop or computer capable of programming with Python.
2. The RoboboSim simulator should be downloaded from the Robobo wiki [15] and installed on each student's computer.

Robobo [16] is an educational robot comprised of a mobile base connected to a smartphone via Bluetooth, forming a single robotic platform with high technical specifications, low cost, and long durability. As depicted on the left side of **Figure 1**, Robobo is equipped with a high-resolution camera, microphone, tactile screen, speaker, WI-FI, Bluetooth, a powerful CPU, and other relevant features for teaching AI at all levels. It supports programming in Scratch and Python and is compatible with ROS [15], offering libraries for computer vision, sound processing, speech production, and recognition, among others.

Furthermore, different simulation tools suitable for various educational levels and skills are available [17]. One of these tools is RoboboSim [15], a 3D realistic simulator used in this TU to introduce students to reinforcement learning. Developed using Unity technology, RoboboSim provides a computationally light and engaging learning environment with video game-like usability and aesthetics. It supports most of the sensors and actuators of the real robot, especially those required for the challenges presented in this activity. The right image of **Figure 1** shows a snapshot of one RoboboSim simulation world, demonstrating its capabilities and interface.



**Figure 1.**  
*Left: Robobo robot. Right: RoboboSim interface.*

### 3.1.2 AI concepts addressed

Throughout this TU, students will learn the fundamentals of reinforcement learning by means of implementing a specific algorithm: Q-learning. They will use the Q-table to guide the robot's decision-making process. By updating the Q-values using the Bellman equation [18], the robot can learn from its experiences and improve its actions over time. In addition, students will explore how the robot actuators enable physical movements and actions, while the sensors provide important information about the environment. This knowledge about the interaction of the robot with its environment is essential for the effective integration of sensor feedback into the robot's decision-making. The robot learns a control program through a reward-based approach utilizing Q-learning. Specifically, through iterative experimentation, Robobo employs the Q-learning algorithm to optimize its actions and autonomously navigate toward illuminated areas. But it is important to note that other control programs required to support Q-learning have been previously developed by students, and they remain predefined during the reinforcement learning process. These control programs correspond to obstacle avoidance and fall prevention. They are programmed by the designer to ensure the safety of both the robot and its environment, a key aspect of autonomous robotics for VET education in terms of the legal, ethical, and responsibility considerations that these students must learn to face real-world jobs.

### 3.1.3 Challenge description

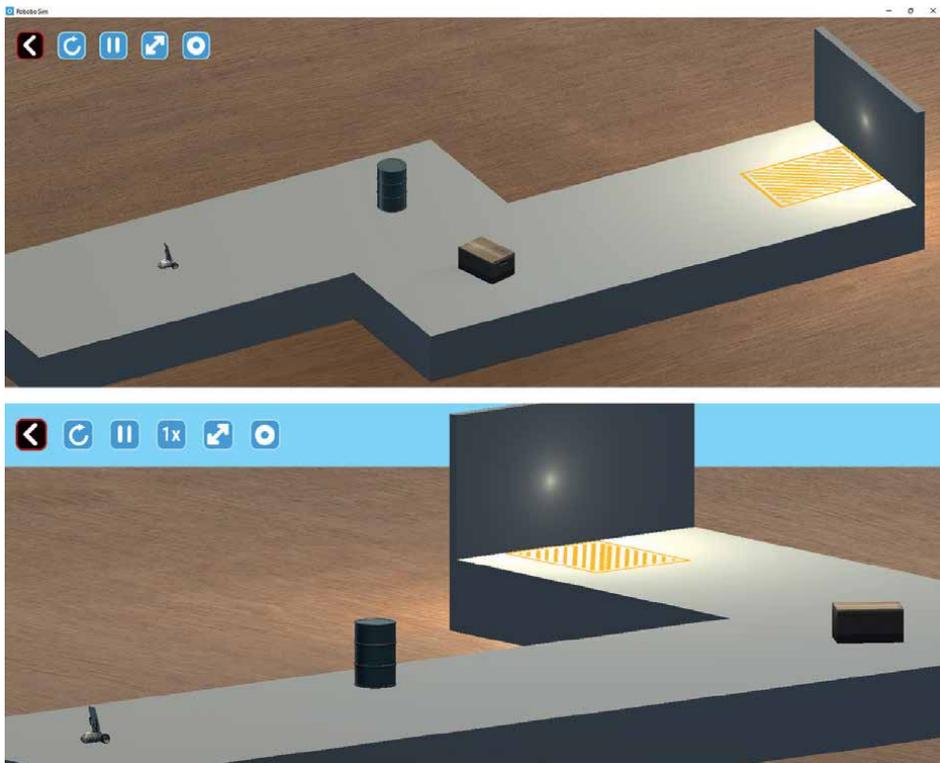
The primary goal of this Teaching Unit (TU) is to equip Robobo with the capability to autonomously navigate toward illuminated areas within unknown environments, identifying obstacles and avoiding falls. This requires students to program Robobo, blending predefined safety controls with the Q-learning algorithm for navigation. The simulation environment for this challenge, including obstacles and light sources, is depicted in **Figure 2**.

Students are tasked with implementing a Python program that integrates control programs with the Q-learning algorithm, enabling Robobo to move autonomously and safely. This involves using Robobo's sensors to measure light levels from various directions and determine the robot's next move based on the light intensity changes, rewarding actions through the Bellman equation, and updating the Q-table accordingly. This setup illustrates the balance between AI adaptability and safety, a crucial aspect of this TU. To achieve these objectives, the TU is structured into focused subtasks, each building upon the last to gradually enhance students' understanding and skills in autonomous navigation and AI adaptation:

1. *Autonomous Patrolling in an Industrial-like Setup*: Students start by familiarizing themselves with Robobo's sensors and actuators – wheels for movement, pans for smartphone rotation, IR sensors for distance measurement, and the light sensor for ambient light level detection. A theoretical background in reinforcement learning and the Q-learning algorithm is provided, encouraging concept acquisition through challenge-solving.
2. *Autonomous Safety: Avoiding Obstacles and Falls with IR Sensors*: The initial task is to program Robobo to autonomously navigate the environment shown in **Figure 2**, avoiding obstacles and falls. This involves dynamic adaptation to sensory inputs,

with a Python template (shown in **Figure 3**) guiding the implementation of fall and collision avoidance behaviors.

3. *Evaluating the State of the Robot: Using the Light Sensor to Define Orientation Toward the Light:* Students develop a function to determine Robobo’s state based on light direction, introducing them to the concept of “state” in reinforcement learning. This task is essential for setting up the logic behind autonomous navigation decisions.
4. *Autonomous Navigation: Executing Actions Using the Q-Table:* This task involves filling in a Q-table (illustrated in **Table 2**) to link states with actions, ensuring



**Figure 2.**  
Simulation environment used in the teaching unit.

|  |  |
|--|--|
| <pre> from robobopy.Robobo import Robobo # import Robobo Library from robobopy.utils.IR import IR # import IR module  rob = Robobo("localhost") # create a instance of Robobo class rob.connect() # connect robobo  speed = 15  rob.moveWheels(speed, speed) rob.wait(0.5)  while True:     # Avoid falls     if (rob.readIRSensor(IR.FrontL) &lt; minIR) or (rob.readIRSensor(IR.FrontR) &lt; minIR):         rob.stopMotors()         rob.moveWheelsByTime(-speed, -speed, 3)         if (rob.readIRSensor(IR.FrontL) &lt; minIR): # Fall Left             rob.moveWheelsByTime(speed, -speed, 1)         else: # Fall Right             rob.moveWheelsByTime(-speed, speed, 1)         rob.wait(0.5)         rob.moveWheels(speed, speed)      # Avoid collisions     if (rob.readIRSensor(IR.FrontC) &gt; closeIRValue) or (rob.readIRSensor(IR.FrontRR) &gt; closeIRValue) or (rob.readIRSensor(IR.FrontLL) &gt; closeIRValue):         rob.stopMotors()         rob.moveWheelsByTime(-speed, -speed, 2)         rob.moveWheelsByTime(-speed, speed, 2)         rob.wait(0.5)         rob.moveWheels(speed, speed) </pre> | <pre> # Avoid falls if (rob.readIRSensor(IR.FrontL) &lt; minIR) or (rob.readIRSensor(IR.FrontR) &lt; minIR):     rob.stopMotors()     rob.moveWheelsByTime(-speed, -speed, 3)     if (rob.readIRSensor(IR.FrontL) &lt; minIR): # Fall Left         rob.moveWheelsByTime(speed, -speed, 1)     else: # Fall Right         rob.moveWheelsByTime(-speed, speed, 1)     rob.wait(0.5)     rob.moveWheels(speed, speed)  # Avoid collisions if (rob.readIRSensor(IR.FrontC) &gt; closeIRValue) or (rob.readIRSensor(IR.FrontRR) &gt; closeIRValue) or (rob.readIRSensor(IR.FrontLL) &gt; closeIRValue):     rob.stopMotors()     rob.moveWheelsByTime(-speed, -speed, 2)     rob.moveWheelsByTime(-speed, speed, 2)     rob.wait(0.5)     rob.moveWheels(speed, speed) </pre> |
|--|--|

**Figure 3.**  
Python template to face task 1 (left) and a possible solution for the teacher (right).

| Q (S,A)    | A0 (Turn right) | A1 (Turn left) | A2 (Go straight) |
|------------|-----------------|----------------|------------------|
| S0 (Right) | 1               | 0              | 0                |
| S1 (Left)  | 0               | 1              | 0                |
| S2 (Front) | 0               | 0              | 1                |

**Table 2.**  
*Q-table manually filled by students.*

| Q (S,A)    | A0 (Turn right) | A1 (Turn left) | A2 (Go straight) |
|------------|-----------------|----------------|------------------|
| S0 (Right) | 1.02            | 0.04           | 0.04             |
| S1 (Left)  | 0.55            | 1.3            | 0.34             |
| S2 (Front) | 1.17            | 1.04           | 1.83             |

**Table 3.**  
*Final values of the Q-table obtained from the execution.*

Robobo navigates effectively without encountering obstacles or falls. Students learn to execute actions based on the highest Q-value for the current state, demonstrating the practical application of Q-learning.

5. *Autonomous Learning: Reward Calculation and Q-Table Update:* The final task focuses on autonomous learning, where students calculate rewards and update the Q-table post-action (as seen in **Table 3**). This includes developing a function for reward calculation based on light intensity changes and updating the Q-table using the Bellman equation, enhancing Robobo's navigation strategies.

By sequentially addressing these subtasks, the TU offers a comprehensive learning experience, from sensor-based obstacle avoidance to sophisticated decision-making via Q-learning, ensuring students gain a thorough understanding of autonomous navigation in robotics. For a more detailed account of this implementation, refer to [19].

### 3.1.4 Outcomes

The initial implementation of this teaching unit occurred between April and May 2023 at CIFP Rodolfo Ucha Piñeiro in Spain, involving six vocational education and training (VET) students with prior RoboboSim experience. During this phase, all students completed task 1, four managed task 3 by identifying states and executing actions from the Q-table, and one student successfully applied the Bellman equation (see **Figure 4**) [18]. Time constraints were noted as a significant challenge, but the engagement and conceptual understanding of the students were evident.

Feedback highlighted the teaching unit's effectiveness, with students finding the balance of theory and practical tasks engaging. Despite some struggles with code errors, likely due to limited programming backgrounds, the overall response was positive. Four students gained new insights into AI, underscoring the importance and interest in the subject matter, which was further supported by teacher observations.

An analysis based on a general evaluation template and student questionnaire revealed that the theoretical content's complexity was seen as challenging but

manageable, with students' perceptions evenly distributed across the complexity spectrum (see **Figure 5**).

Following an in-depth feedback review, we noticed several key issues with the original teaching unit (TU), necessitating a comprehensive review. Key challenges identified included the necessity for clearer, simpler explanations for advanced topics; sufficient time allocation for exploring complex subjects; a solid foundational understanding of mathematical concepts, notably matrices essential for Q-learning; and the need for explicit guidance in applying theoretical concepts, particularly the Bellman equation [18].

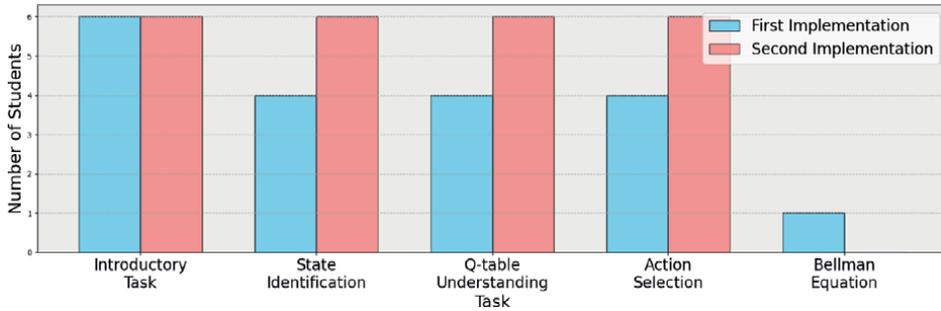
To address these challenges, we introduced significant enhancements in the TU:

- **Enhanced Clarity and Accessibility:** We refined the TU's language for greater accessibility and introduced explicit examples to explain complex ideas such as reward systems and state transitions within Q-learning.
- **Optimized Time Management:** We extended the time allotted to basic concepts, acknowledging the complexity of Q-learning, while making supplementary tasks optional.
- **Mathematical Foundations Support:** We provided students with essential coding tools, including ready-made Q-tables and the Bellman equation [18], facilitating a deeper comprehension of the mathematical concepts.
- **Comprehensive Theoretical Application Guidance:** The updated TU provides a detailed guide through critical tasks, with clear explanations of key operations such as reward calculation and Q-table updates and thorough clarification of function parameters and expected results, minimizing ambiguity.

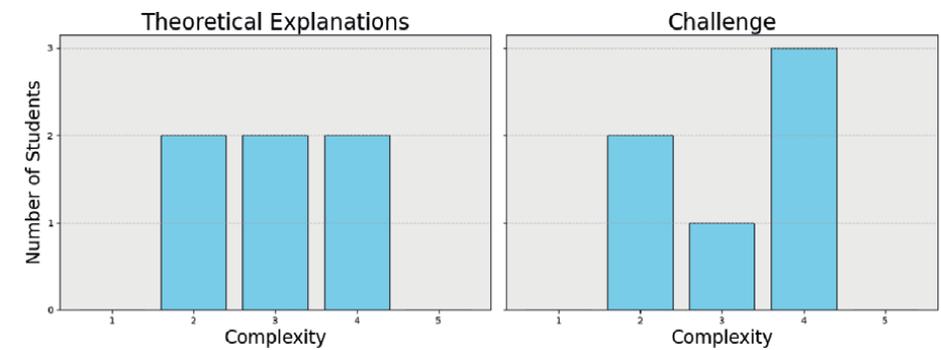
At the training activity, a second implementation of the teaching unit took place with three students from Portugal and three students from Slovenia. Among the six students, five were male and one was female, with ages ranging between 15 and 18 years. Their digital competencies were slightly weaker than those of the Spanish group. Although they were familiar with programming fundamentals, their assimilation of these concepts was not as strong. The materials and questionnaires used in this second activity are accessible at [14].

On the first two days, a total of nine hours were dedicated to introducing RoboboSim and its fundamentals. The third day, with seven hours of class, was dedicated to the specific tasks of this work. During it, students were able to successfully identify states, create their own Q-tables, and execute the corresponding actions. They achieved better results in a significantly shorter time compared to the Spanish group, as displayed in **Figure 4**. This outcome, coupled with positive feedback from teachers, confirmed that feedback from the initial implementation of the first TUs at CIFP Rodolfo Ucha Piñeiro served to improve the preliminary versions, leading to a refined teaching approach.

After completing the robotics teaching unit with six new students who were new to robotics, our experience provided valuable insights into both learning and teaching within this field. Despite the students' varied educational backgrounds, they showed notable engagement and adaptability, especially when allowed sufficient time to delve into complex topics.



**Figure 4.**  
 Level of fulfillment of the tasks by the students among implementations.



**Figure 5.**  
 Complexity rating of the TU contents perceived by students.

Teachers' feedback indicated the positive practical, hands-on approach of the project, though it was also mentioned that a stronger base in programming would be beneficial for future learning. The materials and questionnaires used in this second activity are accessible at [14].

### 3.2 Computer vision

This work package aims to develop computer vision teaching units for VET students, supporting the project's main goals. Computer vision, a key AI component, processes images to derive decision-making information. Grasping its concepts and applications is essential for future use in everyday life. Computer vision can be found in diverse areas like industry, smart homes, and autonomous vehicles. Teaching units therefore focus on critical topics such as unbiased data curation and object recognition, blending classical and deep learning approaches [20, 21]. Practical, real-world application examples are emphasized.

#### 3.2.1 Temporal organization and required resources

The development of the TU takes approximately 10 hours if students have the necessary prior knowledge. It has been organized into 8 tasks, with an approximate load of 1 hour for the first 6 tasks and 2 hours for the last two tasks. In the first task,

students get familiar with the concepts of computer vision in general. In the following tasks, they learn how to load images, modify them, apply filters, perform simple segmentation, continue with detection, and conclude with basics of tracking. For each task, there is a theoretical introduction where the teacher presents the topic, and small challenges are provided to the students with possible solutions discussed collectively. The required resources for this activity are: (1) A computer per student to program with Python in Jupyter Notebooks. (2) Python with necessary libraries such as OpenCV, Pillow, and Numpy. (3) Regular web camera is either available on laptop or plugged into the computer.

Jupyter Notebooks are an open-source web application that allows you to create and share documents containing live code, equations, visualizations, and narrative text. They are incredibly useful for data analysis, machine learning, scientific research, and educational purposes because they allow for interactive computing and data visualization. Jupyter supports over 40 programming languages, including Python, R, and Scala, and integrates with big data processing tools. However, in our case, it was extensively used in conjunction with Python only. One such notebook is shown in **Figure 6**.

The combination of Jupyter, OpenCV, Pillow, NumPy, and others provides a powerful toolkit for processing, analyzing, and visualizing data in an interactive and user-friendly environment. OpenCV, a real-time computer vision library licensed under the open-source Apache 2, excels in elementary computer vision tasks. Complementing it, Pillow extends the capabilities of the Python Imaging Library by enhancing usability and supporting an array of image formats ideal for web integration and batch processing. NumPy ties these tools together with its fundamental array and matrix operations, underpinning scientific packages like SciPy and Pandas, and proving indispensable in fields such as data analysis, machine learning, and engineering. Nevertheless, other libraries are also used to support teaching materials.

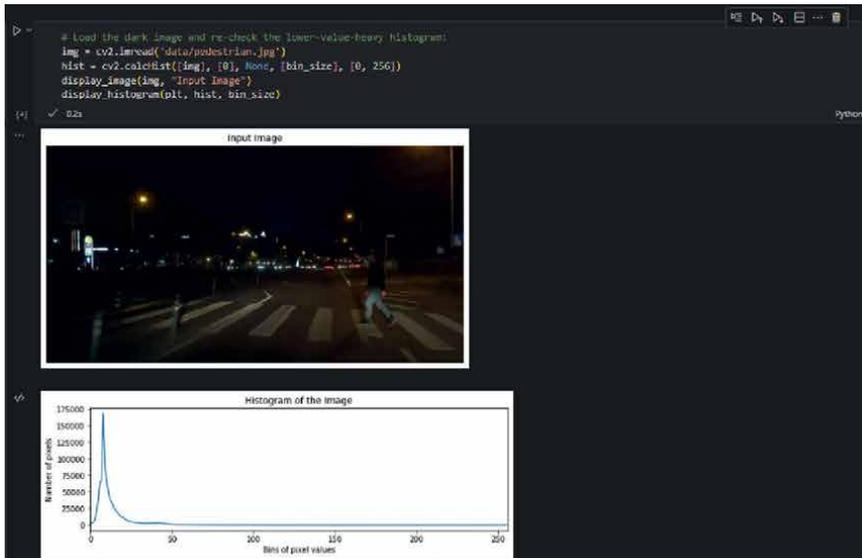
### *3.2.2 AI concepts addressed*

Throughout their studies, students will delve into the complexities of computer vision, honing in on the algorithms that enable machines to interpret and understand visual data. By examining the nuances of simple biometric recognition systems, such as detecting face in live webcam feeds, learners will grapple with the practicalities and challenges of implementing such systems. In the first TA, critical part of their exploration will be the scrutiny of bias in data sets, an issue of crucial importance in not only computer vision but in the wider field of AI. They will learn to identify and mitigate bias, understanding its implications for both the accuracy and fairness of decision-making. As they develop and test biometric algorithms, students will be encouraged to consider the ethical dimensions of AI, such as the potential for discrimination, thereby preparing them for the responsible development of technology in the future.

### *3.2.3 Challenge description*

In this TU, the main goal was to get familiar with basics of common computer vision tasks. This includes loading images, understanding the matrix nature of images (e.g. order of channels), modifying them, performing filtering tasks, doing simple segmentation tasks, trying to detect important parts of images and deriving features out of them, and covering the basics of motion analysis. This establishes

```
# Load the dark_image and re-check the lower-value-heavy histogram!
img = cv2.imread('data/pedestrian.jpg')
hist = cv2.calcHist([img], [0], None, [bin_size], [0, 256])
display_image(img, "Input Image")
display_histogram(hist, bin_size)
```



The problem that we have now is that the pedestrian is not visible very well. If we take a look at the histogram, we can see that the majority of values are below 10 (0 being black, 255 being completely white).

```
# Perform histogram equalization on the image with the following code.

# Convert the image from RGB to YCrCb color space since our histogram function will need it.
# The YCrCb color space is a type of color representation that separates the image into luminance (brightness) and chrominance (color) compo
img_yuv = cv2.cvtColor(img, cv2.COLOR_BGR2YCrCb)
# Split the image into Y, Cr, and Cb channels
y, cr, cb = cv2.split(img_yuv)
# Perform histogram equalization on the brightness channel Y
y_eq = cv2.equalizeHist(y)
# Merge the equalized Y channel with the original Cr (red-green) and Cb (blue-yellow) channels
img_yuv_eq = cv2.merge([y_eq, cr, cb])
# Convert the image back to RGB color space
img_eq = cv2.cvtColor(img_yuv_eq, cv2.COLOR_YCrCb2RGB)

# Show new image with histogram equalization
display_image(img_eq, "Histogram-Equalized Image")

# Recalculate histogram
hist = cv2.calcHist([img_eq], [0], None, [256], [0, 256])
# And display it
display_histogram(hist, min_size)
```



We can see the pedestrian much better now. Visually image looks worse, but typically in computer vision tasks we do not care how good-looking an image would look like to humans, but that needed details (in this case - a pedestrian) are visible as much as possible.

Image how much easier it is now for a self-driving car to detect that pedestrian.

Figure 6.  
An example of a Jupyter notebook with the code for students to play with.

a foundational understanding for students in the domain of computer vision and prepares them to understand more advanced topics, such as person recognition [22], the problems of image generation [23, 24], etc. Each topic covered by the tasks is described in more detail below.

*Basics of Image Processing.* Image processing forms the foundation of computer vision. It involves techniques to enhance raw images for further processing or to extract valuable information. Basic image processing tasks include loading, displaying, and storing images. Understanding how to manipulate the fundamental attributes of an image, such as color channels and intensity levels, is crucial. Grayscale conversion, thresholding, and basic filtering are typical tasks. The importance of these tasks lies in their ability to preprocess images for advanced analysis, improving the performance of complex algorithms in object detection, facial recognition, and more.

*Modifying Images.* Modifying images involves resizing, cropping, altering brightness and contrast, and geometric transformations. These techniques are critical in preparing images for specific applications. For instance, resizing and cropping can focus on regions of interest, enhancing the efficiency of object detection algorithms. Adjusting brightness and contrast makes features more discernible, which is crucial in medical imaging and surveillance. Understanding these transformations is key to customizing image data for varied applications, from automated inspection systems to augmented reality.

*Advanced Image Processing.* Advanced processing encompasses techniques like histogram equalization and convolution operations. Histogram equalization is a method for contrast adjustment using the image's histogram. This is particularly beneficial in improving the visibility of features in images, which is essential in areas like satellite imaging and night-vision processing. Convolutions, involving filters like blurring and sharpening, are fundamental in edge detection and noise reduction, paving the way for higher-level tasks such as feature extraction and image classification.

*Image Segmentation.* Image segmentation divides an image into meaningful regions, facilitating easier analysis. Techniques like thresholding, region-based segmentation, and watershed algorithms play a significant role. In medical imaging, for example, segmentation aids in identifying and isolating pathological regions. In autonomous vehicles, it helps in understanding the driving environment. The significance of segmentation lies in its ability to simplify complex images into analyzable segments, making it a cornerstone in both automated systems and interpretative analysis.

*Feature Detection and Description.* This process involves identifying key points in images and describing them in a way that facilitates matching and recognition. Algorithms like SIFT (Scale-Invariant Feature Transform) and ORB (Oriented FAST and Rotated BRIEF) are instrumental in this. These features are pivotal in tasks like image matching, 3D reconstruction, and motion tracking. They provide robust ways to represent and compare images, crucial in applications ranging from augmented reality to navigation in robotics.

*Object Detection.* Object detection is about identifying and locating objects within images. Techniques like template matching, Haar cascades, and HOG (Histogram of Oriented Gradients) are used for this purpose. Object detection is vital in various domains, such as security surveillance for unauthorized intrusion detection, in retail for inventory management, and in automotive for pedestrian and obstacle detection. The ability to accurately detect objects in diverse conditions is a testament to the evolution and importance of this field.

*Optical Flow and Motion Analysis.* Optical flow techniques, like the Lucas–Kanade method and dense optical flow, estimate the motion of objects between frames in a video sequence. These methods are crucial in understanding the dynamics of scenes and useful in video surveillance for anomaly detection, in sports analytics for player movement analysis, and in video editing for creating special effects. Optical flow provides a deeper understanding of motion patterns, making it invaluable in temporal analysis of videos.

### 3.2.4 Outcomes

Computer vision content presented a valuable learning experience for students, highlighting the practical applications and basic theoretical underpinnings of computer vision. Students engaged in a series of tasks that, hopefully, not only solidified their understanding of computer vision fundamentals but also prepared them for real-world applications or at least gave them motivation for it.

As described above, during the course, students demonstrated proficiency in basic image processing techniques, including image loading, manipulation, and the application of filters. They were introduced to more complex topics such as image segmentation, feature detection, and object detection, culminating in an understanding of motion analysis through optical flow methods. This progression from foundational skills to more advanced concepts allowed students to build a comprehensive knowledge base in computer vision.

One of the key outcomes was the students' ability to modify and apply code made available to them to actual scenarios. For instance, they successfully used and customized algorithms for detecting objects in images, a skill crucial for many applications in industries such as security, automotive, and healthcare. The hands-on approach, facilitated by the use of Jupyter Notebooks and Python libraries such as OpenCV, Pillow, and NumPy, was instrumental in bridging the gap between theory and practice.

Feedback from students and teachers alike underscored the relevance and engagement of the teaching units. Students appreciated the practical challenges, which enhanced their learning experience. They found the tasks engaging and relevant (albeit on the difficult side), reflecting the growing importance of computer vision in various technological domains.

However, similar to other subject areas, challenges were encountered. Time constraints were noted as a significant hurdle, with some students requiring more time to fully grasp complex concepts or not being able to grasp certain concepts at all. This feedback has been invaluable in planning future iterations of the teaching unit, with considerations for more flexible scheduling and possibly more in-depth preparatory sessions on programming fundamentals for students new to Python.

The successful completion of tasks by the students, coupled with their ability to understand and apply computer vision concepts, indicates the effectiveness of the teaching unit in achieving its educational objectives. It has laid a solid foundation for students, equipping them with the skills and knowledge to further explore the field of computer vision and its applications.

Moving forward, the curriculum will be simplified and refined based on the feedback received. This includes enhancing the clarity of theoretical explanations, adjusting the pacing of the course to better match student learning speeds, and incorporating more examples of real-world applications to further illustrate the impact of computer vision technologies. The ultimate goal remains to provide students with a

robust understanding of computer vision, preparing them for future careers in this dynamic and rapidly evolving field.

### **3.3 Ambient intelligence**

The current resource corresponds to the first and second TUs of the Ambient intelligence module of the AIM@VET project, which focuses on sensors and actuators. The ultimate aim of these TUs is for students to learn how sensors and actuators work, as well as how to control them with a microcontroller Arduino Uno. This is the basic principle of sensorization: to develop an entire intelligent ambient with Internet of Things (IoT) environment that can be controlled automatically and using AI. So, the idea is to understand how data is collected and how actuators work in an environment. The next step is to prepare the intelligent agent to act and react to this environment using AI techniques.

#### *3.3.1 Temporal organization and required resources*

The development of Modules 1 and 2, a comprehensive teaching unit on sensorization, requires approximately 24 hours to complete without students having the necessary prior knowledge. However, due to limitations in applying all planned activities during the training session, we have selected five key activities crucial for learning sensorization. Consequently, each of these five activities will require two hours to complete. Moreover, each activity may consist of one or more tasks. The temporal organization of the sensorization teaching unit is thoughtfully structured to facilitate a comprehensive and effective learning experience, focusing the entire curriculum into a total of 10 hours. This approach ensures a dedicated and intensive exploration of the subject matter.

The first activity introduces the foundational concepts within the “Required Knowledge” section, covering Ambient Intelligence (AmI), the Internet of Things (IoT), and the Internet of People (IoP). This introductory phase, lasting about 30 minutes, sets the stage for the hands-on work to follow, ensuring that students have a solid conceptual framework before diving into the more technical aspects. Following the introduction, the activity progresses into more practical tasks. Students start with understanding and setting up the Arduino Uno, a process that takes about 30 minutes. This is a crucial step, as it involves familiarizing themselves with the hardware that will be central to their subsequent activities. Next, they move on to preparing the Arduino Uno for integration with Python. This task, also estimated at 45 minutes, introduces students to the software aspect of their projects, bridging the gap between the physical hardware and the programming environment. A significant portion of the activity is dedicated to hands-on activities involving various sensors. Students spend time learning to use a breadboard, which is essential for assembling electronic circuits. This activity is designed to be brief yet informative, taking about 15 minutes, which finishes the first activity.

The second activity then delves deeper into the application of Python programming with Arduino. Students explore the use of PyFirmata and Pymata libraries, engaging in tasks that require them to build circuits and write code. Each of these tasks is allocated 60 minutes, allowing ample time for experimentation and learning.

The third activity has a unique aspect, which is the inclusion of virtual sensors. Students are introduced to the concept and application of virtual sensors, such as those used for climatological and air quality data. They learn how to access and use

data from APIs like Open Weather Map and Open Air Quality, which involve writing Python scripts to fetch and process this data. These activities are given substantial time, with 45 minutes dedicated to learning the required knowledge and 75 minutes for practical implementation.

Throughout the fourth and fifth activity, students are progressively building their skills and knowledge, culminating in a final project or challenge. This project involves the integration of all the skills they have acquired, requiring them to develop a program for collecting data from sensors using Arduino and Python. The project is not only a test of their technical abilities but also of their capacity to integrate various components into a cohesive system.

The sensorization teaching unit necessitates a range of resources that are integral to the successful delivery and completion of the course. These resources span across various categories, including hardware, software, and additional support materials, ensuring that students have everything they need to effectively engage with and complete the unit.

At the forefront of the required hardware is a reliable WI-FI network with internet connectivity. This is crucial not only for accessing online resources and documentation but also potentially for some of the project tasks that might involve internet-based applications or data retrieval. Additionally, each student needs access to a laptop or computer. These are essential for coding in Python, interfacing with the Arduino, and potentially for other software-related tasks.

Smartphones, specifically Android-based, are also listed among the required hardware. The use of smartphones could be linked to interfacing with the Arduino projects or for testing and running applications developed during the course. Furthermore, the unit requires one Arduino Uno and a set of sensors for every two students. Arduino Uno serves as the foundational hardware for teaching sensor integration and data collection, and the sensors are crucial for hands-on experimentation and understanding real-world data acquisition.

In terms of software, Python is a primary requirement, as it is used extensively for programming the Arduino and data processing tasks. Additional software might include the Arduino Integrated Development Environment (IDE) and other related tools or libraries such as PyFirmata, which are used for interfacing Python with the Arduino.

An often-overlooked but equally important resource is a projector, recommended for displaying teaching unit materials and multimedia resources to all students. This facilitates a more interactive and engaging learning environment, allowing instructors to visually demonstrate concepts and procedures.

In addition to these, there might be requirements for basic electronic components such as breadboards, jumper wires, and power supplies, which are standard in any electronics lab setting. These components are necessary for building and testing circuits, and for interfacing the various sensors with the Arduino Uno.

To support the theoretical learning, there may also be a need for textbooks or online resources. These materials would provide additional reading and reference material to students, helping them to deepen their understanding of the concepts taught in the unit.

### *3.3.2 AI concepts addressed*

The teaching unit begins with an introduction to the Arduino Uno, covering both its hardware and software components. Students will then be guided on how to

prepare the Arduino for Python programming using PyFirmata, along with an explanation of the Firmata protocol. This foundational knowledge will be further enhanced by teaching them about breadboards and how to prepare them for creating electronic circuits. Students will gain practical experience by building simple circuits, programming them in Python, and exploring different approaches to problem-solving. A significant part of this phase involves the introduction and application of an ultrasonic sensor, which students will program and test to understand its functionality.

Virtual sensors represent another critical area of learning, where students will learn to apply these sensors through API calls and data interpretation. They will engage in tasks that involve accessing climatological and air quality data using APIs like Open Weather Map and Open Air Quality, enabling them to work with real-world data in a controlled environment.

Further into the materials, students will explore serial data communication with Arduino, learning to use Digital Read Serial with Python. This will include practical exercises like programming push buttons and LEDs, providing a deeper understanding of digital signal processing. Additionally, the course will cover the control of motor speed using Pulse Width Modulation (PWM), where students will experiment with DC motors and servo motors, learning to adjust their speed through programming in Python.

This structured approach will not only equip students with the necessary technical skills but also foster a deeper understanding of AI concepts through interactive and engaging activities.

### *3.3.3 Challenge description*

The challenge presented in the sensorization teaching unit is a comprehensive and integrative project that encapsulates the skills and knowledge acquired throughout the course. The final objective of this challenge is to develop a program that allows for the collection of data from sensors using Arduino and Python, effectively combining hardware interfacing with software programming in order to, in future, use captured data from sensors, treat it with AI algorithms, and after that actuate on the environment.

Throughout the unit, students are introduced to various concepts and practical skills, starting with an understanding of Ambient Intelligence, the IoT, and the Internet of People. They learn the basics of Arduino Uno, setting it up, and preparing it for integration with Python. An essential part of this is learning to use a breadboard for circuit assembly, which is crucial for any hands-on electronics project.

As students progress, they delve into using specific libraries like PyFirmata and Pymata, which are instrumental in controlling the Arduino through Python. The challenge involves working with various sensors – such as ultrasonic, temperature, and humidity sensors – and understanding how to implement them in practical applications. This not only includes the physical assembly and programming of these sensors but also the interpretation of the data they collect.

A significant part of the challenge is working with virtual sensors. Students are expected to access climatological and air quality data using APIs such as Open Weather Map and Open Air Quality. They develop Python scripts to fetch and process this data, integrating it with the information collected from physical sensors.

The culminating project requires students to bring together all these elements. They need to design and program a system that can collect data from both the physical

sensors attached to the Arduino and the virtual sensors accessed via APIs. This task tests their technical skills in programming and electronics, as well as their ability to process and interpret data. The challenge is not just about building a functional system but also understanding the practical applications of this technology in real-world scenarios.

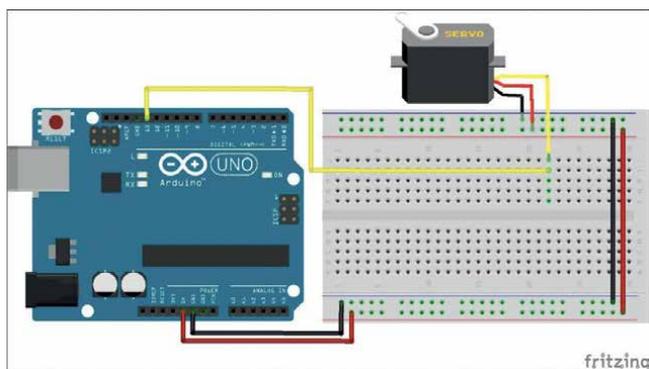
The project is evaluated on various fronts, including technical skill in programming and circuit assembly, the effectiveness of data collection and processing, and the overall integration of different technologies and concepts. This challenge serves as a practical demonstration of the students' learning and proficiency in sensor technology and its applications in the digital world.

### 3.3.4 Outcomes

In completing the challenge of the sensorization teaching units, students are expected to achieve several significant outcomes that demonstrate their understanding and application of the concepts and skills learned throughout the course. Throughout the sensorization teaching unit, we have employed a methodologically rich and diverse approach to learning, which has effectively blended theoretical knowledge with practical skills. This multifaceted methodology has been pivotal in ensuring a comprehensive understanding of sensor technologies, Arduino programming, and Python integration. Here's a reflection on what we have learned so far methodologically and how this approach will continue to evolve and be applied as the course progresses.

Firstly, they will have developed a comprehensive program that successfully integrates Arduino and Python to collect data from various sensors. This involves not only the technical aspects of programming and circuit design but also a nuanced understanding of how different sensors operate and interact. By working with both physical sensors (like ultrasonic, temperature, and humidity sensors) and virtual sensors accessed via APIs, students will showcase their ability to handle diverse data sources. **Figure 7** is an example of a simple circuit.

So far, the course has emphasized a hands-on learning approach. This method is crucial in technical subjects, allowing students to directly interact with the tools and technologies they are studying. By working with Arduino and various sensors, students have gained practical skills that are often difficult to fully grasp through theoretical study alone. This hands-on approach not only aids in solidifying the students'



**Figure 7.**  
*An example of simple activity.*

understanding of sensor technologies but also enhances their problem-solving and critical-thinking abilities.

An important outcome of this challenge is the practical application of the collected data. Students must demonstrate how to process, interpret, and potentially visualize this data in a meaningful way. This might involve identifying patterns, making predictions, or simply understanding the environmental conditions measured by the sensors. The ability to translate raw sensor data into usable information is a crucial skill in many fields, including IoT applications, environmental monitoring, and robotics.

The project also tests the students' problem-solving and critical-thinking skills. They need to integrate different technological components and concepts into a cohesive system. This includes troubleshooting issues that arise during the development process, whether related to hardware, software, or the interfacing between the two.

Additionally, students will have gained hands-on experience in programming with Python and working with Arduino, which are valuable skills in the fields of computer science, engineering, and technology. Their exposure to working with APIs to access virtual sensors like Open Weather Map and Open Air Quality broadens their understanding of how large-scale data can be accessed and used. The incremental learning model adopted in the course has been another key aspect of our methodological approach. We started with basic concepts and gradually moved to more complex topics. This step-by-step progression has ensured that students build a strong foundational knowledge before tackling more advanced aspects of sensor technology and programming. Such a structured approach helps in maintaining clarity and focus, preventing students from feeling overwhelmed by the complexities of the subject matter.

Integration of theory and practice has been a hallmark of our methodology. Theoretical concepts about Ambient Intelligence (AmI), the Internet of Things (IoT), and the role of sensors in digital transformation have been seamlessly tied to practical tasks and projects. This has enabled students to see the real-world applications of their learning, making the educational experience more relevant and engaging.

Lastly, the challenge offers an opportunity for creativity and innovation. Students can explore various applications of the technology, suggest improvements, or even propose new ways of using the sensor data. This fosters a mindset of exploration and innovation, which is crucial in the rapidly evolving field of technology. Also, collaborative learning has also been a focus. While the course has encouraged individual skill development, it has also fostered an environment where students can share knowledge, work together on projects, and learn from each other. This blend of individual and collaborative learning enriches the educational experience and prepares students for the teamwork-oriented nature of the professional world.

Looking forward, the course will continue to build upon these established methodological foundations. We will introduce more complex and challenging projects, encouraging students to apply their learned skills in new and innovative ways. These projects will not only reinforce the students' existing knowledge but will also push them to explore the limits of their creativity and problem-solving skills.

We will also continue to emphasize the real-world application of the skills and knowledge gained. Students will be encouraged to think about how the technologies and methods they are learning can be applied to solve real-world problems. This focus

on practical application is intended to bridge the gap between academic learning and professional skills.

#### 4. Results and discussion

This last section will go over feedback and learning outcomes from Teaching Activity 1 (TA1), pulling together what we've learned from areas like robotics, Ambient Intelligence, and computer vision. We'll look at what worked well, what challenges we ran into, and how we can make our teaching methods better for this AI curriculum.

One of the elements that proved to be essential to take good care of was the engagement of students and their progress in learning. Feedback from these sessions emphasized the critical need to allow students enough time to thoroughly explore and understand complex topics. Given adequate time, students were not only able to comprehend the foundational concepts but also found the tasks to be highly engaging. This underscores an important lesson: the pace at which new information is introduced must be thoughtfully aligned with the content's complexity, ensuring students remain fully engaged and able to grasp the material comprehensively.

There were, however, some important challenges to highlight, particularly when some students struggled with basic mathematical concepts necessary for progressing in more sophisticated tasks. This difficulty revealed a gap in the foundational knowledge of certain participants, highlighting the importance of implementing educational strategies that equip all students with a robust understanding of essential mathematical principles before moving forward with more complex subjects.

Therefore, important aspects noted based on comprehensive feedback focus on making complex subjects more accessible and engaging for all students. This included

| Question  | Rating |
|---|--------|
| Do you think you had enough prior knowledge to tackle this lesson?  | 3.83   |
| How would you rate the theoretical explanations? (1 star very easy, 5 stars very difficult)                                   | 3.28   |
| How would you rate the level of difficulty of the challenges?   | 3.06   |
| Do you think there has been a good balance between theory and practice? (1 star: too much theory; 5 stars: too much practice) | 2.89   |
| How interesting do you think it is to work with a partner compared to working alone?  | 3.50   |
| What do you think about the number of days dedicated to workshops (3 days)? (1 star: too short; 5 stars: too long)            | 2.72   |
| What do you think about the number of hours per day dedicated to workshops? (1 star: too short; 5 stars: too long)            | 4.00   |
| What do you think about the number of hours per day dedicated to activities? (1 star: too short; 5 stars: too long)           | 2.78   |
| Do you feel that this lesson has increased your understanding of AI?  | 3.89   |
| Please rate your overall experience of the first training activity  | 4.17   |

**Table 4.**  
*Quantitative results from students' questionnaires.*

| Question   | Rating |
|--|--------|
| Do you think the students had sufficient prior knowledge to tackle this lesson?  | 2.50   |
| Do you believe the students have acquired relevant knowledge?  | 3.33   |
| How many difficulties have they encountered due to the language barrier? (1 star: few difficulties; 5 stars: many difficulties)                                  | 1.83   |
| How positive has it been to work in international pairs?   | 4.33   |
| How positive has it been to change partners in the middle of the activity?   | 4.33   |
| How many students have actively participated and engaged in the activity?  | 4.50   |
| What do you think about the number of days dedicated to workshops (3 days)? (1 star: too short; 5 stars: too long)   | 2.67   |
| What do you think about the number of hours per day dedicated to workshops? (1 star: too short; 3 stars: ideal duration; 5 stars: too long)                      | 4.17   |
| What do you think about the number of hours per day dedicated to cultural and social activities? (1 star: too short; 3 stars: ideal duration; 5 stars: too long) | 2.83   |

**Table 5.**  
*Quantitative results from teachers’ questionnaires.*

simplifying the instructional language to ensure clarity, adjusting the curriculum to allow more time for foundational concepts, providing practical tools like code templates for bridging gaps in mathematical understanding, and offering detailed walkthroughs for the theoretical application of concepts.

At the end of the TA1, a questionnaire was administered to the students and the teachers regarding various aspects of the workshop. **Tables 4** and **5** show the quantitative results provided.

The student feedback from the AI training session revealed a positive overall experience with a notable increase in AI understanding. However, while students felt somewhat prepared and engaged with the material, they also indicated that the number of workshop hours per day was higher than ideal. Despite this, the practical elements and partner collaboration were well-received, suggesting a successful integration of AI learning into the curriculum with room for adjustment in scheduling.

Teachers’ feedback from the questionnaire indicates a mixed assessment of the AI training program. They observed that students came with a moderate understanding of the subject matter. The acquisition of relevant knowledge during the course was satisfactory. Language barriers did not significantly impede learning. Collaborative aspects of the program, such as working in international pairs and rotating partners, were highly regarded. Student engagement was notably high. However, teachers felt that the workshop days were slightly longer than ideal, and the hours allocated to workshops each day were deemed excessive. Conversely, they considered the time for cultural and social activities to be marginally insufficient.

The synthesis of feedback from Teaching Activity 1 (TA1) highlights a generally positive experience from both students and teachers, marking the project’s success in integrating AI into vocational training. Students valued the practical application of AI, noting an effective balance between theory and practice, and showed keen interest in exploring more AI tools like ChatGPT. On the other hand, teachers pointed out the students’ need for stronger foundational knowledge in AI and suggested shorter workshop hours for future sessions. Overall, the positive reception of TA1

underscores its contribution to enhancing AI education in vocational settings, reflecting its alignment with the evolving requirements of the job market.

## 5. Conclusions

The first Training Activity (TA1) within the AIM@VET project showcased a practical approach to integrating Artificial Intelligence (AI) into Vocational Education and Training (VET) curricula. Focusing on autonomous robotics, computer vision, and ambient intelligence, TA1 provided VET students with direct experience in applying AI concepts and techniques. This activity not only improved their technical skills in AI but also equipped them with essential knowledge of the impact of AI technologies, preparing them for the digital workforce.

The structured methodology adopted for the first Training Activity (TA1), involving a mix of theoretical lessons and practical tasks, has proven effective among students. The collaborative and cross-cultural learning environment also contributed to the educational experience, promoting a broader perspective on the impact of AI technologies.

Feedback from both students and teachers underscores the success of the project in achieving its educational objectives. Students have gained not only a theoretical understanding of AI principles but also hands-on experience in applying these concepts through projects and challenges. The positive reception of the teaching units, as evidenced by the high level of student engagement and interest, indicates a strong appreciation for the relevance and practicality of the curriculum.

Teachers have highlighted the importance of a balanced approach between theory and practice, and the feedback received has been instrumental in refining the teaching units for future implementations. The adjustments made based on this feedback, such as simplifying language, allowing more time for complex topics, and providing practical tools for mathematical concepts, have enhanced the accessibility and effectiveness of the curriculum.

The initial Training Activity (TA1) within the AIM@VET project was also key in refining our protocols for lesson creation and standardization. This refinement led to a more unified and standardized curriculum, improving coordination among project partners. The protocols addressed the creation of templates and set criteria for content creation, student assessment, and the standardization of complexity levels, lesson durations, and prerequisite knowledge.

The move toward standardization was necessary for collaborative curriculum development across different research groups. It brought together the work of various teams, resulting in a coordinated approach to educational content. Additionally, it allowed for the recognition of each partner's work and conceptual modules, finding a common base that will aid in future curriculum development with multiple working groups.

As these protocols are further refined and utilized, they also establish a framework for collaborative and coherent curriculum design, not only in AI education within VET programs but in general in any project-based learning curriculum.

Therefore, the AIM@VET project will serve as a model for future initiatives aimed at integrating AI education into VET programs. The insights gained from TA1 offer valuable guidance for educators and policymakers on how to design and implement AI curricula that are both engaging and informative. The project's focus on practical

skills, collaboration, and cross-cultural exchange aligns with the evolving needs of the workforce, preparing students for the challenges and opportunities of the digital age.

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## Chapter 9

# Teacher Educator Professionalism in the Age of AI: Navigating the New Landscape of Quality Education

*Olivia Rütli-Joy, Georg Winder and Horst Biedermann*

### Abstract

This conceptual chapter discusses how requirements for teacher educator professionalism may be impacted by the integration of Artificial Intelligence (AI) in teacher education. With the aim to continuously facilitate high-quality teacher education, teacher education institutions must evolve in alignment with the rapidly changing landscape of AI and the respective shifting educational needs. Amidst this evolution, we argue that profound AI Literacy and AI-related ethical knowledge constitute two additional and inextricably intertwined knowledge facets of teacher educator professionalism essential for an ethical and effective integration of AI into teaching practices – and thus crucial for high quality teacher education. The paper explores avenues through which these facets of teacher professional competence and quality education can be fostered on the micro, meso and macro levels of institutional education. By consolidating the specific requirements in a framework for teacher educator professionalism in the age of AI, we highlight the necessity for continuous adaptation of teacher education institutions, ongoing multidisciplinary collaboration, and the provision of periodic professional development of educators. Finally, the chapter presents a concrete practical example and future research directions in AI and education with the aim to contribute to the advancement of quality education in the AI era.

**Keywords:** artificial intelligence in education (AIEd), quality education, quality teacher education, teacher educators' professional competence, teacher professionalism, professional development, AI literacy, AI ethics, organisational development, institutional adaptation

### 1. Introduction

The rapid proliferation of artificial intelligence (AI<sup>1</sup>)-powered technologies [1, 2] carries the potential to reshape the foundations of education [3] and to significantly change the demands of the teaching profession [4]. With education's

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<sup>1</sup> While the term AI is highly debated [5, 6] and there is no universally valid definition of AI [7], we adopt Southworth et al.'s [1] broad interpretation of AI to account for its interdisciplinary nature of AI in education, where "AI refers broadly to include related expertise and disciplines when used with AI (e.g., such as statistics and data science)" (p. 2).

chief performance mandate to enable future generations for responsible participation in societal, political, cultural and economic processes [8], educational institutions are urged to adapt to the changing requirements of the educational and vocational domains to safeguard high-quality, relevant and fit-for-purpose teaching and research practices [1, 9]. To ensure education continues to optimally prepare forthcoming generations to succeed in their complex futures, curricula need to be aligned with the relevant skills and knowledge that will be relevant in the future [10]. The plethora of frameworks and guidelines that attempt to predict these skills [11, 12] – while not without their challenges [12, 13] – reinforce the importance of inclusive quality education and lifelong learning opportunities to contribute to a progressive and healthy society [14]. In the age of AI, such a society can harness the affordances of AI productively and mitigate its risks and challenges responsibly [15]. To ensure quality education, enhanced students' learning experience and improved learning outcomes [1], theories and applications of AI thus need to be constructively integrated as essential elements into education [1, 16]. As teachers and teacher educators bridge schools' and universities' AI policies and learners' needs, they play a critical role in fulfilling this task [16]. Accordingly, teacher educators need to acquire the professional competences needed to convey the relevant knowledge related to understanding, using, applying and teaching AI; validating knowledge and information and knowing about fairness, accountability, transparency and ethics related to AI [17–19].

Part of the responsibility of high-quality teacher education thus involves institutional adaptations and professional development initiatives to enable teacher educators (1) to use AI effectively and ethically in their teaching and research practice (as well as in their everyday lives) and (2) to teach AI skills and knowledge – including AI-related ethical knowledge – to their pre-service teachers to promote the cascading effects of passing on that knowledge to future generations.

This conceptual chapter addresses the evolving demands on teacher educator professionalism and the role of teacher education institutions in the age of AI. Synthesising the conceptual and empirical literature on Artificial Intelligence in Education (AIEd) and teacher professionalism, we propose that AI knowledge and skills and AI-related ethical knowledge, subsumed in the concept of AI Literacy, constitute additional and inextricably intertwined facets of knowledge of (teacher) educator professional competence that are crucial for enabling an ethical and effective integration of AI into education [20]. Based on these elaborations, we propose a framework of ten areas of development at the micro (learners, pre-service and in-service teachers, teacher educators), meso (schools, teacher education institutions, professional development providers, the teaching profession as a system) and macro level of teacher education (educational policy and politics at state, federal, and global levels) that can be seen as driving forces to facilitate avenues for up-to-date teacher professionalisation and high-quality teacher education amidst the AI transformation. Accordingly, we argue that AI Literacy needs to be incorporated in teacher education institutions, teacher education curricula and the conceptualisation of teacher professionalism to ensure equitable and inclusive AIEd practices [20, 21]. We outline the theoretical background, rationale and method for integrating AI Literacy into the conceptualisation of teacher educator professional competence [22], discuss the deduction of each area of development of the framework and present a case study of implementing AI in teacher education based on the developed framework before concluding with considering future empirical research trajectories.

## **2. Rethinking (teacher) educator professionalism in the age of AI**

For future generations to be able to navigate AI-permeated societies responsibly, they will require profound AI-related knowledge [18, 23, 24]. To ensure educational institutions convey this knowledge in their curricula, educators need to become “fluent” in AIED [21, 25, 26] and develop the respective professional competence to meet the changing demands of their vocation [27]. “Professional competence” is a core constituent of “professionalisation” and “professionalism” [27]. In the context of teacher education, professionalisation is generally understood as the development of professionalism, that is, developing professional competence and “becoming professional” [28]. Professionalism, on the other hand, refers to meeting the requirements of the profession [29]. Professionalisation and professionalism are understood to be both individual (micro level) and collective (micro and meso level) phenomena that are inextricably intertwined [30]. As an individual phenomenon, professionalism describes the extent to which educators’ professional competence is developed to cope with the demands of their profession [31, 32]. As a collective phenomenon, professionalisation refers to the aim of an evidence-based modernisation of the teaching profession through clear task descriptions, the identification of educational goals and standardised professional development obligations [32].

Due to the multiplicity of theoretical models [31] and methodological approaches, the discourse on both concepts is multifaceted [30]. Building on Weinert’s definition of competence [33], the competence-theoretical approach as one of the most prominent approaches in the German-speaking research tradition defines areas of competence and knowledge dimensions that are constitutive for mastering the tasks and challenges of the teaching profession [34]. Subsumed under the term “professional competence,” these competences are conceptualised as profession-related abilities [31] that encompass the latent potential, the process that leads to the decision to act and the performance as the action itself [30]. The present chapter uses Baumert and Kunter’s generic COACTIV model of teachers’ professional competence as its theoretical foundation [22]. According to this model, professional competence is composed of the four aspects: (1) professional knowledge (i.e., knowledge and skills, including its distinct domains of knowledge and respective facets); (2) professional values, beliefs and goals; (3) motivational orientations and (4) professional self-regulation skills. While all aspects of competence are categorically separated, they interact with one another, and it is through their interaction that professionally competent behaviour arises [22]. The following sections of this chapter address professional competence and teacher educator professionalism in the context of AI in teacher education with a particular focus on teacher educators. Based on a review of the affordances of AI that may contribute to, and challenges that may hinder high-quality teacher education during rapid transitions, the subsequent sections investigate whether any of the above aspects of competence require revisiting and adaptation in alignment with the rapidly changing educational needs in an AI-mediated society and whether AI-related knowledge and skills can and should be conceptualised as additional domains or facets of knowledge of any of the model’s aspects of competence [35].

## **3. AI in education: essentials and perspectives on benefits and challenges**

AI is considered a powerful instrument to facilitate new opportunities for instructional design, independent and self-directed learning, educational innovation and educational research [4]. Successfully integrating, applying and teaching AI in education,

however, raises profound questions and poses a range of challenges, such as revisiting and realigning research and teaching practices to ensure high-quality education that remains focused on the human learner [36]. This endeavour demands profound evidence-based knowledge about the background, affordances, challenges and prevailing questions related to AIED. Among others, Bond et al.'s [20] meta-systematic review (i.e., a review of reviews) of AI in higher education provides a solid evidence base. By rigorously analysing a corpus of 66 reviews, they synthesised 12 categories of benefits and 17 categories of challenges of AIED from a sub-corpus of 31 reviews. Among the 12 identified categories of the former, the top 6 benefits encompass: (1) personalised learning (e.g., customising educational materials to fit individual learners' needs), (2) greater insight into student understanding (e.g., using machine learning and analytics to classify patterns, model student profiles, identify learning issues or provide customised guidance or adaptive feedback), (3) positive influence on learning outcomes (despite very little empirical evidence of impact), (4) reduced planning and administration time for educators (e.g., streamlining administrative workflows, using AI to facilitate lesson planning or handle student inquiries), (5) greater equity in education (e.g., AI enhancing accessibility to education and expert systems) and (6) precise assessment and feedback (e.g., enhancing the likelihood for timely, objective and error-free grading or monitoring student progress).

Among the 17 identified categories of challenges, the 5 most imminent concerns of AIED across all 31 reviews include: (1) a lack of ethical consideration, (2) issues related to curriculum development (e.g., disconnection between AI technology and educational systems), (3) infrastructure (e.g., technical, literacy and financial barriers, or access to stable high-speed internet), (4) a lack of educator knowledge (e.g., widespread misconceptions and unawareness of AI, lack of technological skills and knowledge, lack of pedagogical knowledge and pedagogical content knowledge to apply AI [35], or limited time resources to effectively integrate AI into the curriculum) and (5) shifting authority (e.g., misconceptions of AI's potentials and challenges that could lead to a transfer of authority from professionals to AI systems). While all the above categories may significantly shape how educational institutions appropriate AI [36], we argue that two categories are particularly central and demand more emphasis:

1. **AI Literacy:** The AI Literacy construct refers to AI-related knowledge and skills. By outlining their importance, the construct addresses questions such as what educators, learners and the public need to know about AI; how entire sectors of society can be trained in these competences; what pedagogy is most suitable to achieve this goal and who carries the responsibilities to initiate, fund and facilitate these processes.
2. **Ethical Considerations:** AI-related ethical knowledge and skills include, among others, the ability to address risks such as data privacy and unreflective use of information, understanding and uncovering biases in and ignorance regarding AI algorithms or overcoming the digital divide. Prioritising these concerns is necessary to ensure AI's integration into education is efficient and equitable and that it safeguards individual rights and societal standards.

If a lack of AI Literacy and an absence of AI-related ethical knowledge compound, problematic use and negative consequences of AIED could propel and limit or reduce the quality of educational programmes. In alignment with Bond et al. [20], both categories are thus pivotal to ensure constructive collaboration with AI. As ethical knowledge about AI is inextricably intertwined with AI Literacy [23], it can be considered a subdimension of the broader AI Literacy construct.

#### **4. AI literacy in education**

AI Literacy is generally understood as “a set of competencies that enables [nonexpert] individuals to critically evaluate AI technologies, communicate and collaborate effectively with AI, and use AI as a tool online, at home, and in the workplace” [23]. While the publications on AI Literacy have increased significantly since the early 2020s [19, 25, 37], empirical research in this area is still in its infancy [25] and construct definitions vary [18, 23, 24]. For the purpose of this paper, we use Long and Magerko’s definition of AI Literacy [38]. Their framework outlines 17 competences that make up AI Literacy, spanning from the ability to distinguish between tools that use and do not use AI to identify problems that AI can or cannot solve well, to recognise how computers reason and make decisions, to critically interpret data, or to understand ethical concerns related to AI. With education’s responsibility to prepare individuals for personal and professional success [36], teacher education institutions are, among others, responsible for mitigating the benefits and concerns of education’s AI-transformation [21]. Meeting this performance mandate crucially depends on teacher educators’ readiness [16] and knowledge of AI, including the implications of applying and integrating AI to pedagogy, teaching and assessment [35]. In other words, in order to be able to convey the necessary AI-knowledge to their learners, educators need to become AI-literate [18, 19]. This prerequisite has come to be so prominent that AI Literacy has even been predicted to become as important as literacy in its original sense [18]—the ability to think (at least) in the first language and mathematical language, to use these abilities effectively to cope with professional and private tasks and the ability to read and write [39].

#### **5. AI-related ethical knowledge and skills in education**

Ethical concerns related to AI in education are among the most mentioned across the AIEd literature [35, 40–43] and are inextricably linked with AI Literacy. Among the 17 competences outlined in Long and Magerko’s AI Literacy framework [38], competency 16 relates to ethics. Accordingly, AI-related ethical knowledge and skills refers to the ability to “identify and describe different perspectives on the key ethical issues surrounding AI (i.e., privacy, employment, misinformation, the singularity, ethical decision making, diversity, bias, transparency, accountability)” (p. 7). Further ethical concerns include apprehensions relating to fairness [41], issues relating to data sources and data sourcing (e.g., corporatisation and commodification of data, unethical treatment of staff who source the data), (data) ownership (e.g., increased potential to leak or misuse user data when AIEd systems are developed by for-profit organisations [44]), authorship and copyright (e.g., can AI tools be considered authors and own copyright [45]?), and authority and responsibility (e.g., can AI tools be held accountable and “responsible” for the content they produce [45]?). While ethical codes and policy on the use of AI-generated data [42, 46] and the implementation of AI-powered tools in professional practice [47] have been discussed in disciplines such as law, engineering and social science, the discussion (and scientific research) thereof is largely absent in education [35, 46]. This absence including a lack of a regulated AI ethics policy in education render ethical considerations in AI-permeated education especially pressing [47]. Aside from the need for a regulated AI ethics policy, enabling responsible and ethical use of AI in education will require a move away from closed, corporate-owned and guarded datasets to the generation

of large, open datasets so that models appropriate and suitable for education can be developed, trained and validated [36]. Such a move necessitates the need for creating or improving ethical frameworks [48], alongside a deeper understanding of the social implications of AI more broadly. This development involves educating learners and educators about ethical principles, their own ethical behaviour and the ethical use of AI [41]; equipping them with necessary skills and knowledge required to navigate and shape a desirable future [3] and empowering educators to develop and uphold their professional ethics (i.e., professional ethos).

## **6. Connecting the dots: AI literacy and AI-related ethical knowledge as knowledge facets of professional competence**

Despite AI's pervasive impact, a general lack of understanding about AI, its decision-making algorithms and the role humans play in AI interactions prevails [16, 23, 40, 49]. This lack is coupled with widespread confusion and misunderstanding surrounding AI [50], indicating a gap in teacher educators' AI-related professional competence that is paramount to be addressed. Indeed, carefully embedding AI in education and fostering teacher educators' AI Literacy [21] are crucial to empower not only learners but also themselves as professional educators and individuals to leverage AI for creating opportunities rather than incurring opportunity costs [18, 19]. To embed AI Literacy development - with a particular focus on the development of its sub-dimension "AI-related ethical knowledge" - effectively into education, an appropriate competence model is necessary. As mentioned above, the present chapter uses Baumert and Kunter's COACTIV model of teacher professional competence [22] as its theoretical foundation. Following this model, we propose reconsidering teacher professional competence by locating the AI Literacy construct with its subdimension "AI-related ethical knowledge" within the knowledge domain of "professional knowledge". We thereby conceptualise AI Literacy with its 17 competences as outlined by Long and Magerko [38] as facets of content knowledge (CK [51]) and, combined with its effective application to pedagogy, as facets of pedagogical content knowledge (PCK [51]). As professional values and beliefs are central functions of professional ethics, that is, teacher professional ethos [52], we situate AI Literacy's subdimension "AI-related ethical knowledge and skills" additionally as a domain in the professional competence aspect "professional values, beliefs and goals" [22].

In line with the competence-theoretical approach to teacher professionalism [34], these proposed conceptualisations of AI Literacy and AI-related ethical knowledge as knowledge facets include both teacher educators' latent potential, the process that leads to their decision to act and their performance visible in their actions itself (e.g., selecting suitable AI-tools based on ethical principles, using AI responsibly when planning and conducting lessons, incorporating AI equitably and effectively in pedagogy, using AI for enhanced student engagement and outcome, using AI for assessment and evaluation etc.). This proposal rests on mere theoretical reasoning. To determine whether AI Literacy and AI-related ethical knowledge indeed constitute facets of professional knowledge, and to verify whether they can indeed be situated in Baumert and Kunter's COACTIV model [22], empirical research and validation is indispensable. For now, we use the above theoretical elaborations as a foundation for reflecting on how these competence facets can be incorporated in institutional teacher education to contribute to a successful integration of AI—and consequently to contribute to safeguarding high-quality teacher education.

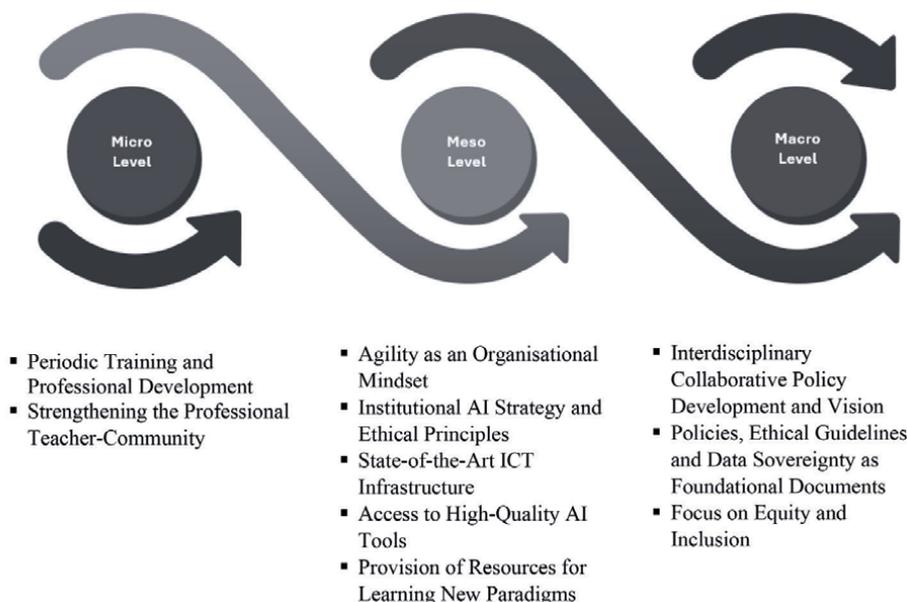
## 7. Establishing a framework for teacher educator professionalisation in the AI era

With teacher professionalism being both an individual (micro level) and collective (micro and meso level) phenomenon, questions regarding the development of teacher professional competence need to also be approached on the level of institutionalised teacher education including its structures, routines and cultures (meso and macro level) [30]. The elaborations on AI Literacy and AI-related ethical knowledge indicate that part of teacher education institutions' responsibility is to proactively and continuously address both facets by means of a coherent, strategic, holistic and adaptable approach—an approach that constructively intertwines the interrelated individual, micro level (professional development), the collective, organisational meso level (organisational development) and the overarching macro level (politics and policy). In the following sections, we propose a framework that outlines areas of development deducted from the literature to contribute to the development of AI Literacy and AI-related ethical knowledge. The aim of the framework is to thus suggest avenues for enabling a more aligned professionalisation process of teacher educators and teacher education from the perspective of AIEd (see **Figure 1**).

Underlying the framework is the need for a continuously growing degree of agility and flexibility in teacher education institutions—organisations known for their systemic resistance to adapt to change [36]—to sustain the fitness for purpose and continued high quality of their study programmes.

### 7.1 Micro level: teacher educators, in- and pre-service teachers and learners

In the process of teacher professionalisation, individuals develop the knowledge and skills necessary to cope with the demands of their profession [32]. In the age of



**Figure 1.**  
*Framework for teacher educator professionalisation in the AI era.*

AI, the demands on teacher professional competence continue to change rapidly. Thus, it is not just individuals but also the teaching profession as a system that need to adapt continuously [32]. This section proposes two areas of development that may contribute to an up-to-date professionalisation process both at the individual as well as the systemic level. We thereby conceptualise the individual level to correspond with the micro level of institutional teacher education and the systemic level to bridge the micro and meso level of institutional education.

### *7.1.1 Periodic training and professional development*

A prerequisite for effective professionalisation for AI is for educators to learn to understand, use, monitor and critically reflect AI [19, 23] and building thereupon to facilitate their teaching and develop their students' AI Literacy [26]. Both require knowing and using suitable AI technologies for learning (e.g., adaptive learning systems, intelligent learning environments, data analytics or automated scoring and feedback systems) to understand students' learning progress and needs in an AI-mediated education, to promote equitable personalised learning and the development of evaluative judgement and to foster students' ethically responsible, critical and constructive engagement with AI [19]. Teacher education institutions thus need to provide regular comprehensive training and professional development opportunities for developing educators' AI Literacy [21].

Both the development and support of teacher educators in their professionalisation as well as the integration of new technologies into their teaching are an ongoing and long-term tasks. Employing suitable and empirically sound educational models and didactic concepts (e.g., digitality-related pedagogical and content knowledge DPaCK [21, 53] or the Frankfurt triangle model for education in the digitally connected world<sup>2</sup> [17]) is crucial for achieving these tasks.

### *7.1.2 Strengthening the professional teacher-community*

As a multifaceted and complex process, the professionalisation of educators transcends the individual and constitutes a collective endeavour. As such, strengthening the teaching community as teacher educators further develop their individual and collective professional competence is highly important. This becomes particularly salient in the context of AIEd. In this rapidly evolving domain, the facilitation of effective practices and discourse concerning diverse AI solutions is pivotal for successfully integrating AI into education. Consequently, the establishment of a supportive and collaborative environment is paramount. One way of supporting the collective teacher community is through initiatives such as platforms (online or analogue) to facilitate the knowledge transfer and encouraging sharing experiences as educators navigate the complexities of integrating AI into their teaching practices. This approach not only fosters an environment of continuous learning but also ensures that the educational community remains at the forefront of technological and methodological advancements.

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<sup>2</sup> The "Frankfurt-Dreieck" is also known as and often referred to as "Dagstuhl-Dreieck" (cf. Brinda et al., [17]; Gesellschaft für Informatik e.V. [54]).

## **7.2 Meso level: educational institutions**

The meso level encompasses schools, teacher education institutions, professional development providers, decision-makers in educational institutions, (educational) companies and the teaching profession as a system. This section presents avenues for promoting the teacher educator professionalisation process both at the level of organisational development as well as the level of teacher education as a system.

### *7.2.1 Agility as an organisational mindset*

For individuals, organisations and policy makers to be able to establish favourable conditions for the development of AI-related professional competence and a successful appropriation of AI in education, stakeholders at all levels need to become increasingly more agile and flexible. This is relevant because the AI-environment is fast-paced, dynamic and unpredictable. As teacher education institutions are particularly known for systemic resistance to change [36], this area of development may present a considerable challenge for institutions to overcome. However, overcoming this resistance to change is considered pivotal for successful integration AIED [55].

### *7.2.2 Institutional AI strategy and ethical principles*

A unified institutional AI strategy including ethical principles on AI use is essential. The development of such strategy should involve a multidisciplinary team of all stakeholders and provide a clear framework for an ethically responsible use of AI in education [56]. At the same time, the strategy needs to be flexible enough to allow for adapting to rapid changes in the AI and educational landscape. Higher education institutions across a variety of countries have been developing such principles over the past years, and such developments have proliferated since the launch of Open-AI's Chatbot ChatGPT-3 in November 2022 (e.g., [57]). As institutional strategies may significantly influence the professionalisation of teacher educators [32], it is important that they align with initiatives to aid teacher educator professionalisation and teacher education institution development.

### *7.2.3 State-of-the-art ICT infrastructure*

Maintaining up-to-date ICT infrastructure is vital for the effective use of AI in educational settings [58]. Without the respective infrastructure, AI cannot effectively be appropriated to education and its affordances cannot be efficiently harnessed. This maintenance is highly dependent on and intertwined with stakeholders of the macro level of institutional education, such as educational policy, state funding or political decisions.

### *7.2.4 Access to high-quality AI tools*

Like the need for state-of-the-art ICT infrastructure, it is crucial to ensure equitable access to AI tools across all stakeholders in institutionalised teacher education. This aims to prevent a disparity in learning opportunities and seeks to avoid reproducing inequalities among students from different economic backgrounds.

### *7.2.5 Provision of resources for learning new paradigms*

Institutions should provide resources that enable educators and students to explore and learn knowledge paradigms that may emerge with the AI-transformation of education and society as a whole [58]. In addition to making relevant resources available (e.g., time, targeted further training opportunities, highly qualified support staff and curricular freedom), it is important that an atmosphere of open discourse, innovative spirit and mutual support prevails across the institution.

## **7.3 Macro level: politics and policy**

The macro level of institutional education spans dimensions such as educational policy and politics at state, federal and global levels. This section suggests foundational aspects that are relevant on this level to contribute to the development of professional competence and its cascading effects.

### *7.3.1 Interdisciplinary collaborative policy development and vision*

Institutions must collaborate to update existing policies and develop a clear vision for the (ethical) use of AI in education [20]. Amidst the rapid technological advancements, teacher education institutions need to establish consensus among trans- and interdisciplinary teams (including students) that enables adopting and responding to technological AI-development to provide guidance to all its stakeholders. Furthermore, it is crucial to fund and conduct extensive research into the affordances, limitations, perils and impact on student and teacher outcomes and learning in (teacher) education [56]. This includes the establishment of full-time research positions at higher education institutions to foster and strengthen international collaboration on AI research [56]. Co-developing and sharing “good practices” and experiences across institutions will be crucial for establishing guiding principles for AI Literacy and AI-related ethical knowledge development across all levels of the educational sector.

### *7.3.2 Policies, ethical guidelines and data sovereignty as foundational documents*

Establishing comprehensive ethical guidelines is paramount to a successful appropriation of AI in education. These guidelines should serve as the foundation for all AI-related activities in institutionalised education, ensuring that the selection and application of AI technologies aligns with ethical standards and values.

### *7.3.3 Focus on equity and inclusion*

To support the creation of an ethical foundation for achieving a “Good AI Society” [15, 16], a clear ethical policy and integrity guidelines at the macro level are pivotal [59]. A prerequisite for meeting this requirement is to ensure that the adoption of new technologies does not widen existing disparities in education. Cascading from the macro level to the meso level, equitable access to AI tools and services needs to be provided to all students, pre-service and in-service teachers as well as teacher educators alike.

## **8. Implementing AI at the St. Gallen University of Teacher Education**

In connection to the areas of development outlined in the present framework, this section discusses the St. Gallen University of Teacher Education's (PHSG) approach to appropriating AI in teacher education as a case study. With the goal to gradually incorporate AI into all its domains, the PHSG has taken a holistic approach by recently developing an institutional AI-Policy (meso level). The policy outlines five key initiatives that encompass the institution's commitment to (1) continuous assessment of stakeholders' needs and experiences with AI; (2) the provision of professional AI Literacy-development opportunities; (3) fair and reliable educational assessment including support on aspects such as academic integrity, ethics and legal implications of AI use; (4) the collaborative development of strategies for AI use in academic research and student written assignments and (5) a collaborative approach to appropriating AI in education that complies with guidelines, ensures knowledge transfer and facilitates faculty training.

Targeting the micro level, the PHSG is developing various learning modules on the continuing education platform [www.aprendo.ch](http://www.aprendo.ch) designed to enhance educators' digital and AI-related competences [60]. The platform aims to offer around 100 learning modules in the future that facilitate synchronous and asynchronous learning opportunities and target the development of six competence dimensions in relation to digitality and AI [60].

Another development project of the PHSG constitutes [www.zitbox.ch](http://www.zitbox.ch) [61], an online platform designed to promote discussions among educators, grow the (teacher) educator network and strengthen the teaching community. It facilitates discussions related to the digitalisation and AI-transformation of education beyond individual school units. First, user feedback indicates that the platform is effective in facilitating active communication and networking among educators. With regard to AI, this interaction focuses on discussing and sharing insights about the possibilities and limitations of AI in schools.

Further, to enhance educators' AI Literacy and empower them to effectively integrate AI into their teaching, the PHSG has developed a multitiered curriculum for its continuing education programmes (meso and micro level). Designed based on the Frankfurt triangle model [17], the curriculum constitutes a theory-based blended-learning approach to AI integration in higher education. It is designed to accommodate a diverse audience, including participants with no or little prior AI experience. The curriculum covers a wide range of topics, including machine processing of natural language, the impact of AI tools on didactic processes, experimentation with AI tools across various disciplines, the influence of AI on assessment and the application of AI in academic writing. The programme starts with a kickoff event to introduce participants to independent learning modules that focus on foundational AI concepts. Subsequent face-to-face sessions prepare participants for incorporating AI tools into their teaching. Participants' experiences thereof are then discussed and reflected in a follow-up session to reinforce learned concepts. An array of supplementary resources, including webinars, lectures and regular AI roundtable discussions, is designed to enhance participants' practical skills and knowledge, particularly in the performance dimension of AI-related professional competence. The programme aims to ensure participants not only understand AI's fundamental concepts and educational applications but also develop expertise in areas like prompt engineering and the critical assessment of AI's benefits and challenges in university teaching.

## **9. Future directions: research needs and development trajectories**

Even though the use of AI and AI research in education has increased significantly since 2020, empirical literature on the application of AI to and impact of AI on teaching and learning [35, 62, 63], relationships between AI technologies and learning outcomes for students and teachers [35]—also beyond immediate concrete applications [41]—and theoretical concepts of AI in education [2, 25] are still scarce. Thus, the needs for further research in this area are manifold [20]. Most crucially, future research is required to further ethical considerations and attention within AIEd, both as a topic of research as well as a pivotal issue in conducting empirical research [20]. Research into ethical issues connected to bias, storage and use of teaching and learning data, fairness and accountability of AI use in education and AI Literacy development among learners and educators is urgently needed [20]. Closely intertwined with such endeavours are research required efforts into examining challenges associated with data sources, ownership and authorship as well as authority [36]. Furthermore, considerable efforts are required in the development of policy and institutional guidelines to increase the responsiveness of education systems to rapid changes driven by AI [36].

A specific call for more research relates to the current lack of educational frameworks underpinning the development and incorporation of AI tools in educational settings [20]. More research efforts are required in investigating the appropriateness, suitability and effectiveness of AI tools for pedagogical purposes—as well as their impact on learning, cognition, affect and overall competence development [20].

To ensure that the needs of minorities and marginalised people are reflected in AI development [35] and to prevent the potential of proliferating inequity and inequality caused by algorithmic bias, future research needs to involve a broader range of stakeholders across a wider range of disciplines [20].

Finally, to determine the appropriateness and validity of situating AI Literacy and AI-related ethical knowledge as facets of knowledge and aspects of professional competence in Baumert and Kunter's COACTIV model [22], extensive empirical research needs to be conducted. Similarly, to determine the effectiveness of initiatives to develop AI Literacy and to appropriate AI in education such as the PHSG-approach presented above, empirical investigations are necessary. Both strands would require intervention studies of pre-post designs with experimental and control groups.

## **10. Conclusion**

In this chapter, we have argued that teacher professionalism in the age of AI requires the development of AI Literacy and AI-related ethical knowledge as new knowledge facets of professional competence. Fostering their development in teacher education not only aims to enable educators to become responsible navigators, ethical stewards and competent teachers of AI technology but also seeks to ensure high-quality teacher education that is up-to-date and fit-for-purpose as the AI-mediated landscape evolves. Continuously meeting the performance mandate of education requires a multifaceted and holistic approach that interlaces the micro, meso and macro levels of institutional education. As agents of change, teacher education institutions will need to harmonise the technological with the pedagogical and the ethical with the practical. Based on the above elaborations and identified needs, we proposed a framework for teacher educator professionalisation in the AI era that attempts to

support such endeavours. Based on the therein contained areas of development, we advocate for embedding the development of AI Literacy and AI-related ethical knowledge into teacher education's core curriculum and ongoing professional development programmes. We further suggest establishing structures that promote strengthening the teaching community as teacher educators further develop their individual and collective professional competence. Furthermore, we maintain that promoting the development of ethical frameworks on institutional and educational policy level to sustain an equitable and inclusive use of AI in educational settings, investing in state-of-the-art ICT infrastructure with access to cutting-edge AI tools and encouraging interdisciplinary collaboration constitute central components of teacher education professionalism in the age of AI. Finally, with AI Literacy and AIEd research still being in their infancies, extensive empirical research will be required to investigate the suitability and effects of the above recommendations on quality teacher education. As we move forward, embracing the transformative potential of AI in education with foresight and appropriate knowledge will be crucial for ensuring that the educators of today and tomorrow are empowered to harness the potential of AI.

### **Conflict of interest**

The authors declare no conflict of interest.

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# Perspective Chapter: Leveraging Artificial Intelligence in a Blotch Academic Environment

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## Abstract

We look into leveraging artificial intelligence (AI) to enhance the academic environment within our institution. We aim to streamline administrative tasks by integrating AI-powered tools, personalising student learning experiences and facilitating data-driven decision-making. This will improve efficiency, increase student engagement and improve resource allocation. AI can assist in automating routine administrative processes, providing data-driven insights for course improvement and offering personalised recommendations to students. By embracing AI, we can create a more dynamic and responsive academic ecosystem, ensuring that our institution remains at the forefront of educational innovation where learning problems can be thoroughly addressed in the learning environment.

**Keywords:** leveraging, artificial intelligence, blotch, academic, environment

## 1. Introduction

Artificial intelligence (AI) is the general term for developing computer systems that can do tasks that typically require human intelligence. These tasks include solving problems, learning, perceiving, understanding language and making decisions. AI seeks to create devices that can simulate or replicate human cognitive functions. This refers to AI systems developed and trained for a specific goal. Although they are less diverse and have a lower learning capacity than human intelligence, they are better in that sector. AI is used in education [1], including features like plagiarism detection and exam integrity [2]. Researchers in the field are constantly looking into new techniques, approaches and algorithms to enhance the capabilities of AI systems. Growing emphasis will be placed on ethical concerns, reducing bias and developing AI responsibly as technology advances. It is imperative to keep in mind that the sector is constantly evolving. Regrettably, however, organisations and scholars worldwide minimise the hazards associated with artificial intelligence while praising its negative impacts. Those unable to understand technology may soon be met with a world that increasingly resembles magic and makes them feel left behind [3].

Researchers worry that by 2030, the AI revolution will focus on enhancing benefits and societal control, but it will also raise contentious ethical questions. Regarding AI's positive effects on morality and life, opinions diverge significantly [4]. The advancement of AI also raises several concerns around morality, behaviour, privacy and trust, to name a few. There are various ethical concerns with the use of AI in education. Many scholars are exploring the field more thoroughly. Our classification of AI in education is based on three levels. First and foremost is the technology itself—its developer, manufacturer, etc. Third are the effects on the student or learner, then the teacher.

Artificial intelligence (AI) integration has become a revolutionary force in the constantly changing academic scene, providing hitherto unseen chances to improve and expedite administrative processes. AI-powered solutions offer a promising way to lessen the load of administrative duties as academic institutions need help with growing complexity and the requirement for efficiency.

Routine administrative work automation is a notable area where artificial intelligence can significantly impact. AI can analyse massive volumes of data quickly and accurately, saving human administrators much time and effort on tasks like monitoring student records and course registrations. A subset of artificial intelligence called machine learning algorithms can use data patterns to forecast future trends, allowing organisations to plan and allocate resources and student support services wisely [5].

Using chatbots with AI capabilities is an additional way to increase administrative effectiveness. These clever virtual assistants can respond quickly to often-asked queries and manage routine requests from staff, instructors and students. This improves the user experience while freeing human administrators to work on more challenging and worthwhile duties. Chatbots can be easily incorporated into various platforms, including mobile apps and websites, providing smooth and convenient communication for the academic community.

Beyond mere automation, AI's data processing capabilities provide insightful information for tactical decision-making. By predicting enrolment trends, predictive analytics can assist educational institutions in better allocating resources and optimising their course offerings. Furthermore, patterns in student performance data can be found using AI-driven analytics, allowing for prompt interventions to support students with academic difficulties.

AI integration can also be beneficial for educators' time-consuming grading procedures. AI-powered automated grading systems can quickly and accurately evaluate homework, tests and quizzes while giving students immediate feedback. This speeds up the grading process and frees teachers to work with students more individually, creating a more engaging learning environment.

AI can also help in the administration of research projects in academic settings. It can speed up the research process by assisting with literature reviews, recommending pertinent books and offering summaries. Furthermore, enormous volumes of research data may be analysed by AI algorithms, making it easier to find patterns and trends that may escape the notice of conventional techniques [6].

Even with all the benefits, ethical and privacy issues must be carefully considered when integrating AI into academic settings. Ensuring transparency in AI algorithms and protecting sensitive data is critical to preserving trust in the academic community.

To put it another way, the use of AI-powered tools in academic settings has the potential to transform administrative duties completely. Artificial intelligence (AI)

has the potential to improve productivity, lessen burden and foster a more adaptable and responsive learning environment by automating repetitive tasks and delivering actionable insights. Institutions stand to gain from embracing these technological innovations regarding operational effectiveness and cultivating an innovative and adaptive culture.

## **2. Integration of AI-powered tools in university administrative tasks: perspectives of academics**

Integrating artificial intelligence (AI) into university administrative tasks has sparked both academic agreement and disagreement. This debate concerns the potential benefits and challenges of adopting AI-powered tools to streamline various administrative processes.

### **2.1 Agreement**

Proponents of AI integration in university administration highlight several advantages that could enhance efficiency and productivity. One key argument is the potential for AI to automate routine and time-consuming tasks, allowing administrative staff to focus on more complex and strategic aspects of their roles. This, they argue, could lead to a significant reduction in human error and increase overall operational efficiency [7].

Furthermore, AI-powered tools have the potential to analyse large datasets quickly, facilitating data-driven decision-making in areas such as admissions, enrolment management and resource allocation. This analytical capability is valuable for universities seeking to make informed, strategic decisions that align with their goals [8, 9].

In the context of student services, Duan et al. [10] stated that AI tools can provide personalised assistance, ranging from academic advising to student support services. Chatbots equipped with natural language processing capabilities can offer timely responses to student queries, enhancing student experience.

Financial considerations also come into play, as proponents argue that the initial investment in AI technology can lead to long-term cost savings through increased efficiency and reduced administrative workload. This, they assert, allows universities to allocate resources more effectively and invest in other critical areas, such as research and faculty development [11].

### **2.2 Disagreement**

Despite the possible advantages, sceptical have doubts and worries regarding the extensive use of AI in university management. The fear of losing one's employment is a significant topic of dispute. Opponents contend that using AI to automate administrative activities could result in job redundancies, impacting administrative staff members' livelihoods [12].

Concerns about ethics and privacy are also significant points of contention. When AI is used, enormous volumes of sensitive data are handled, which raises concerns about data security, confidentiality and the possibility of bias in algorithms used to make decisions. Before AI is widely used, academics stress the significance of developing solid ethical standards and security safeguards to allay these worries [13].

Furthermore, there are concerns regarding AI technologies' adaptability and user-friendliness. According to sceptics, the learning curve of new technology might make it more challenging to incorporate AI seamlessly into current administrative procedures. Adoption of AI may encounter pushback from faculty and staff if changes upset established workflows [14].

Nonetheless, there is a complicated interaction of viewpoints in the discussion around integrating AI-powered tools into university administrative responsibilities. Supporters draw attention to the potential for increased productivity, data-driven decision-making and improved student services; detractors raise issues with job displacement, privacy and the flexibility of AI systems. Universities navigating the rapidly changing world of learning technology must balance utilising AI's benefits and attending to these justifiable concerns [13].

### **3. Conceptual model: the spectrum of academic perspectives on AI integration in university learning system**

#### **3.1 Agreement spectrum**

Scholars who enthusiastically support and welcome the use of AI-powered tools in learning system tasks. They think AI has much to offer universities regarding possible advantages, efficiency gains and resource optimisation.

Academics who embrace AI integration pragmatically and approach it with a more measured and pragmatic attitude are those who recognise its benefits. They favour its implementation when AI proves beneficial and improves education without detaching the human element.

Though willing to investigate AI integration, open-minded explorers wait to make a firm endorsement until they have more data, study and real-world applications. Although they are open to the idea, they are somewhat sceptical once the benefits are demonstrated [15].

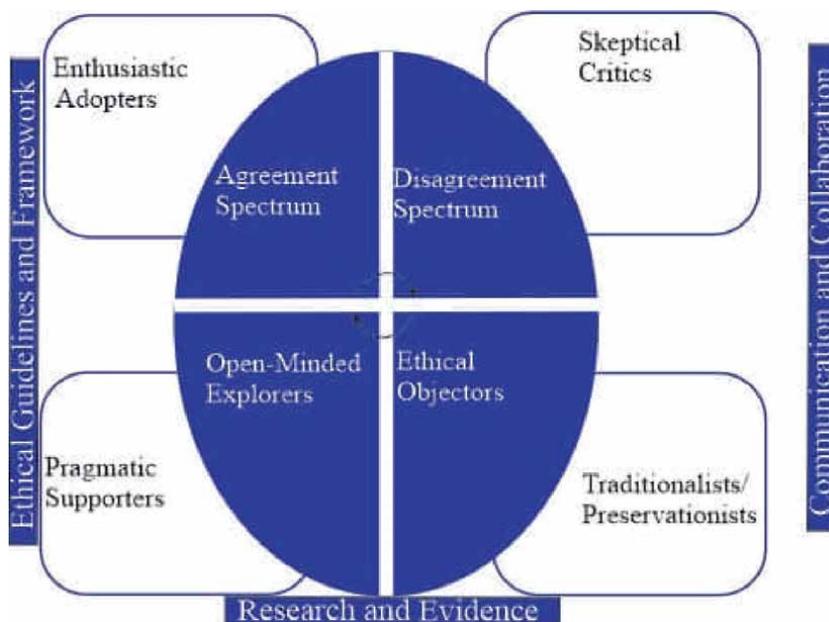
#### **3.2 Disagreement spectrum**

Academics who are sceptics regarding using AI in teaching and learning tasks likewise harbour misgivings and concerns. Concerns about potential biases in AI systems, ethical issues or job displacement might be on their minds. They think that until these issues are sufficiently resolved, we should continue to take a cautious approach.

Scholars vehemently disagree with the incorporation of AI and support the preservation of conventional techniques. They contend that when it comes to some parts of academic decision-making, human touch, experience, and judgement are irreplaceable. Academics emphasise issues with algorithmic unfairness, data privacy and the possible abuse of AI in administrative decision-making as the ethical foundation for their disagreement. Before any integration occurs, they need strict ethical guidelines and protections [16].

#### **3.3 Connecting threads**

**Figure 1** illustrates how the degree of acceptance or rejection frequently depends on the availability of solid data and research demonstrating the benefits of integrating AI into academic administration and instruction. To find common ground, supporters



**Figure 1.**  
*Conceptual model of AI connecting threads.*

and opponents must communicate effectively. A more balanced strategy can be formed *via* constructive communication, addressing issues and exchanging insights. To allay worries and guarantee responsible deployment, it is imperative to establish explicit ethical standards and frameworks for the application of AI.

This conceptual model acknowledges the range of viewpoints within academia concerning the integration of AI-powered tools for teaching and learning activities in academic settings.

#### **4. Personalised student learning experiences through AI: enhancing education for the future**

Artificial intelligence (AI) has been a transformational force in educational settings in recent years, with many benefits that reach deep into the core of academic experiences. The ability of AI to tailor student learning experiences to individual needs, strengths and learning styles is one of the most exciting developments in education. This method conforms to the changing expectations of academics on using AI in the classroom and creates a more dynamic and productive learning environment [16].

#### **5. Advantages of tailored education for students**

##### **5.1 Tailored learning routes**

AI-powered systems can generate customised learning routes by analysing individual students' performance data and preferences. This maximises comprehension

and retention by ensuring students receive knowledge in a format that best fits their learning styles and is delivered promptly.

AI-driven tests have the ability to change their difficulty level and provide instant feedback in real time in response to a student's answer. This adaptive exam helps students grasp concepts more deeply and enables teachers to pinpoint and help each student's areas of difficulty [14].

Teachers can provide customised instruction to students of different skill levels in the same classroom because of personalisation. In order to satisfy each student's unique needs, AI technologies can suggest various materials, tasks and evaluations, promoting a more inclusive learning environment.

AI makes self-paced learning experiences easier, enabling students to move through the content at a speed that works for their schedules and skills. This adaptability fosters a sense of independence and accountability for one's education while accommodating a range of learning velocities.

AI can give prompt, helpful feedback on tasks, projects and evaluations. This quick feedback loop helps students learn more effectively by helping them recognise their errors, fix them and keep getting better. Through ongoing data analysis, AI can recognise early indicators of learning gaps or academic difficulties. This makes it possible for teachers to step in quickly, providing extra help to pupils with difficulties and halting the progression of any learning gaps [17].

## **6. Expectations of academics in AI usage in classroom activities**

Academics anticipate that AI will simplify repetitive chores related to teaching and learning, freeing them up to concentrate more on individualised education, mentorship and developing creative and captivating learning opportunities. Time that might otherwise be spent on essential student interactions is freed up by automating administrative tasks such as attendance monitoring and grading. Teachers hope AI will enable them to get practical insights from data analysis. Teachers can improve the overall quality of education by using student performance data to influence decisions about curriculum design, instructional tactics and resource allocation [18].

Academics should consider using AI to create platforms and tools that simplify altering lesson plans and assignments. This personalisation helps educators create specialised learning environments that meet their pupils' varied needs and interests. AI tools are anticipated to make it easier for parents, students and instructors to collaborate and communicate. A more cohesive and encouraging learning community can be created with improved communication channels, online collaborative areas and AI-driven insights [19].

Academics emphasise the significance of moral AI practices in teaching. People anticipate transparent, bias-free and inclusively designed AI systems. For academics to embrace AI in the classroom, the algorithms must refrain from reinforcing or magnifying existing disparities. To stay current with the latest developments in artificial intelligence and educational technology, instructors should consider pursuing professional development opportunities and continuous training before implementing all these critical changes. Academics can maximise the benefits of AI technologies for student learning by integrating them into their teaching practices through continuous learning.

Furthermore, the individualised learning experiences that AI enables for students mark a paradigm change in the field of education, meeting the demands of scholars

for a more effective, data-driven and student-centred method of instruction. For the benefit of students everywhere, the partnership between educators and AI promises to form an increasingly influential, flexible and inclusive educational environment as technology advances [17].

Teachers' perspectives on individualised learning with artificial intelligence (AI) in underdeveloped technical environments are varied, considering both the opportunities and difficulties of introducing such cutting-edge technologies in settings with inadequate infrastructure. The following are some viewpoints that teachers may have:

### **6.1 Educators' perspectives on personalised learning with AI in technology-disadvantaged areas: challenges and concerns**

Teachers may voice worries about students' access to devices and internet connectivity in places with limited technology resources. Personalised learning frequently uses digital tools and online platforms, which can be problematic in places with differences in technology access. It is possible that educators should be more concerned with their own and their students' technological literacy. To effectively integrate AI-powered technologies into their teaching practices, educators may require additional training and a certain level of technological expertise [19].

It is possible to worry about making already-existing disparities worse. The educational divide could grow if confident kids can access AI-powered personalised learning tools while others do not. When using technology in underserved communities, it is imperative to ensure equity and inclusion.

### **6.2 Possible advantages**

Teachers might know how AI might give kids with different learning needs individualised support. AI solutions can adjust to each learner's unique learning style and provide focused support to close educational gaps.

AI-powered personalised learning promises resource optimisation, freeing teachers to concentrate on areas that need more excellent care while technology takes care of regular teaching duties. This can be especially helpful in settings with limited resources. Students' acquisition of twenty-first century abilities, such as digital literacy, problem-solving and critical thinking, can be aided by AI integration. Teachers might value getting their kids ready for a world with more advanced technology.

### **6.3 Techniques for putting education front and centre in technologically disadvantaged areas**

Steps should be taken to improve these conditions in locations with limited device access and dependable internet connectivity. In order to solve these infrastructural issues, public-private partnerships (PPPs), government programmes and community involvement can be significant.

### **6.4 Empowerment and community engagement**

It is critical to include parents and the neighbourhood in the educational process. Even in places with limited access to technology, families can be empowered to assist their children's education through workshops, training sessions and awareness campaigns.

It is critical to implement tech solutions that can work in low-tech settings. In places with inadequate access to technology, personalised learning can be made possible by investigating mobile applications, offline resources and other creative strategies [20].

### **6.5 Teacher training and professional development**

To improve teachers' technological literacy, it is crucial to give them continual training and assistance. Programmes for professional development can give educators the tools they need to incorporate AI-powered resources successfully.

### **6.6 Policies and assistance from the government**

Policies that emphasise the use of technology in education can be put into place by governments and educational authorities, especially in underprivileged areas. The quality of education can be significantly impacted by funding and support for curriculum creation, teacher preparation and technology infrastructure.

### **6.7 Public-private partnerships**

Working with tech companies *via* PPPs can help underserved areas of technology by providing resources, knowledge and creative solutions. These collaborations can help create and implement specialised educational technology solutions.

Stated differently, although educators in under-technologicalized regions might be apprehensive about integrating AI-powered personalised learning, noteworthy prospects exist for noteworthy benefits. Education can be promoted by strategies prioritising teacher preparation, community involvement, infrastructure development and supportive legislation. This will guarantee that all children, irrespective of their technological surroundings, have access to high-quality, customised learning experiences.

## **7. Empowering education through AI: facilitating data-driven decision-making in teaching and research**

Data-driven decision-making has emerged as a potent tool for educators to improve teaching efficacy and make significant contributions to research in the constantly changing field of education. Through data-driven insights, educators can make well-informed decisions, customise instruction to meet the requirements of specific students and forward research goals. This essay explores how teachers and researchers may support data-driven decision-making.

### **7.1 Instructional environments**

Real-time awareness of student comprehension can be gained by routinely gathering and evaluating formative assessment data. Teachers might modify their pedagogical approaches in light of this information to better meet their students' unique requirements and difficulties. Teachers can identify each student's strengths and weaknesses using personalised feedback from assessment data. Thanks to this tailored feedback, students can comprehend their success and areas for growth, which creates a more flexible learning environment.

These days, learning analytics-capable educational technology platforms provide helpful information on student performance, engagement and learning trends. Teachers can use these insights to modify the curriculum, change the pace and pinpoint children who are in danger and may require more assistance. Additionally, data are used by adaptive learning platforms to design customised learning pathways for students. Educators can guarantee that every student obtains a customised learning experience that aligns with their needs and skills by monitoring individual development and making content adaptations depending on performance.

## **7.2 Early intervention techniques**

Students' patterns of learning gaps can be found through data analysis. Teachers can address these gaps early on and stop them from worsening by using targeted interventions such as extra resources, remedial sessions or customised instruction. Predictive analytics models may be used to identify kids at risk of falling behind. Teachers can take proactive measures to support kids experiencing academic or socio-emotional difficulties by examining a variety of indications [21].

## **7.3 Research settings**

The development of research questions can benefit from data analysis. Educators can formulate hypotheses and study objectives using available data to discover trends, patterns or knowledge gaps. Educators can perform fundamental data analysis before undertaking large-scale research to determine their research questions' viability and possible impact. Thanks to this iterative approach, research activities are concentrated and aligned with educational objectives [7].

## **7.4 Design and execution of experiments**

Experiment parameters can be refined with the help of data-driven insights. Educators can ensure that their study is rigorous and yields significant results by optimising their research design through the analysis of pilot data or small-scale experimentation. Educators can use data to pinpoint essential variables to measure their research. This guarantees that the research gathers complete and pertinent data, which advances our understanding of the educational phenomenon being studied [7].

## **7.5 Data-driven publication strategies**

Teachers can choose which journals to submit their manuscripts to by looking at impact factors and publication trends. Educators may optimise sharing their study findings by carefully selecting publications with a large readership and impact. Research publications have a more significant impact when they use effective data visualisation. Educators can help readers understand and become more engaged by using data visualisation tools to communicate facts clearly and appealingly.

## **7.6 Cross-cutting techniques**

Teachers can receive the necessary skills in data literacy through data literacy training. Effective data collection, analysis and interpretation are abilities that

educators must possess. The data literacy of educators can be improved through workshops, courses and chances for continuous professional development.

However, working with experts or data scientists can increase the influence of data-driven decision-making. The knowledge of experts in data analysis can be beneficial to educators, providing them with more complex and nuanced views.

### **7.7 Moral aspects to take into account**

Teachers need to put student privacy and research participant data protection first. Robust data protection protocols, informed permission and adherence to ethical standards are essential components of responsible data-driven decision-making. Transparency about the use of data is something that educators should uphold in both teaching and research contexts. Trust is developed among students, coworkers and the larger educational community when it is communicated how data influences decisions.

Data-driven decision-making has the potential to completely transform education by improving instructional strategies and generating influential research. Teachers can use data to discover areas for improvement, personalise learning and expand the body of knowledge in their subject. Teachers have a critical role in determining the direction of education by adopting data-driven practices and encouraging a culture of continuous improvement [22].

## **8. To create a more dynamic and responsive academic ecosystem that remains at the forefront of educational innovation and promotes inclusiveness, institutions can implement the following strategies**

Dynamic and captivating learning environments can be produced through interactive learning platforms, virtual classrooms and online collaboration tools. To ensure that all students can take advantage of digital resources, give faculty members the assistance and training they need to incorporate technology into their teaching strategies successfully.

### **8.1 Encourage an innovative culture**

Promote a culture that rewards creativity and innovation. Create avenues for staff, students and teachers to collaborate on creative projects. Establish innovation hubs or centres to facilitate research, experimentation and the creation of novel teaching strategies.

### **8.2 Put into practice adaptable curriculum framework**

Provide a curriculum that is adaptable and flexible to different learning styles, inclinations and speeds. Permit students to select courses and learning pathways based on their interests and professional aspirations. Use multi-disciplinary methods to solve practical issues while encouraging teamwork and critical thinking.

### **8.3 Utilise data to make well-informed decisions**

Use data analytics to monitor student satisfaction, engagement and performance. Utilise this information to pinpoint areas in need of development, tailor lessons to the

needs of each student and offer early interventions to struggling students. Examine demographic information to ensure the programme is inclusive and to find and fix inequalities in academic performance.

#### **8.4 Encourage cooperative education**

Create a cooperative learning atmosphere that promotes group work and peer engagement. Teamwork, a sense of community and a diversity of ideas are all fostered *via* collaborative learning. Use technology-enabled collaboration solutions to promote inclusivity and break geographical barriers by facilitating communication and group work.

#### **8.5 Set priorities development of faculty**

Invest in your academic members' ongoing professional development and instruct staff on the newest teaching techniques, educational tools and classroom promotion tactics. Faculty members should be encouraged to publish their findings and research cutting-edge teaching techniques to enhance the institution's standing as an educational leader.

#### **8.6 Make inclusive learning environments**

Ensure all students, including those with impairments, have access to physical and virtual learning environments. Make sure that tools, online courses and classrooms are inclusively created. Provide a network of support for kids with a range of needs by providing resources, including counselling, tutoring and adjustments for accessibility.

#### **8.7 Form collaborations and partnerships**

Encourage collaborations with businesses, other academic institutions and neighbourhood associations. Collaborative projects expose students to various viewpoints and give education a real-world context. Engage in cooperative research initiatives, exchange schemes and internships to enhance the academic experience and equip students for the intricacies of the global labour market.

#### **8.8 Encourage a student-centric perspective**

Place the students at the centre of the learning process. Use focus groups, questionnaires and student involvement on committees to frequently collect feedback about your students' needs and preferences. Provide a system of support for students that addresses their emotional, social and academic needs to help them feel engaged and significant.

#### **8.9 Ongoing assessment and enhancement**

Build a robust AI-driven system to evaluate courses, instruction and institutional policies continuously. Make informed decisions and adapt to changing learning environments with the help of feedback and data. Encourage a culture of continuous development whereby the company searches for fresh, creative approaches to increase the calibre and relevance of its training.

By putting these concepts into reality, educational institutions may remain at the forefront of educational innovation while creating a more adaptable and dynamic academic ecosystem that actively supports diversity and meets various learning needs. This plan ensures that the school can keep up with the evolving needs of the students and prepares them for success in a world that is changing swiftly [17].

## **9. Addressing potential ethical issues that arises from integrating AI into education**

While there are many chances to improve learning experiences when artificial intelligence (AI) is integrated into education, there are also ethical issues that must be carefully considered. Among the possible moral dilemmas are:

**Fairness and bias:** AI systems may inherit biases from the training data, leading to biased outcomes that affect pupils according to socioeconomic position, gender or race. This problem can be lessened by putting in place rigorous procedures for data validation and cleaning, using a variety of datasets and routinely checking AI systems for bias. Fairness and diversity should be given top priority in ethical norms.

**Privacy issues:** AI frequently requires gathering and examining enormous volumes of student data. Inadequate protection of sensitive information can result in misuse or unauthorised access, making privacy infringement dangerous. Obtain informed consent, anonymize data, create strong data protection policies and abide by privacy laws (such as family educational rights and privacy act (FERPA) and general data protection regulation (GDPR)). It is essential to communicate openly about data usage with parents, teachers and students.

**Explainability and transparency:** AI algorithms, particularly those used in machine learning, can be difficult to understand and intricate. Decisions that are difficult to grasp might become ‘black box’ problems due to a lack of openness and explainability. Enhancing trust and understanding can be achieved through emphasising transparency in algorithmic decision-making, giving explicit explanations for suggestions or assessments provided by AI and incorporating parents, teachers and students in the development process.

**Equity in access:** Inequalities in schooling can be made worse by unequal access to technology. Students who do not have as much access to AI-powered resources as their peers might be at a disadvantage. It is imperative to guarantee equitable access to technology, especially in impoverished communities. To close the digital divide, policymakers, educators and software developers must work together.

**Decision-making accountability:** When AI systems make choices that affect students’ academic careers, accountability issues arise. It could be difficult to determine who is responsible for mistakes. The responsible use of AI in education can be ensured by putting in place explicit accountability structures, involving humans in crucial decision-making processes and creating appeal and redress channels.

**Depersonalisation of education:** If AI is used too much, it could result in a depersonalised learning environment where students require more individualised attention and important human interactions. It is crucial to strike a balance between preserving human ties and integrating AI. AI should not be seen as a replacement for human interaction in education, but rather as a helpful tool that allows for customised learning.

AI in education raises concerns about job displacement for teachers because it may allow automated systems to replace some teaching responsibilities. Reassuring people that AI is designed to support educators rather than take their place can allay fears.

Programmes for professional development can equip teachers to work efficiently using AI tools in collaboration.

**Security risks:** Artificial intelligence (AI) systems are susceptible to cyberattacks, which could result in student data breaches or interfere with instructional procedures. To protect against security concerns, it is crucial to implement strong cyber security measures, conduct frequent system audits and give administrators and instructors cyber security training [17].

**Long-term effect on learning:** It is important to evaluate how AI will affect students' ability to think critically, improve their cognitive abilities and be creative in the long run. This issue can be addressed by prioritising a balanced approach that incorporates both AI and conventional teaching approaches, integrating educators in the evaluation process, and doing continuing research on the educational implications of AI.

**Ethical AI education:** If ethical AI use is not taught in schools, students may misuse AI tools unknowingly or inadvertently. Students who comprehend the consequences of AI in education can be produced by addressing the integration of ethical AI education into school curricula, educating educators on responsible AI use and cultivating an ethically conscious culture [13].

In order to address these ethical issues, educators, legislators, technology developers and the general public must work together. For ethical AI integration into education to be implemented responsibly, it is imperative to establish transparent norms and give fairness and inclusivity first priority. The advantages of AI in education can be maximised while lowering any potential ethical hazards with the help of regular assessments, feedback loops and a dedication to continuing ethical discussions. OpenAI, 2024. Large-scale language model ChatGPT (3.5). OpenAI Chat <https://chat>

## **10. Some potential biases that faculty members should be aware of when using AI in the classroom**

It is important for instructors to be aware of any potential biases in AI systems when they employ them in the classroom. These prejudices could unintentionally have an impact on pupils, grades and the general educational process. The following are some possible biases to be aware of:

**Algorithmic bias:** Preexisting biases in the training data may be inherited by AI algorithms. An AI system may reinforce and magnify biases if the historical data it was trained on is biased. It may lead to unfair results, giving some student groups less of an advantage due to things like socio-economic class, gender or colour. Verify and audit AI algorithms on a regular basis for bias. While training, make use of representative and heterogeneous datasets. Put in place fairness-aware algorithms that give equitable results priority.

**Cultural bias:** AI systems may reproduce cultural biases seen in the data, which could result in instructional content that is less sensitive to or relevant to other cultures. The information may not be as inclusive or relatable to some cultural groups, which could hinder learning and participation. Make sure that teams creating material are diverse. Verify the instructional content's sensitivity to and inclusion of different cultures. Include a range of viewpoints in datasets used for AI training.

**Gender bias:** Due to social assumptions or disparities in historical data, AI systems may display gender bias. Gender stereotypes may be reinforced if it leads to kids having different chances or expectations based on their gender. Examine comments and

material carefully for gender neutrality. Ensure that all students, regardless of gender, receive fair treatment by routinely evaluating and modifying algorithms.

**Socio-economic bias:** AI systems may unintentionally maintain gaps in educational achievements if they are trained on data that reflects socioeconomic prejudices. There may be obstacles or prejudices that lower socio-economic backgrounds students must overcome in order to maximise their learning potential. Adopt strategies that are tailored to the requirements of pupils from various socio-economic backgrounds. To reduce socio-economic prejudices, algorithms should be regularly evaluated and adjusted.

**Language bias:** Due to biases in training data, AI systems may favour particular dialects or linguistic styles over others. AI-powered technologies may make it difficult for students from diverse linguistic backgrounds or skill levels to comprehend or express themselves. Make sure the training datasets are linguistically diverse. Use language models that are flexible and mindful of many dialects and linguistic styles.

**Accessibility bias:** Unintentionally favouring particular learning formats or styles, AI systems may exclude students who have particular accessibility needs. Participating in AI-driven activities or gaining access to educational content may provide challenges for students with disabilities. Give accessibility top priority while developing and deploying AI solutions. Audit accessibility to make sure AI systems can meet a range of learning requirements.

**Historical data bias:** AI systems that have been trained on historical data may reinforce biases that are reflected in that data, such as discriminatory or inequitable past actions. Inadvertent perpetuation of past prejudices could result in unequal chances or treatment for particular student populations. Update training data frequently to reflect prevailing social norms and values. Put procedures in place to recognise and address biases in historical data.

**Involvement bias:** Unintentionally favouring particular learning styles or behaviours might cause AI systems monitoring student involvement to produce biased evaluations of student participation. It is possible that students with diverse communication or learning styles will receive unjust evaluations. Put in place inclusive and diverse engagement metrics. In order to prevent favouring particular learning types, take into account a variety of engagement and comprehension markers.

In order to overcome prejudices, faculty members should actively assess and monitor AI systems, work with tech developers to eliminate biases and promote moral AI practices in educational environments. To guarantee that AI in the classroom fosters justice, inclusivity and equal opportunity for all students, awareness and proactive measures are crucial [13].

## **11. Use of generative AI**

A kind of artificial intelligence called ‘generative AI’ uses patterns found in existing data to create new content, frequently text, graphics or other media. Applications for generative AI can be found in many different fields, demonstrating the technology’s capacity for creativity, invention and problem-solving. Here are a few noteworthy applications of generative AI:

### **1. Creation of content:**

Generating AI is able to produce text, images and videos that are realistic and cohesive by identifying patterns from vast datasets.

Applications: Text generation: Composing poetry, essays or even conversation for computer games.

Producing lifelike representations of inexistent objects or scenes is known as picture synthesis.

2. Creative arts and design: Innovative compositions, artworks and designs are created in the creative arts through the application of generative AI.

Applications: Creating original artwork, such as paintings, sculptures or digital art.

Making original music or coming up with melodies is known as music composition.

3. Chatbots and virtual assistants: Conversational agents are powered by conversational AI, which comprehends and produces responses that resemble those of a human.

Applications: Customer support: Offering instantaneous help and automated responses.

Personal assistants: Using speech recognition to carry out tasks.

4. Video game design: Synopsis: Using generative AI, video game content may be made more dynamic and adaptable.

Applications: Procedural content generation: Creating situations, game levels and characters.

Creating branching tales according to player decisions is known as narrative generation.

5. Medical image synthesis: To create synthetic images for machine learning model training, medical imaging uses generative AI.

Applications: Adding more medical photos to increase the variety of training datasets is known as data augmentation.

Simulation: Creating plausible medical situations in order to provide instruction.

6. Language translation: Coherent and contextually correct translations are produced through the application of generative AI in language translation.

Applications: Enabling smooth communication between speakers of several languages through the use of cross-language technology.

Translation services: Improving language translation's accuracy and speed.

7. Code generation: Using high-level instructions as a guide, generative AI can help create code fragments or even whole programmes.

Uses:

Auto-completion: Provides code snippets to programmers to help them while they work.

Code synthesis is the process of creating code from specifications in natural language.

8. Content summarisation: Long texts can be condensed and coherently summarised by generative AI.

Uses:

News articles: Condensing news stories for rapid reading.

Document summarisation is the process of reducing long papers to make them easier to read.

9. Fashion design: To create original designs and forecast future trends, generative AI is applied in the fashion industry.

Uses:

Inventive and ground-breaking fashion designs serve as inspiration for designers.

Customisation: Creating unique clothes designs according to personal tastes.

10. Scientific inquiry: By producing ideas, simulating experiments or analysing large, complicated datasets, generative AI supports scientific inquiry.

Uses:

Creating molecular structures for possible medications is known as drug discovery.

Building models for scientific studies is known as simulation modelling.

The uses of generative AI are expected to grow as it develops further, opening up new avenues for anything from scientific research and healthcare to creative and entertainment industries. The ethical and appropriate application of generative AI is still vital to address potential biases and societal repercussions, even though it offers great benefits [10].

## **12. Integrating artificial intelligence (AI) into learning management systems (LMS)**

There are numerous advantages of integrating artificial intelligence (AI) with learning management systems (LMS), which improve the quality of education for students and teachers alike. Here are a few main benefits:

**Personalised learning:** AI can customise content and activities to match each learner's preferences, learning styles and performance statistics, resulting in a personalised learning environment. Students receive individualised instruction that targets both their areas of strength and weakness, increasing comprehension and engagement.

**Learning routes** that are dynamically adjusted by AI algorithms in response to students' success guarantee that they are suitably challenged. This is known as adaptive learning paths. By moving at their own speed, students avoid becoming bored or frustrated and are encouraged to keep becoming better.

**Predictive analytics:** AI can evaluate data to forecast academic achievement and spot possible problems or areas in which help might be needed. Teachers are able to optimise their teaching tactics, proactively address learning gaps and offer timely help.

Automated grading and assessment: AI-driven solutions have the capacity to automatically grade assignments and tests, giving students immediate feedback. Lessens the administrative load on teachers, enabling them to concentrate on more intricate facets of instruction.

Natural language processing (NLP): With NLP in AI, chatbots and virtual assistants may converse in natural language and offer learners immediate assistance, improves responsiveness, accessibility and help availability, fostering a more encouraging learning environment.

Data-driven insights: AI is capable of analysing large amounts of data to produce useful insights about learning trends, student performance and engagement. Teachers get important knowledge that helps them make wise decisions, enhance their teaching methods and maximise the curriculum.

Content recommendation: Based on each student's interests and learning background, AI algorithms can recommend pertinent reading materials, websites and activities. It enhances learning, promotes experimentation and aids students in finding more material that is relevant to their interests.

Effective resource allocation: AI is capable of optimising the use of educational resources, such as budgetary allocation, classroom utilisation and faculty time. It guarantees a financially responsible learning environment, optimises resource utilisation and improves operational efficiency.

Routine administrative chores, including scheduling, enrolment and record-keeping, can be handled by AI for automated administrative chores. It lessens the administrative burden on teachers so they may concentrate on instruction and strategic planning [23].

### **13. Conclusion**

AI has a significant impact on the education industry. Even though it helps with many academic and administrative activities and improves education, its worries regarding security, privacy, ethical considerations and the choice of learning resources should not be disregarded. Even in institutions with technology issues, incorporating artificial intelligence (AI) into teaching and learning can drastically change educational methods. While there are special issues when integrating AI capabilities into a university that is underperforming in its teaching programme, academics can effectively navigate this process by grasping the underlying concepts and using calculated strategies. When integrating AI into teaching and learning in a university that is lagging behind, academics should be aware of and take the following crucial insights and actions. Scholars ought to carry out a comprehensive evaluation of the university's existing IT setup. To ascertain whether AI integration is compatible, be aware of the hardware, software and internet connectivity that are available.

Acknowledge the unique technological limitations and difficulties faced by the university, such as restricted access to fast internet, obsolete technology or a dearth of technical assistance.

Clearly state the purposes and goals of AI integration as it relates to education. This can entail enhancing educational objectives, raising student involvement or simplifying administrative procedures. Determine the areas with the most potential for AI influence, taking into account resource limitations. This could entail emphasising data-driven decision-making in academic planning, automated assessment systems or adaptive learning platforms. Provide faculty members with thorough programmes

in AI literacy. Make sure teachers are knowledgeable on the fundamentals of artificial intelligence (AI), how to use it in the classroom and how to incorporate AI technologies into their lesson plans.

Encourage academics, technologists and educational researchers to collaborate across disciplinary boundaries. The exchange of best practices and creative solutions can be encouraged by this cooperative approach. Seek AI solutions that can be tailored to the unique circumstances of the underperforming university. Seek for adaptable platforms that can take into account differences in educational objectives and technical infrastructure. Take into consideration integrating AI in stages or incrementally. Begin with pilot projects, evaluate their effects and then progressively expand them in light of positive results and lessons discovered.

Stress how crucial it is for AI algorithms and decision-making procedures to be transparent. Faculty members ought to be conscious of potential biases, ethical issues and the necessity of accountability and fairness in AI applications. Put strong data security procedures in place to protect the privacy of students. Make sure data usage adheres to ethical standards and that AI tools meet privacy requirements. Give inclusiveness in AI applications top priority. Take into account a variety of student demographics and make sure AI technologies accommodate varying learning preferences, aptitudes and cultural contexts.

Establish precise measurements to evaluate the effects of integrating AI. This can entail raising engagement levels, raising student achievement or increasing administrative process efficiency. Get input from educators, learners and other stakeholders on a regular basis. Utilise these comments to pinpoint problem areas, resolve issues and enhance AI deployments. Use an iterative process while integrating AI. Handle it as a continuous process of improvement, being willing to modify tactics in response to changing requirements and developments in technology.

Seek the leadership's assistance in promoting AI integration programmes at the university. A culture that supports experimentation and growth can be established by a top-down commitment to innovation. Engage the academic community in conversations around the integration of AI. Encourage knowledge and comprehension of the advantages and difficulties of using AI in the classroom. Encourage faculty members to participate in peer-to-peer learning opportunities. Promote the exchange of AI integration best practices, insights and experiences. Prepare for probable obstacles that may arise during the integration of AI and create backup strategies. This could entail fixing technical issues, offering more faculty assistance or modifying plans of action in response to changing conditions. Put strong cyber security measures in place to protect against such dangers. In AI applications, maintaining system security and data integrity is essential.

Demonstrate effective AI applications at the university. Honour the accomplishments of the faculty, the creative methods of instruction and the gains in student performance brought about by the incorporation of AI. Talk about your accomplishments with the larger educational community. Engage in publications, conferences and cooperative networks to increase awareness of the university's artificial intelligence programmes.

Investigate working together with AI-focused research universities and partners in the industry. Collaborate on projects together, pool resources and take advantage of outside knowledge to improve AI applications in education. Academics at a university that is falling behind can incorporate AI into their teaching and learning processes, resulting in better educational outcomes, increased innovation and increased inclusivity across the academic community by adopting these concepts and

taking calculated action. It necessitates a deliberate, cooperative and flexible strategy that takes into account the particular opportunities and problems present by the university.

## **14. Recommendation**

1. A certain amount of AI technology must be used in teaching and learning to preserve human cognition.
2. Training should be provided to educators and students before implementing AI technology.
3. The other issues with AI in education that need to be investigated can be researched.
4. Comparable research in different parts of the nation is possible.

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# Teachers in the Age of Artificial Intelligence: Preparation and Response to Challenges

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Stefanía Johanna Cedeño-Tapia, Luis Alberto Computaro  
and Christian Oscar Orlando Aparicio-Escalante*

## Abstract

In the field of higher education, artificial intelligence (AI) stands as a transformative axis, presenting challenges and opportunities for both teachers and students. This chapter profiles the innovative teacher, whose responsibilities expand toward guaranteeing quality education that is adaptive to current technological demands. Students' digital competence is critically examined, identifying the gap that exists when entering higher education and focusing on the ethical and practical challenges inherent in the use of AI. The importance of continuous teacher training and strategies that promote active involvement in AI is emphasized, to cultivate a deep understanding and effective application of these technologies in the educational process. It is recognized that AI can provide personalized and self-regulated learning, but it does not replace the essence of human mentoring, essential for its capacity for empathy and creativity.

**Keywords:** automated learning, educational innovation, twenty-first century skills, teacher professional development, technological integration

## 1. Introduction

The question of the ability of machines to think was first raised in 1950 by Alan Turing [1]. Based on this, the theoretical foundations were established to develop a technology that was capable of imitating human thinking. With this background, the term Artificial Intelligence (AI) was first raised at the Dartmouth Founding Conference in 1956 by John McCarthy [2]. AI is a technology that is made up of algorithms that run continuously to predict and complete complex tasks in seconds. This sequencing algorithm takes back information learned through the machine learning (ML) process [3]. Machine learning is defined as “a subfield of artificial intelligence that includes software capable of recognizing patterns, making predictions, and applying the newly discovered patterns to situations that were not included or covered by its initial design” [4]. In education, main elements of AI are machine learning, educational data mining, and learning analytics [5]. UNESCO defines

Artificial Intelligence as “systems capable of processing data and information in a way that resembles intelligent behavior, and generally encompasses aspects of reasoning, learning, perception, prediction, planning or control” [6].

The focus on AI as an element of interest for society accelerated in 2023 with the emergence of an update to the ChatGPT application from the company OpenAi [7–9]. This application made it possible to integrate with other applications and digital technologies, which led to greater accessibility to AI for the population. Several economic and social sectors have begun their adapt to the use of this advanced digital technology as a basic and daily element of the activities demanded by their sector [10].

The educational field has not been the exception in the adoption of AI, since it provides the facilities for personalized training and self-regulated learning. A study from the United States of America reported that 38% of students use some AI at least once a month [11]. A global survey identified that 50% of university students, globally, have used AI to study and typically enter one or two questions a day [12]. As for teachers, other surveys identified the importance of training them on AI topics. The most notable results show that 65% should be trained to integrate it into their teaching methods, 70% think that teachers should teach students how to properly use AI and another important element is related to the ethical implications of the learning process, since 71% of people agree that teachers should receive training to identify the originality of educational tasks, such as essays, among other activities [13]. These results give indications that we are beginning a new educational era, that of Artificial Intelligence.

Due to the multiple challenges faced by the integration of AI in higher education, in this chapter, we want to reflect on the contributions of Artificial Intelligence in Education (AIED) and the challenges they pose for teachers. Additionally, we want to talk about the ethical dilemma that this technology presents in the educational field.

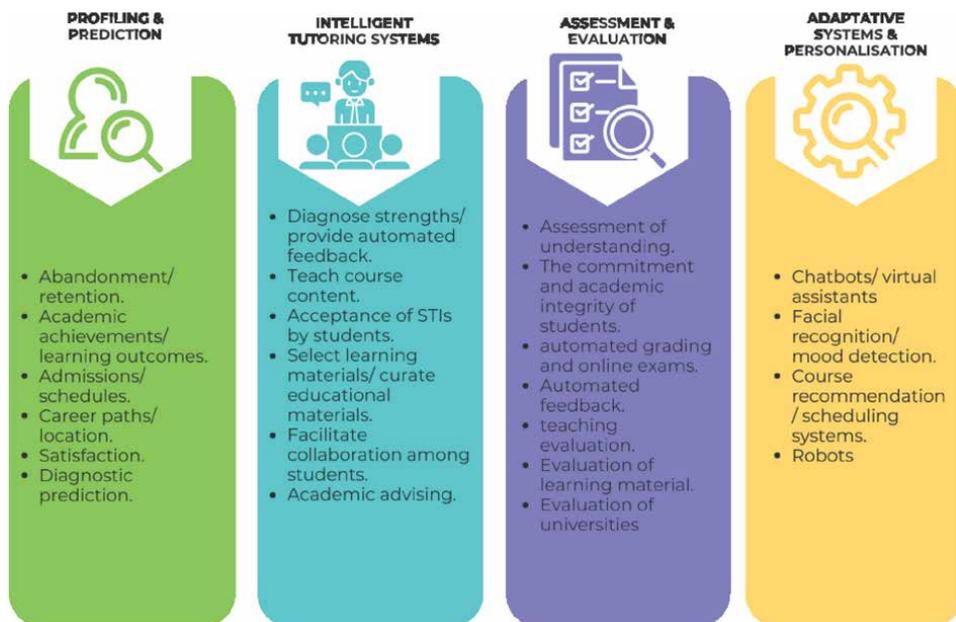
## **2. Artificial Intelligence in education**

Although we are facing a new era, interest in integrating Artificial Intelligence for educational uses has developed since the end of the last century. In 1993, to help with the advancement of knowledge and the promotion of research in the field of Artificial Intelligence in education, The International Society of Artificial Intelligence in Education (IAIED) [14] was created, which in turn time publishes a magazine related to the subject [15].

A meta-systematic review identified six main benefits of the integration of AIED: personalise learning; greater insight into student understanding; positive influence on learning outcomes; reduced planning and administration time for teachers; greater equity in education and precise assessment & feedback [16].

Likewise, four AIED typologies have been identified: profiling and prediction, intelligent tutoring systems (ITS), assessment and evaluation, and adaptive systems and personalization [15]. In turn, these have given guidance on the classification of the application of AI in education (**Figure 1**) [16].

*Profiling and prediction* in the use of data collected by AI to provide information that helps in forecasting the possible academic trajectory of students. Likewise, it provides a diagnosis that will guide the decision-making of the senior teacher to design effective teaching strategies that improve academic performance. It provides the administrative body of the universities with the elements to identify the student retention route and avoid abandonment. Another of its virtues is that it offers a vision of the areas where the student will need support [15, 16].



**Figure 1.**  
*AEd applications. Source: Based on Bond et al. 2014 [16].*

*Intelligent tutoring systems* (ITS) help students with self-regulated and personalized learning, giving them tools that allow them to enrich their learning experiences. ITS provide them with immediate, automated feedback. Among the benefits of these systems is that they help recommend teaching materials that fit the needs of the student. In addition, it makes it easier for them to collaborate with their peers. They provide teachers with the information necessary to diagnose students' learning needs and strengths [15].

*Assessment and evaluation* help educational institutions evaluate students, their understanding of content, and acquisition of skills and provides automated qualifications and online exams, among others. It also allows evaluating the quality of teaching and evaluates teachers and the effectiveness of the learning methodologies used [15, 16].

*Adaptive systems and personalization* contribute to personalized student learning. They guide them on different learning routes that fit their needs. They contribute to self-regulated learning and facilitate a deeper understanding of the knowledge they wish to acquire. They help teachers improve their teaching process through recommendations for the design of a pedagogical route, and they also help them monitor students [15, 16].

For example, chatbots can provide study guides tailored to learning needs and personalized educational resources [17]. Research showed that ChatGPT support for students who had self-regulated learning experiences performed well in activities related to the planning and facilitation of educational materials; however, it was not shown to be sufficiently appropriate for an evaluation that provides effective feedback [9].

The literature on the subject shows that human tutoring is more effective than that assisted by AI since it offers human qualities such as emotional support, intuition, compassion, empathy, and creativity [18, 19]. This makes it easier for students to obtain highly informative feedback that allows them to improve and acquire the

expected learning results [20], which, when effective, helps improve motivation, self-regulation, self-efficacy, and metacognition [21]. Some studies have identified that students positively value the soft or socio-emotional skills of their teachers. These emotions provide elements in favor of not replacing the university professor with AI [22].

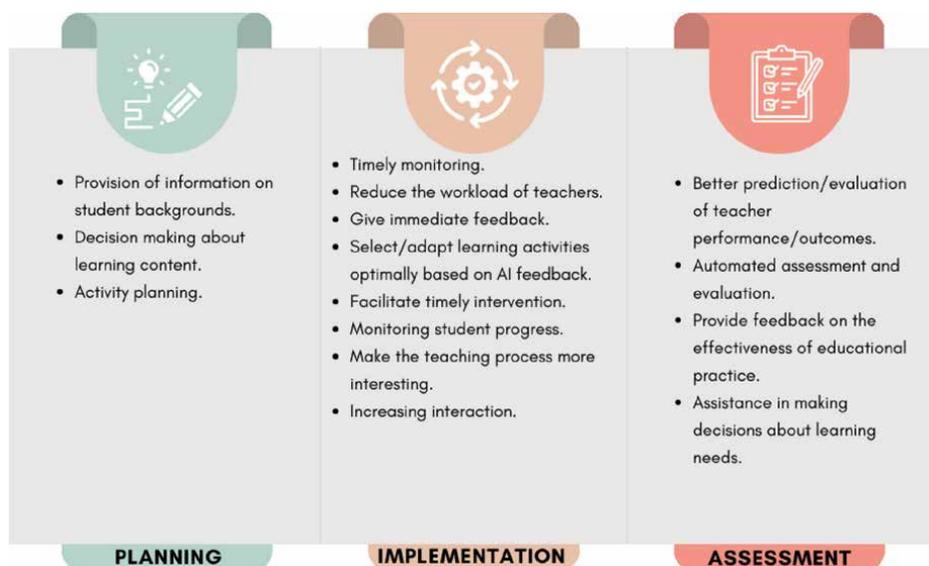
### 3. Challenges in the application of AI in higher education

Despite the imminent impact of AI on teaching and learning in higher education, a UNESCO survey revealed that less than 10% of universities have formal guidance on the use of AI [23]. This shows that, although AI offers great opportunities to enhance learning, its integration into the educational system is still beginning. This represents various challenges for pedagogical agents such as teachers.

A systematic review identified the advantages that AI can bring to teachers in the educational field. To do this, it takes up three moments of the pedagogical act: Planning, Implementation, and Evaluation (**Figure 2**) [24].

However, these advantages it offers also come with challenges. In this section, we highlight the limitations in teachers' preparation to integrate AI into teaching in ways that foster meaningful and situated learning for their students. Teachers are the main educational actors for improving educational quality [25]. For this reason, the training and preparation of university teachers in IAEd requires proposals that provide solid foundations on how to integrate it into the pedagogical act. In the literature, we identified some AI training proposals that consist of three stages: understanding AI, using AI tools, and experiencing AI programs [26].

In the first stage, teachers are intended to understand concepts related to AI, such as, for example, automated learning and how it works. Once this theoretical knowledge is obtained, it is expected that they will be more receptive to applying it for educational purposes. This will help them increase their confidence and overcome the



**Figure 2.** AI advantages for university teaching. Source: Based on Celik et al. 2022 [24].

algorithm aversion effect, characterized by the loss of credibility in automated recommendation systems after making an error, and instead tolerating the same error when it is made by other people [27]. Overcoming this bias will make them understand that AI has limited capacity for some activities but still provides tools that can be leveraged to apply in teaching.

Furthermore, we consider that at this time, some myths related to educational technology must also be analyzed and overcome, such as pedagogical materialism, which defends that digital technologies are the only educational materials available on the Internet added to teaching [28].

The second stage is core; this seeks to encourage the teacher to explore and experiment with different AI tools to learn about their functions and usefulness for teaching. The importance of this stage is related to overcoming the three elements of the Technology Acceptance Model (TAM), which are perceived ease of use, perceived usefulness, and attitude toward use [29, 30].

A study identified that teachers' perception of risk [31] and feelings of anxiety [29] negatively influence the adoption of AI in education. That is why, at this stage, teachers are encouraged to develop a positive attitude about the use of AI through experimentation with different applications and tools; this will help them increase their confidence. Practice will help them reduce their anxiety and reduce the feeling of risk.

In the third stage, experimentation with different AI programs is interesting. These types of experiences will reaffirm knowledge about the uses and limitations of this technology in various tasks or activities. At this stage, it is considered necessary for teachers to return to the three elements of reflective practice: (1) collect data, (2) data analysis and evaluation, and (3) triangulation of information [32]. The integration of these three elements will help them with key moments of the pedagogical act, such as planning, implementing, and evaluating the educational task efficiently.

Data collection is important because it guides the teacher about what is happening in student learning, for example, learning styles, the impact of the strategies used, time use. For the second and third elements, teachers must have the basic knowledge to interpret AI-based learning analytics [27]; this skill will help them make more effective decisions for teaching.

#### **4. Ethical and practical challenges of AI in education**

To obtain data that feeds AI machine learning (ML), the applications must have confidential information from students and teachers, which represents an ethical dilemma for their use [15].

The lack of security and critical thinking about information shared through AI poses great risks for students, teachers, and educational institutions. Access to digital environments and advanced technologies does not guarantee that current and future students are competent in the use of technology [28, 33]. Despite being immersed in it since its birth, its effectiveness in safely using different technological tools has been questioned. It has been found that they are more likely to share personal and confidential information in different applications without investigating the possible consequences on their security and privacy [34].

These ethical dilemmas regarding the use of confidential and private data of students and teachers for educational purposes are not recent [35, 36]. For this reason, it is an issue that is on different political agendas to impose measures that guarantee the security and privacy of information [5]. For this reason, guidelines have emerged

that allow the implementation of a safe, fair, responsible, transparent AI, guaranteeing the privacy and data protection [37, 38]. In the educational field, this concern has been shared by organizations such as UNESCO, which demands the creation of robust policies to ensure that advances in AI do not compromise privacy or exacerbate existing inequalities [39].

Researchers and educators must work together to ensure the responsible use of AI. This includes the development of regulations and policies that oversee its use, in line with the laws of each country.

## **5. Teaching competencies to integrate AI**

Faced with the above, we ask ourselves: What are the key competencies that university teachers must develop in order to integrate AI efficiently into the teaching and learning process? Within the whole range of response possibilities, we consider digital teaching skills and socio-emotional skills to be fundamental. Digital teaching skills due to its relationship with the pedagogical use of digital technologies; and socio-emotional skills due to the need for humanization and management of emotions in the use of AI in education.

Teachers' digital competencies are the set of knowledge, skills, and abilities of teachers to provide solutions to the different challenges presented in their educational actions from an ethical, safe, and responsible point of view in synergy with the use of digital technologies and tools in the teaching and learning process.

It has been shown that one aspect that benefits teachers' self-efficacy is emotional intelligence. This is an individual's ability to understand and regulate their emotions [40, 41]. Accordingly, social-emotional skills are the "... a set of skills that allow us to manage our own feelings and emotions and those of others, with the intention of guiding thought and actions towards satisfactory performance, dealing in the best way with different emotional states as a way of motivation and meaning in life..." [41].

Considering that emotional intelligence and emotional skills are fundamental for teaching efficiency, there is a need to put them into practice in educational settings. This is why the need arises for the development of socio-emotional competencies, considered "Emotional awareness"; acquiring the ability to use and regulate them in different social contexts and educational environments [42].

Due to the predominance of digital technologies in education, the construct of digital emotional competence emerged, which is a fusion of digital competencies with emotional intelligence [43, 44].

Therefore, any educational activity in which AI is used must have a strong human component that supports the regulation and management of the emotions of the educational actors involved.

In addition, it is considered pertinent for higher education institutions to manage the incorporation of the aforementioned competencies for teacher education and training activities.

## **6. Conclusion**

Exposure to technology does not guarantee the development of digital competencies; oftentimes, we possess intelligent technological resources, and their full potential is not exploited. It is necessary to take a critical and comprehensive position

on these new generations, based on designing educational proposals that promote and evaluate the development of these skills.

Promoting critical thinking is crucial in a landscape where technology infiltrates all aspects of teaching. AI, although it is a powerful tool, must be the subject of detailed analysis for its effective incorporation into the educational environment. Educators must cultivate this quality, encouraging students to critically analyze and question both the information and the technological solutions they encounter.

For these methods to be effective, educators must be willing to acquire new competencies and keep up to date with technological and pedagogical developments. This includes participating in professional development programs and collaborating interdisciplinary to integrate AI into the classroom to enrich the learning experience. The creation of communities of practice and professional support networks will be essential for the exchange of ideas and strategies that facilitate the effective adoption of AI in teaching.

Understanding teacher professional development as a dynamic and adaptable process, rather than as a static requirement, is vital. By prioritizing continuous training, teachers can be prepared to lead the era of AI in education.

## **7. Key questions and reflection**

Given the above, we ask ourselves: What are the key competencies that university teachers must develop to integrate AI efficiently into the teaching and learning process?

## **Conflict of interests**

The authors declare that they have no conflicts of interest.

## **Notes/thanks/other declarations**

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## **Appendices and nomenclature**

|      |                                      |
|------|--------------------------------------|
| AI   | Artificial Intelligence              |
| AIEd | Artificial Intelligence in Education |

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# The Influence of Affect in Help-Seeking Behaviors and Performance in a Math Intelligent Tutoring System

*Ana Paula S. Loures-Elias and Matthew L. Bernacki*

## Abstract

This study investigates the association between help-seeking behaviors (hints, hints per step, hints with steps requests, and hint to error), affect (boredom, confusion, frustration, happiness, and engagement), and performance in seventh and eighth-grade students using the Cognitive Tutor Bridge to Algebra as a self-regulated learning environment. Analyses focused on correlations between students' help-seeking behaviors and their affect in units 4 and 14. Affect was also used to predict help-seeking behaviors in the next units (e.g., 5 and 15). Moreover, we examined how associations between help-seeking behaviors and performance differed as a function of affect. The results showed that a pattern emerged in which students showed more executive help-seeking behaviors rather than instrumental ones. Students feeling bored, confused, and frustrated tended to use more hints, and they were less likely to switch to external help-seeking sources. Also, those feeling happy or engaged were less likely to use hints.

**Keywords:** help-seeking, affect, academic emotions, math intelligent tutoring system, performance

## 1. Introduction

Help-seeking is a self-regulatory strategy in self-regulated learning (SRL) in which learners use help-seeking to sustain cognition, behavior, affect, and motivational factors in order to achieve goals in a domain-specific activity [1, 2]. According to Aleven [1], help-seeking is defined “[...] as episodes in which a learner, in the context of a specific learning activity [...] takes the initiative to seek assistance from a source within or outside of the learning environment, as opposed to persisting at trying to make progress independently” (p. 312). Help-seeking can be an instrumental (adaptive) strategy, in which learners seek to learn with understanding, or executive (maladaptive), when learners seek prompted answers without developing understanding [1, 3].

Previous research shows that help-seeking has been studied within the math domain [4–11]. Du and colleagues [12] showed that help-seeking was positively

associated with math homework interest at the individual and class levels in eighth graders. The role of peers is a significant predictor of help-seeking in middle and high school students [11, 13–16]. Perfectionism and feedback were also positively related to help-seeking behaviors [4, 10, 17, 18]. Adaptative help-seeking behaviors significantly predicted mastery-approach goals in middle and high school students [13, 19]. In addition, perceived parent achievement goals predicted students' help-seeking and help-avoidance behaviors in middle school students' achievement goals [6]. Regarding gender, female students are more likely to demonstrate adaptative help-seeking behaviors, whereas boys are more likely to exhibit executive help-seeking behaviors [8, 15, 18, 20].

Help is a typical feature in intelligent tutoring systems (ITSs), and it is usually provided at students' request through the form of hints, internal help-seeking sources, or switches, and external help-seeking sources such as glossaries or hyperlinks. Previous research showed that high school students in a math help forum adopted executive help-seeking behaviors [9]. Best and colleagues [21] demonstrated that social support was increased and stigma was reduced by adolescent males seeking help online. Roll and colleagues [7] showed that high school students asking for help in online Geometry Cognitive Tutor had more productive learning, whereas those who over-used it had poor learning. Contrary to previous research, avoiding help was associated with better learning. Otieno and colleagues [5] showed that hints and glossaries in the Cognitive Tutor Geometry differed from the answers in the questionnaire they gave to high school students, yet with a high prediction of learning. Roll and colleagues [4] showed that high school students were able to transfer their learning from a Geometry Cognitive Tutor to a new domain-level content.

The decision to seek help is influenced by metacognitive, affective, and social competencies. Affect can be understood “[...] as a generic term that includes emotions, mood, feelings, attitudes, etc.” (p. 65) [22]. Students are likely to experience boredom, confusion, frustration, happiness, and engagement in intelligent learning environments (ILE) because they are affectively charged experiences [23]. Previous research shows that affect has been studied within the math domain. Positive academic emotions such as engagement, enjoyment, joy, contentment, and hope have been associated with adaptative behavior and lower math difficulties. However, negative academic emotions such as anxiety, confusion, frustration, shame, and hopelessness have been associated with executive behaviors and higher math difficulties [24–30]. Academic emotions and learning motivation were also studied in which students were more motivated when they exhibited positive academic emotions such as hope, pride, and enjoyment [31–33]. In addition, students exhibiting higher enjoyment and lower boredom had higher subsequent achievement, but pride was negatively correlated with achievement [29, 34].

Affect influences learning outcomes in face-to-face and mediated learning environments. Previous research has studied the effect of ITS on affect [33, 35–43]. In addition, an ITS provided transition from negative to positive affective states in high school students, and it improved their frustration and confidence by using online learning companions [24]. San Pedro and colleagues [25] showed that high school students who felt more engaged made more careless mistakes and those who felt confused or bored made fewer careless mistakes. Pre-school children demonstrated engagement and valence behaviors to nonverbal behaviors from the social robot tutor [44]. Padrón-Rivera and colleagues [28] showed in a math action units study that high school students experiencing confusion had better learning than those experiencing frustration.

However, to the best of our knowledge, no research was found about the influence of affect in students' help-seeking behaviors in math ITSs until the present date. Thus, more research is needed on how students' affect and motivation may influence learners' decisions to seek or not to seek help in ITSs [45]. According to D'Mello [23], there is still the need to understand "[...] how affective states arise, morph, decay, and impact learning outcomes [...]" (p. 2).

The purpose of this study was to examine affect and its implications for help-seeking as an SRL process. According to D'Mello [23], "Affective impacts of technologically infused learning environments are not very well understood" (p. 2). In addition, Karabenick and Gonida [3] acknowledged the need for additional research to better understand help-seeking as an SRL process. We aimed to investigate how students' academic emotions correlated with help-seeking within one task and if affect was a significant predictor of help-seeking on a subsequent task. Thereafter, we examined the effects of help-seeking on performance and the ways affect moderates this relationship. We attempted to answer the following research questions: (1) does students' affect after learning correlate with their help-seeking behavior within a unit of math problem-solving? (2) Is students' affect reported in one unit significant predictor of help-seeking in the next? (3) How do students' help-seeking behaviors and affect relate to their performance in a consecutive unit of math problem-solving tasks? We also hypothesized that, first, students presenting academic emotions such as happiness and engagement are less likely to switch to external help-seeking sources and make errors, and they are more likely to use hints as an internal help-seeking source and respond correctly to the questions. Secondly, students presenting academic emotions such as boredom, confusion, and frustration are less likely to use hints and respond correctly to the questions, and they are more likely to switch to external help-seeking sources and make errors.

## **2. Method**

### **2.1 Participants**

One hundred and ten students from math courses at a suburban, public middle school participated in the study. Students were 50% male and 50% female, and 96% were Caucasian. 71.8% reported low socioeconomic status (SES), and they were eligible for a free or reduced lunch from the school. Students were primarily enrolled in the seventh grade, but there were students from the eighth grade. Participation occurred in two math periods per week (45–50 minutes each) across the whole academic year as part of regular classroom activities through online questionnaires about math exercises, their academic emotions, and motivation using the Cognitive Tutor Bridge to Algebra [46].

### **2.2 Materials**

The Cognitive Tutor Bridge to Algebra [47] collected fine-grained traced data about students' help-seeking behaviors in pre-algebra exercises in 54 units being units 4, 5, 14, and 15 used for this study, and it presented online questionnaires with a Likert scale ranging from 1 to 5 for students to report their academic emotions starting with boredom, confusion, frustration, happiness, and engagement, respectively [2, 48]. The unit topics comprised "Lowest Common Multiple" in unit 4,

“Greatest Common Factor” in unit 5, “Converting Fractions to Decimals” in unit 14, and “Decimal Operations” in unit 15. Units 4, 5, 14, and 15 were chosen because they represented the most challenging ones for students in which the difficulty was operationalized by time per unit and time per problem.

### **2.3 Procedures**

This study focused on unit and problem level assessments employing a microgenetic and longitudinal approach. In the microgenetic approach, transactions were examined at unit and problem levels to understand the relationship between help-seeking, affect, and performance [2]. Researching at the transaction level allows to correlate help-seeking tools to affect and how the latter may predict the former in consecutive units. With longitudinal and microgenetic data, it is possible to determine if there is a correlation between help-seeking and academic emotions and how this correlation changes when it is investigated at unit and problem levels [2, 48].

In order to investigate the unit and problem level assessments, the Cognitive Tutor Bridge to Algebra uses the model of desired help-seeking behavior developed by Aleven and colleagues [49]. Briefly, students should start by thinking about the problem. If the problem is familiar and they know what to do, students make an attempt. If the problem is familiar but they do not know what to do, students switch to use the glossary to learn more about the problem. If they know what to do after consulting the glossary, students make an attempt. If not, they may either use the glossary again or ask for a hint. If the problem is not familiar, students ask for a hint, spend time reading it, and decide if the hint is helpful. If yes, they make an attempt. If not, students ask for another hint. If students make a correct attempt, the problem is complete. If not, students may require another hint and/or make a new attempt. In this study, hints reflect the total number of hints requested in raw terms. Hints per step normalize these requests to the amount of problem steps students had to complete. Steps with hints normalize the hint requests to account for steps in which students ask for one or more hints. Hint to error ratio reflects the proportion of times students opted to use a hint, rather than to make an attempt at a step that ultimately yielded an incorrect answer. Switch reflects the total number of glossary requests in raw terms [45, 49].

### **3. Results**

Analyses focused on correlations between students’ help-seeking behaviors and their affect in units 4 and 14. Affect was also used to predict help-seeking behaviors in the next units (e.g., 5 and 15). Moreover, we examined how associations between help-seeking behaviors and performance differed as a function of affect. The alpha level was set at .05 for simple correlations and multiple regressions.

Missing data were observed on 28 of the 34 variables examined. In unit 4, 20.9% of the data were missing on the boredom variable, 20% of data were missing on confusion, 19.1% of data were missing on frustration, happiness, engagement, hints, hints per step, steps with hint requests, and hint to error. In unit 5, 19.1% of data were missing on performance, hints, hints per step, steps with hint requests, and hint to error. In unit 14, 18.2% of data were missing on boredom, confusion, and frustration, 20% of data were missing on happiness and engagement, 12.7% of data were missing on hints, hints per step, steps with hint requests, and hint to error. In unit 15, 11.8% of data were missing on performance, hints, hints per step, steps with hint requests, and hint to error.

Rubin [50] proposed a taxonomy of missing data mechanisms to explain why the choice of missing data method impacts model parameters. The missing data were found to be consistent with a missing completely at random (MCAR) mechanism as determined by Little's [51] omnibus MCAR test,  $d2(199) = 213.907$ ,  $p = .223$ . Therefore, listwise deletion ( $N = 97$ ) was used to handle missingness for the present research problems because it is in accordance with the MCAR mechanism and it does not bias the parameter estimates generated by the correlations and multiple regression analyses. **Table 1** shows the descriptive statistics for affect, help-seeking behaviors, and performance in units 4, 5, 14, and 15. Happiness and engagement had the highest coefficients in units 4 and 14. Hints also had the highest coefficients with the exception of unit 5 in which switch exceeded hints. This may be due to the highest level of difficulty of the unit. Moreover, it demonstrated that students favored the usage of hints as an adaptative help-seeking behavior.

**Table 2** answers the first research question if students' affect after learning correlates with their help-seeking behavior within a unit of math problem-solving. It shows correlations between affect components and help-seeking behaviors in units 4 and 14. In contrast to hypotheses one and two and the assumptions by Karabenick [52], a positive moderate correlation of .213 between hints and boredom was found in unit 4. Students feeling boredom were more likely to use hints in unit 4 as an instrumental help-seeking behavior. However, this correlation was nonsignificant in unit 14. Negative moderate correlations of  $-.218$  and  $-.209$  between happiness and hints per step and between happiness and steps with hints requests, respectively, were found in unit 14. They are also in contrast with hypotheses one and two. Students feeling happy were less likely to use hints per step and steps with hints requested in unit 14. It might indicate an executive type of help-seeking behavior. No other correlations were significant in units 4 and 14.

|                            | Unit 4 |        | Unit 5 |        | Unit 14 |       | Unit 15 |        |
|----------------------------|--------|--------|--------|--------|---------|-------|---------|--------|
|                            | M      | SD     | M      | SD     | M       | SD    | M       | SD     |
| Affect                     |        |        |        |        |         |       |         |        |
| Boredom                    | 4.70   | 1.84   | —      | —      | 4.94    | 1.76  | —       | —      |
| Confusion                  | 4.08   | 1.97   | —      | —      | 4.80    | 1.97  | —       | —      |
| Frustration                | 3.81   | 2.19   | —      | —      | 4.54    | 2.01  | —       | —      |
| Happiness                  | 5.83   | 1.19   | —      | —      | 5.84    | 1.25  | —       | —      |
| Engagement                 | 5.43   | 1.48   | —      | —      | 5.45    | 1.47  | —       | —      |
| help-seeking behaviors     |        |        |        |        |         |       |         |        |
| Switch                     | 0.54   | 1.94   | 19.25  | 14.35  | 3.72    | 5.69  | 0.88    | 1.96   |
| Hints                      | 6.34   | 11.45  | 6.34   | 11.45  | 39.12   | 77.94 | 11.03   | 13.02  |
| Hints per step             | 0.22   | 0.04   | 0.22   | 0.04   | 0.13    | 0.14  | 0.03    | 0.03   |
| Steps with hints requested | 274.82 | 115.77 | 274.82 | 115.77 | 227.8   | 110.8 | 332.62  | 113.11 |
| Hint to error              | 0.18   | 0.24   | 0.18   | 0.24   | 0.77    | 0.77  | 0.26    | 0.23   |
| Performance                |        |        | 0.94   | 0.03   |         |       | 0.93    | 0.03   |

*Note.* Listwise  $N = 110$ .

**Table 1.**  
 Descriptive statistics for help-seeking behaviors and affect in units.

| Variable    | Switch | Hints             | Hints per step     | Steps with hints requested | Hint to error |
|-------------|--------|-------------------|--------------------|----------------------------|---------------|
| Unit 4      |        |                   |                    |                            |               |
| Boredom     | 0.097  | .213 <sup>*</sup> | 0.189              | 0.143                      | 0.094         |
| Confusion   | 0.034  | 0.186             | 0.164              | 0.102                      | 0.017         |
| Frustration | 0.107  | 0.065             | 0.109              | 0.021                      | -0.051        |
| Happiness   | -0.182 | -0.064            | -0.089             | 0.012                      | -0.038        |
| Engagement  | -0.110 | -0.022            | -0.008             | -0.039                     | -0.029        |
| Unit 14     |        |                   |                    |                            |               |
| Boredom     | -0.062 | -0.025            | -0.001             | -0.031                     | -0.046        |
| Confusion   | -0.044 | -0.043            | 0.000              | 0.027                      | -0.042        |
| Frustration | -0.001 | 0.033             | 0.072              | 0.09                       | 0.053         |
| Happiness   | -0.146 | -0.197            | -.218 <sup>*</sup> | -.209 <sup>*</sup>         | -0.186        |
| Engagement  | -0.039 | -0.108            | -0.137             | -0.09                      | -0.128        |

*Note.* Listwise  $N = 87$ .  $p = 0.05$ .

**Table 2.**  
Correlations between affect components and help-seeking behaviors in units.

Multiple linear regression analyses with ordinary least squares estimations were conducted to answer the second research question. It was investigated if students' affect (boredom, confusion, frustration, happiness, and engagement) reported in units 4 and 14 were significant predictors of help-seeking behaviors (hints, hints per step, steps with hints requested, hint to error ratio, and switch) in the next units 5 and 15, respectively (Table 3).

The first significant regression equation was found when predicting hints in unit 5 from affect components in unit 4 ( $F(5, 80) = 2.768, p = .023, r^2 = .148$ ). Boredom reported in unit 4 was a statistically significant predictor of the total number of hints requested in unit 5 ( $b = 3.344, SE = 1.139, p = .004, 95\% CI = 1.077, 5.610; \beta = .406$ ), such that, for each unit increase in boredom, total hint requests were predicted to increase by 3.344. Frustration reported in unit 4 was also found to be a statistically significant predictor of hints in unit 5 ( $b = -2.134, SE = 1.050, p = .045, 95\% CI = -4.224, -.044; \beta = -.304$ ). For each unit increase in frustration, students were predicted to request 2.134 fewer hints. Predicting hints per step in unit 5 from boredom in unit 4 yielded another significant regression equation ( $F(1,85) = 5.101, p = .026, r^2 = .057$ ). Boredom reported in unit 4 was a statistically significant predictor of hints per step in unit 5 ( $b = .002, SE = .001, p = .026, 95\% CI = .000, .005; \beta = .238$ ), such that, for each unit increase in boredom, hints per step were predicted to increase by .002 points. Models regressing steps with hints, hint to error ratio, and switch on reported affect components were not statistically significant,  $F(5,80) = 1.301, p = .272, r^2 = .075$ . Collectively, a pattern emerged where boredom increased tendency toward help-seeking, while frustration led to help avoidance. It demonstrates that frustration was the only significant predictor that corroborates with hypothesis two but not with hypothesis one, in which students feeling frustrated predicted to be less likely to use hints and respond correctly to questions in the subsequent unit. We next examined the stability of relations in units 14 and 15.

| Variable                          | F     | Df   | p     | R <sup>2</sup> | b       | SE     | β      | p     |
|-----------------------------------|-------|------|-------|----------------|---------|--------|--------|-------|
| Unit 5 from unit 4                |       |      |       |                |         |        |        |       |
| <i>Switch</i>                     | 1.301 | 5,80 | 0.272 | 0.075          |         |        |        |       |
| From boredom                      |       |      |       |                | 1.194   | 0.952  | 0.181  | 0.214 |
| From confusion                    |       |      |       |                | 1.425   | 0.970  | 0.228  | 0.146 |
| From frustration                  |       |      |       |                | -1.462  | 0.878  | -0.260 | 0.100 |
| From happiness                    |       |      |       |                | 0.318   | 1.238  | 0.031  | 0.798 |
| From engagement                   |       |      |       |                | -1.086  | 1.012  | -0.132 | 0.287 |
| <i>Hints</i>                      | 2.768 | 5,80 | 0.023 | 0.148          |         |        |        |       |
| From boredom                      |       |      |       |                | 3.344   | 1.139  | 0.406  | 0.004 |
| From confusion                    |       |      |       |                | 0.598   | 1.161  | 0.077  | 0.608 |
| From frustration                  |       |      |       |                | -2.134  | 1.050  | -0.304 | 0.045 |
| From happiness                    |       |      |       |                | 1.622   | 1.48   | 0.127  | 0.276 |
| From engagement                   |       |      |       |                | -2.253  | 1.211  | -0.22  | 0.067 |
| <i>Hints per step</i>             | 5.101 | 1,85 | 0.026 | 0.057          |         |        |        |       |
| From boredom                      |       |      |       |                | 0.002   | 0.001  | 0.238  | 0.026 |
| From confusion                    |       |      |       |                | -0.001  | 0.001  | -0.077 | 0.618 |
| From frustration                  |       |      |       |                | 0.000   | 0.001  | -0.053 | 0.730 |
| From happiness                    |       |      |       |                | 0.002   | 0.002  | 0.096  | 0.425 |
| From engagement                   |       |      |       |                | -0.002  | 0.002  | -0.174 | 0.157 |
| <i>Steps with hints requested</i> | 0.955 | 5,80 | 0.450 | 0.056          |         |        |        |       |
| From boredom                      |       |      |       |                | 11.984  | 24.336 | 0.072  | 0.624 |
| From confusion                    |       |      |       |                | 36.745  | 24.803 | 0.232  | 0.142 |
| From frustration                  |       |      |       |                | -40.521 | 22.436 | -0.285 | 0.075 |
| From happiness                    |       |      |       |                | -11.455 | 31.631 | -0.044 | 0.718 |
| From engagement                   |       |      |       |                | -14.937 | 25.879 | -0.072 | 0.565 |
| <i>Hints to error</i>             | 1.274 | 5,80 | 0.283 | 0.074          |         |        |        |       |
| From boredom                      |       |      |       |                | 0.039   | 0.019  | 0.300  | 0.041 |
| From confusion                    |       |      |       |                | -0.021  | 0.019  | -0.171 | 0.273 |
| From frustration                  |       |      |       |                | 0.006   | 0.017  | 0.052  | 0.738 |
| From happiness                    |       |      |       |                | 0.010   | 0.024  | 0.052  | 0.670 |
| From engagement                   |       |      |       |                | -0.024  | 0.020  | -0.150 | 0.227 |
| Unit 15 from unit 14              |       |      |       |                |         |        |        |       |
| <i>Switch</i>                     | 0.087 | 5,81 | 0.994 | 0.005          |         |        |        |       |
| From boredom                      |       |      |       |                | -0.016  | 0.205  | -0.013 | 0.937 |
| From confusion                    |       |      |       |                | -0.125  | 0.252  | -0.116 | 0.621 |
| From frustration                  |       |      |       |                | 0.103   | 0.239  | 0.095  | 0.667 |
| From happiness                    |       |      |       |                | 0.072   | 0.239  | 0.042  | 0.764 |
| From engagement                   |       |      |       |                | -0.032  | 0.206  | -0.022 | 0.877 |

| Variable                          | F     | Df   | p     | R <sup>2</sup> | b       | SE     | β      | p      |
|-----------------------------------|-------|------|-------|----------------|---------|--------|--------|--------|
| <i>Hints</i>                      | 2.639 | 5,81 | 0.029 | 0.140          |         |        |        |        |
| From boredom                      |       |      |       |                | -1.735  | 1.133  | -0.239 | 0.13   |
| From confusion                    |       |      |       |                | 0.135   | 1.392  | 0.021  | 0.23   |
| From frustration                  |       |      |       |                | 2.679   | 1.324  | 0.414  | 0.046* |
| From happiness                    |       |      |       |                | -1.326  | 1.321  | -0.13  | 0.319  |
| From engagement                   |       |      |       |                | -0.282  | 1.139  | -0.033 | 0.805  |
| <i>Hints per step</i>             | 3.018 | 5,81 | 0.015 | 0.157          |         |        |        |        |
| From boredom                      |       |      |       |                | -0.006  | 0.003  | -0.32  | 0.041* |
| From confusion                    |       |      |       |                | 0.001   | 0.003  | 0.078  | 0.720  |
| From frustration                  |       |      |       |                | 0.007   | 0.003  | 0.430  | 0.037* |
| From happiness                    |       |      |       |                | -0.002  | 0.003  | -0.098 | 0.447  |
| From engagement                   |       |      |       |                | -0.001  | 0.003  | -0.039 | 0.764  |
| <i>Steps with hints requested</i> | 0.855 | 5,81 | 0.515 | 0.05           |         |        |        |        |
| From boredom                      |       |      |       |                | -5.017  | 10.788 | -0.076 | 0.643  |
| From confusion                    |       |      |       |                | 3.996   | 13.255 | 0.069  | 0.764  |
| From frustration                  |       |      |       |                | 9.503   | 12.612 | 0.162  | 0.453  |
| From happiness                    |       |      |       |                | -11.066 | 12.581 | -0.12  | 0.382  |
| From engagement                   |       |      |       |                | 1.459   | 10.844 | 0.019  | 0.893  |
| <i>Hints to error</i>             | 4.483 | 5,81 | 0.001 | 0.217          |         |        |        |        |
| From boredom                      |       |      |       |                | -0.075  | 0.019  | -0.576 | <.001* |
| From confusion                    |       |      |       |                | 0.013   | 0.024  | 0.11   | 0.598  |
| From frustration                  |       |      |       |                | 0.059   | 0.023  | 0.506  | 0.011* |
| From happiness                    |       |      |       |                | -0.001  | 0.023  | -0.005 | 0.965  |
| From engagement                   |       |      |       |                | -0.004  | 0.02   | -0.026 | 0.836  |

\*p < or = .05.

**Table 3.** Multiple linear regression predicting help-seeking behaviors from affect.

When predicting hints in unit 15 from frustration in unit 14, a significant regression equation was found ( $F(5,81) = 2.639, p = .029, r^2 = .140$ ). Frustration reported in unit 14 was a statistically significant predictor of hints in unit 15 ( $b = 2.679, SE = 1.324, p = .046, 95\% CI = .044, 5.314; \beta = .414$ ), such that, for each unit increase in frustration, hints were predicted to increase by 2.679 points. Another significant regression equation was found ( $F(5,81) = 3.018, p = .015, r^2 = .157$ ) when predicting hints per step in unit 15 from affect components in unit 14. Boredom reported in unit 14 was a statistically significant predictor of hints per step in unit 15 ( $b = -.006, SE = .003, p = .041, 95\% CI = -.011, .000; \beta = -.320$ ). For each unit increase in boredom, hints per step were predicted to decrease by .006 points. Frustration reported in unit 14 was also found to be a statistically significant predictor of hints per step in unit 15 ( $b = .007, SE = .003, p = .037, 95\% CI = .000, .013; \beta = .430$ ), such that, for

each unit increase in frustration, hints per step were predicted to increase by .007 points. The final significant regression equation was found ( $F(5,81) = 4.483, p = .001, r^2 = .217$ ) when predicting hint to error in unit 15 from affect components in unit 14. Boredom reported in unit 14 was a statistically significant predictor of hint to error in unit 15 ( $b = -.075, SE = .019, p < .001, 95\% CI = -.114, -.037; \beta = -.576$ ), such that, for each unit increase in boredom, hint to error were predicted to decrease by .075 points. Frustration reported in unit 14 was also found to be a statistically significant predictor of hint to error in unit 15 ( $b = .059, SE = .023, p = .011, 95\% CI = .014, .104; \beta = .506$ ), such that, for each unit increase in frustration, students' use of hints rather than to make an attempt at a step that resulted in an error was predicted to increase by .059 points. The pattern that emerged was flipped in units 14 and 15 in which frustration increased the tendency toward help-seeking, while boredom led to help avoidance. Contradicting hypotheses one and two, students feeling frustrated were predicted to be more likely to use hints and respond correctly to questions in the subsequent unit. On the contrary and in accordance with hypothesis two, students feeling bored were slightly less likely to use hints and respond correctly to questions in the subsequent unit. Models regressing steps with hints and switch on reported affect components were not statistically significant ( $F(5,81) = .855, p = .515, r^2 = .05$ ). All models appear in **Table 3**.

We next examined the third research question on whether the association between help-seeking behaviors and academic performance differs as a function of the affect. Prior to conducting substantive analyses, help-seeking behaviors were centered, and the help-seeking behaviors-by-affect components product term was generated via multiplication of centered help-seeking behaviors with the affect components. The continuous predictors, as well as their product terms, were entered into simultaneous regression models. Significant and nonsignificant regression equations were found, but only significant ones are presented in **Table 4**. There were no significant associations between switch as a help-seeking behavior and academic performance differing as a function of affect. It suggests that the interaction between the switch and affect was not a significant predictor of performance in subsequent units.

Significant interaction effects were found in multiple units. In unit 4, a hint  $\times$  frustration interaction effect indicates that every unit increase in frustration led to a slight but statistically significant additional effect where hint use conducted while frustrated predicted an even poorer subsequent performance (e.g., as measured by the percent of first attempts at problem steps) over and above the negative effect of hint use as a help-seeking method. A hints per step  $\times$  frustration interaction effect indicates that every unit increase in frustration led to a slight but statistically significant additional effect, where hints per step predicted an increase of .064 units on subsequent performance after help-seeking.

In unit 14, a hints per step  $\times$  boredom interaction effect indicates that every unit increase in boredom led to a slight but statistically significant additional effect, where hints per step predicted an increase of .036 units on subsequent performance. A hints per step  $\times$  confusion interaction effect indicates that every unit increase in confusion led to a slight but statistically significant additional effect, where hints per step predicted an increase of .030 units on subsequent performance. A hints per step  $\times$  frustration interaction effect indicates that every unit increase in frustration led to a slight but statistically significant additional effect, where hints per step predicted an increase of .039 units on subsequent performance. A hint to error  $\times$  boredom interaction effect indicates that every unit increase in boredom led to a slight but statistically significant

| Variable                                  | b     | SE   | $\beta$ | t       | p     | F     | df     | p     | R <sup>2</sup> |
|---|-------|------|---------|---------|-------|-------|--------|-------|----------------|
| Unit 4 predicting performance in unit 5   |       |      |         |         |       |       |        |       |                |
| Constant                                  | .946  | .006 | –       | 170.610 | <.001 | 3.862 | (3,84) | .012  | 121            |
| Hints                                     | –.001 | .000 | –.560   | –2.783  | .007  |       |        |       |                |
| Frustration                               | –.002 | .001 | –.181   | –1.766  | .081  |       |        |       |                |
| <i>Hints × frustration</i>                | .000  | .000 | .420    | 2.086   | .040  |       |        |       |                |
| Constant                                  | .945  | .006 | –       | 167.640 | <.001 | 2.969 | (3,84) | .036  | 096            |
| Hints per step                            | –.403 | .172 | –.553   | –2.349  | .021  |       |        |       |                |
| Frustration                               | –.002 | .001 | –.178   | –1.709  | .091  |       |        |       |                |
| <i>Hints per step<br/>X frustration</i>   | .064  | .031 | .484    | 2.056   | .043  |       |        |       |                |
| Unit 14 predicting performance in unit 15 |       |      |         |         |       |       |        |       |                |
| Constant                                  | .947  | .009 | –       | 109.715 | <.001 | 5.652 | (3,86) | .001  | 165            |
| Hints per step                            | –.225 | .073 | –1.076  | –3.080  | .003  |       |        |       |                |
| Confusion                                 | –.003 | .002 | –.156   | –1.549  | .125  |       |        |       |                |
| <i>Hints per step<br/>X boredom</i>       | .036  | .014 | .869    | 2.485   | .015  |       |        |       |                |
| Constant                                  | .945  | .008 | –       | 124.354 | <.001 | 5.961 | (3,86) | .001  | 172            |
| Hints per step                            | –.186 | .055 | –.887   | –3.380  | .001  |       |        |       |                |
| Confusion                                 | –.002 | .001 | –.150   | –1.489  | .140  |       |        |       |                |
| <i>Hints per step<br/>X confusion</i>     | .030  | .011 | .693    | 2.633   | .010  |       |        |       |                |
| Constant                                  | .946  | .007 | –       | 136.648 | <.001 | 7.732 | (3,86) | <.001 | 212            |
| Hints per step                            | –.223 | .059 | –1.073  | –3.772  | <.001 |       |        |       |                |
| Frustration                               | –.003 | .001 | –.181   | –1.838  | .070  |       |        |       |                |
| <i>Hints per step<br/>X frustration</i>   | .039  | .012 | .906    | 3.189   | .002  |       |        |       |                |
| Constant                                  | .950  | .009 | –       | 110.651 | <.001 | 5.242 | (3,86) | .002  | 155            |
| Hints to error                            | –.041 | .016 | –1.113  | –2.569  | .012  |       |        |       |                |
| Boredom                                   | –.003 | .002 | –.189   | –1.882  | .030  |       |        |       |                |
| <i>Hints to error<br/>X boredom</i>       | .007  | .004 | .875    | 2.016   | .047  |       |        |       |                |
| Constant                                  | .946  | .007 | –       | 135.838 | <.001 | 7.213 | (3,86) | <.001 | 201            |
| Hints to error                            | –.046 | .014 | –1.270  | –3.385  | .001  |       |        |       |                |
| Frustration                               | –.003 | .001 | –.192   | –1.933  | .056  |       |        |       |                |
| <i>Hints to error<br/>X frustration</i>   | .009  | .003 | 1.074   | 2.866   | .005  |       |        |       |                |

**Table 4.** Interaction effect between help-seeking behaviors and affect in subsequent performance unit.

additional effect, where greater use of hints compared to making errors predicted an increase of .007 units on subsequent performance. A hint to error × frustration interaction effect indicates that every unit increase in frustration led to a slight but statistically significant additional effect, where hint to error predicted an increase of .009 units on

| Variable         | Unit 4 | Unit 5 | Unit 14 | Unit 15 | Total |
|------------------|--------|--------|---------|---------|-------|
| Switch users     | 17     | 88     | 52      | 28      | 185   |
| Non-switch users | 93     | 22     | 58      | 82      | 255   |

**Table 5.**  
*Use of switch as a help-seeking behavior in units 4, 5, 14, and 15.*

subsequent performance. These patterns contradicted hypotheses one and two in which students feeling bored, confused, and frustrated combined with the usage of hints predicted additional performance in subsequent units.

Subsequently, we examined how many students used switch as a help-seeking behavior in units 4, 5, 14, and 15. **Table 5** shows that students used more switch in unit 4. However, there were more students who overall preferred not to use switch across the four units analyzed in this study. It corroborates with descriptive findings from **Table 1** in which hints had the highest coefficients yielding students' preference.

Eventually, a series of independent t-tests were conducted in order to compare affect components including boredom, confusion, frustration, happiness, and engagement between students who used switch and those who did not use it as a help-seeking behavior. There were no systematic differences between cases with switch users and nonswitch users, according to **Table 6**. The group of students using switch did not have a significantly higher number of affect scores than the group of nonswitch users. These results suggest that switch does not have an effect on affect components such as boredom, confusion, frustration, happiness, and engagement. It contradicts both hypotheses stated in this article. Students presenting academic emotions such as happiness and engagement are less likely to switch to external help-seeking sources, whereas students presenting academic emotions such as boredom, confusion, and frustration are more likely to switch to external help-seeking sources.

| Variables        | N  | M    | SD    | t                | p    |
|------------------|----|------|-------|------------------|------|
| Unit 4           |    |      |       |                  |      |
| Boredom          |    |      |       | $t(85) = -1.192$ | .236 |
| Switch users     | 17 | 5.18 | 2.128 |                  |      |
| Non-switch users | 70 | 4.59 | 1.757 |                  |      |
| Confusion        |    |      |       | $t(87) = -.637$  | .526 |
| Switch users     | 17 | 4.35 | 2.290 |                  |      |
| Non-switch users | 72 | 4.01 | 1.895 |                  |      |
| Frustration      |    |      |       | $t(86) = -.773$  | .442 |
| Switch users     | 17 | 4.18 | 2.128 |                  |      |
| Non-switch users | 71 | 3.72 | 2.212 |                  |      |
| Happiness        |    |      |       | $t(87) = .256$   | .799 |
| Switch users     | 17 | 5.76 | 1.147 |                  |      |
| Non-switch users | 72 | 5.85 | 1.206 |                  |      |

| Variables        | N  | M    | SD    | t               | p    |
|------------------|----|------|-------|-----------------|------|
| Engagement       |    |      |       | $t(87) = -.134$ | .894 |
| Switch users     | 17 | 5.47 | 1.663 |                 |      |
| Non-switch users | 72 | 5.42 | 1.451 |                 |      |
| Unit 14          |    |      |       |                 |      |
| Boredom          |    |      |       | $t(88) = .046$  | .963 |
| Switch users     | 47 | 4.94 | 1.686 |                 |      |
| Non-switch users | 43 | 4.95 | 1.851 |                 |      |
| Confusion        |    |      |       | $t(88) = .384$  | .702 |
| Switch users     | 47 | 4.72 | 1.942 |                 |      |
| Non-switch users | 43 | 4.88 | 2.014 |                 |      |
| Frustration      |    |      |       | $t(88) = .537$  | .593 |
| Switch users     | 48 | 4.44 | 1.945 |                 |      |
| Non-switch users | 42 | 4.67 | 2.103 |                 |      |
| Happiness        |    |      |       | $t(86) = .600$  | .550 |
| Switch users     | 47 | 5.77 | 1.255 |                 |      |
| Non-switch users | 41 | 5.93 | 1.253 |                 |      |
| Engagement       |    |      |       | $t(86) = .131$  | .896 |
| Switch users     | 46 | 5.43 | 1.241 |                 |      |
| Non-switch users | 42 | 5.48 | 1.700 |                 |      |

\* $p < or = .05$ .

*This statistically significant result means that no effect was observed.*

**Table 6.**

*T-tests comparing switch as a help-seeking behavior with affect in units 4 and 14.*

#### 4. Discussion

This study was a response to Karabenick and Gonida’s [3] call for additional research on help-seeking as a self-regulatory process, and it also examined the ways affect influenced their help-seeking intentions, behaviors, and performances within an ITS context. Students’ affect—boredom, confusion, frustration, happiness, and engagement—related to students’ concurrent problem-solving and help-seeking behaviors, predicted future help-seeking and moderated performance.

Students were more likely to use hints in unit 4 when they felt bored. This may indicate a trace of disengagement from the task and executive help-seeking behavior [52]. It contradicted hypothesis two that students feeling bored are less likely to use hints. On the other hand, students who reported they felt more positive were less likely to select multiple hints per step and rely on hints across more steps in unit 14. It does not corroborate with hypothesis one in which students feeling happy were thought to be more likely to use hints and respond correctly to the questions. According to Karabenick’s [52] description, this may instead be construed to reflect engagement in the task and trace executive help-seeking behaviors.

When predicting future help-seeking behaviors from students’ affect reported in previous units, results showed that students feeling bored in unit 4 were more likely to

use hints and hints per step in unit 5 contradicting hypothesis two. On the other hand, students feeling frustrated were less likely to use hints in the subsequent unit which corroborates with hypothesis two. In unit 14, this relationship flipped and those who felt frustrated were more likely to use hints (overall, per step, and compared to making errors) in unit 15. Those who felt bored were less likely to use hints in the subsequent unit also corroborating with hypothesis two. This may indicate executive help-seeking behaviors because students were trying to keep engaged in the task by seeking help through hints while feeling bored or frustrated which contradicted the prior hypothesis. There is a need for future research to investigate the reasons why this relationship flipped from one unit to the other. Researchers should investigate more units and more students across time which was one of the limitations of this study. We hypothesized that it may be due to the level of difficulty of the unit in which Decimal Operations in unit 14 may have led to a greater frustration than Greatest Common Factor in unit 4.

Aleven and colleagues [45] acknowledged the need to investigate whether help-seeking as an SRL component could lead to improved students' performance in later units on ITSs. Thus, we examined whether the association between help-seeking behaviors and academic performance differs as a function of affect. In unit 4, the usage of hints when students felt greater frustration predicted an even poorer subsequent performance in unit 5 than hint usage alone. This may indicate an instrumental help-seeking behavior in unit 4 which slightly undermined students' performance in unit 5 due to the effect of frustration. On the contrary, the interaction between hints per step and frustration led to a slight increase in unit 5 performance. This may indicate an executive help-seeking behavior in unit 4 which slightly increased students' performance in unit 5 due to the effect of frustration. In unit 14, the association between hints per step and affect (boredom, confusion, and frustration) and between hint to error and affect (boredom and confusion) led to a slight increase in students' performance in unit 15. These results contradicted hypotheses one and two in which students feeling happy or engaged should be more likely to use hints, but no significant interactions were found. Additionally, students feeling bored, confused, and frustrated were more likely to use hints, and it led to subsequent performance. This may also indicate an executive help-seeking behavior in which students are trying to keep engaged in the task perhaps without developing much understanding in the present unit so they can progress to the next one.

We also examined how many students used switch as a help-seeking behavior in units 4, 5, 14, and 15, and we investigated if switch had an effect on affect components such as boredom, confusion, frustration, happiness, and engagement. The results showed that students used more switch only in unit 4, Greatest Common Factor. It also demonstrated that switch did not yield a significant effect on affect components. We hypothesized that it may be because students may consult other sources even if they know the answer to reach full certainty. It could also be because they were not aware of how helpful this resource could be in an ITS. There is also the need to investigate switches, as an external help-seeking source, in relation to other internal help-seeking sources and affect components.

## **5. Conclusion**

These findings contribute to the growing body of SRL literature because it demonstrates new ways students are regulating their actions and seeking for help in ITSs in relation to affect. The results from the present article showed that a pattern emerged in which students showed more executive help-seeking behaviors rather than instrumental ones. Students feeling bored, confused, and frustrated tended to

use more hints, and they were less likely to switch to external help-seeking sources. Also, those feeling happy or engaged were less likely to use hints. It may be because students were feeling disengaged from the task or because of the level of difficulty of the task in the ITS. There is a need to research more units across time and investigate if these patterns hold.

Future research may assess students' affective states which could shed light on the affective conditions that lead students to use hints and to profit from hint use. These results suggest a complex relationship between affect and hint use where affect explains variance in the tendency to use hints, but the directions of affect sometimes contradict the prior theory [52].

Moreover, future research may also focus on students' help-seeking behaviors and affect in relation to their self-efficacy beliefs in ITSs. Efficacy beliefs influence peoples' thinking process, goals, effort, commitment, outcomes, resilience, and how much stress or depression they tend to feel when performing a task [53]. Students' usage of hints may be related to their sense of efficacy, and it may be a product of hint usage across the span of different units.

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## **Declaration of interest**

The authors declare no conflict of interest.

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# Using ChatGPT to Create Constructively Aligned Assessment Tasks and Criteria in the Context of Higher Education Teaching

*Niclas Schaper*

## Abstract

The chapter deals with the question, how ChatGPT can be used to support and facilitate the planning of competence-oriented written university examinations. Therefore, the possibilities and potentials of ChatGPT in the formulation of learning outcomes, the derivation of examination tasks from the outcomes and the formulation of assessment criteria are exemplarily demonstrated and analyzed. First, it is explained what ChatGPT actually is and which aspects should be considered when using it. Then didactic concepts and requirements for designing higher education examinations (especially the constructive alignment concept) are presented, which ChatGPT can support. The focus is on the competence-oriented design of written examinations with open answer formats. Therefore, the use of ChatGPT in the generation of learning outcomes, examination tasks and assessment criteria as well as the critical review and optimization of the drafts will be presented using an example from the domain of work and organizational psychology.

**Keywords:** ChatGPT, constructive alignment, competence oriented examinations, higher education teaching, written exam tasks, assessment criteria, learning outcomes

## 1. Introduction

Several authors claim that the fastest impact of ChatGPT in university teaching was seen in the area of examinations after this generative AI was made freely available to the public in November 2022 [1, 2]. In particular, for unproctored written exams in the form of seminar papers, for example, students were already experimenting with how ChatGPT could take over writing tasks in December 2022 [3], and in January the first students were already caught having their papers written by ChatGPT [4]. In a survey of US-American students conducted at the same time, 30% of respondents stated that they were already using ChatGPT for assignments [5]. University teachers also tested relatively early on whether their exams could be solved by ChatGPT, which was confirmed for exams in Business Information Systems [6] and Astrophysics [7]. Naturally, such examples prompted alarmists to think about how to prevent the

misuse of chatbots in higher education (cf. e.g., Fleck [8], Gamage et al. [2] or Sullivan et al. [9]). According to a recent survey by Solis [10] at German universities, the use of ChatGPT is therefore completely prohibited in a small number of universities (approx. 2%) and only permitted for certain purposes (e.g., research) in just over a fifth of the universities surveyed.

However, ChatGPT can also be put to good use, for example, as an effective learning aid for students [1, 11]. ChatGPT can, for example, help with reading academic texts (e.g., by asking the bot to summarize texts or explain sections of text that are difficult to understand in more detail) or help with learning (e.g., by asking ChatGPT to extract the most important key terms from a textbook chapter or ask questions about specific course content) or help with writing (e.g., by having ChatGPT suggest outlines or key questions on a topic or give feedback on text passages). University teachers can also use ChatGPT not only for writing academic texts, but also for teaching tasks. For example, texts can be generated from keyword lists or text summaries can be created (e.g., for exercises in seminars). To illustrate teaching content, ChatGPT can help to develop examples and counter-examples. ChatGPT can also be used to test comprehension and application skills in seminars or lectures by creating quiz questions or short tests (see, e.g., Patel [12]). ChatGPT therefore harbors both risks and potential for scientific activities and university teaching. Although, it is understandable to try to avoid or minimize the risks, also the potential and benefits of AI can and should be used for one's own work.

As someone who teaches and designs teaching myself, but also accompanies other teachers in workshops to deal with questions about the design of competence-oriented teaching and in particular corresponding examination formats, I am familiar with how laborious it often is to determine and formulate learning outcomes or competence-oriented learning objectives and to develop teaching processes and learning objective-oriented examination tasks and assessment criteria on this basis. This requires not only subject-specific but also didactic expertise at an advanced level, as well as time and cognitive resources, which are often scarce in the everyday life of an academic. For inexperienced university teachers in particular, such tasks are not only laborious but also associated with uncertainties, doubts and considerable motivational challenges.

This raises the question of whether the design of these didactic components—in particular the learning outcomes and the corresponding examination tasks and assessment criteria—can be meaningfully supported and made more efficient or less time-consuming with the help of AI technologies. If this can actually be realized and ChatGPT can be an effective support for teaching and examination tasks, it would make things much easier for many teachers and offer support for a qualitative improvement of teaching and examinations.

The aim of this chapter is therefore to test and analyze the extent to which the AI tool ChatGPT can be used sensibly to support and facilitate the conceptual tasks and requirements described, especially in the area of examinations. On the one hand, the possibilities and potentials of ChatGPT in the formulation of learning outcomes, the derivation of examination tasks from the outcomes and the formulation of assessment criteria and schemes for the learning goal-oriented evaluation of learning achievements are to be demonstrated and analyzed by way of example. Since generative language models are prone to errors and inaccuracies in their answers, we will also look at how AI answers can be concretized and improved with regard to incorrect, incomplete and too vague information.

## **2. What is ChatGPT and what should I bear in mind when using it? (hier weiterlesen)**

ChatGPT is a ChatBot that not only answers (knowledge) questions, but can also write its own texts (e.g., term papers or speech manuscripts), summarize articles, program or solve mathematical problems. The core of ChatGPT is an AI-supported language model that has been trained to compose texts that correspond to a high degree to human conversation or text contributions with regard to the respective topics addressed. For this purpose, a neural network of the language model was fed with an enormous amount of texts in order to learn the characteristics and content of the linguistic representation. In simple terms, the program's language-generative mechanism works by using a highly complex statistical algorithm to generate one word after another so that they fit together in a meaningful way with a specific context or linguistic requirement.

The language model is also further refined using human feedback. Output generated by the model is manually evaluated by humans. However, this is usually not done by experts but by the so-called "clickworkers" in the form of students or unemployed academics (e.g., from India or Kenya), who evaluate the responses generated by the model with regard to content and linguistic characteristics (e.g., with regard to the use of offensive words) [13]. Clickworkers often only have 2–3 minutes for the content fact check to examine the truth of a statement with a short research. Wikipedia articles (which should also be treated with caution as a source of information) are often used as a benchmark to determine whether a statement made by the chatbot is true or false. In view of the precarious working conditions and the high time pressure under which the clickworkers carry out such checks, the fact checks can be characterized as rather inaccurate and unreliable. They only superficially conceal the susceptibility of the language model to errors. Against this background, the best open source language models achieve an average accuracy of 73% at best [13, 14]. Even ChatGPT 4 only achieves a hit rate of just over 80% for two topics, while the rest fluctuate between 60% and 80%. Overall, it can therefore be assumed that the quality of ChatGPT's responses varies greatly.

The procedure described above attempts to train the language models so that they answer as many questions as possible correctly and helpfully. In principle, however, the program itself cannot check and decide whether its answers are correct or incorrect or good or bad [13, 14]. This applies in particular to answers about complex issues or questions where there are several possible answers. Although a language model such as ChatGPT can calculate an answer, it cannot check how good or correct this answer is. This requirement is therefore left to the user of ChatGPT. In areas where a high degree of accuracy is required and even the smallest errors can cause major damage (e.g., in medicine), other expert systems are needed to provide reliable answers. However, if one is aware of these problems of language models, they can be used in areas where the accuracy of the solution is not that important, but rather the clarification of the basic solution path. In such cases, precision and quality can also be generated and guaranteed by human users themselves. This includes in particular the aspect that the quality of chatbot answers can be significantly improved by the way in which they are prompted (e.g., giving detailed instructions, providing examples or a step-by-step instruction) [15, 16].

A major benefit of ChatGPT, as well as other language models, is the program's ease of use. A simple text interface is used to formulate a question, to which ChatGPT

responds directly (usually after a few seconds). However, as already mentioned, the quality and fit of the answers to the questions depends to a large extent on the way in which the questions or prompts are formulated. In general, it is recommended to develop an incremental, dialogic approach, that is, instead of a difficult and complex question in the form of a long prompt, start with simple questions and gradually increase the complexity of the questions [17]. The structure of the prompt should also be based on the ROMANE scheme [18]:

- R stands for role assigned to the AI (who or what is being simulated)
- O stands for the goal of the prompt
- M stands for instructions or assistance (what to do and in what order)
- A stands for application examples or content specifications (what exactly or specifically is it about)
- N stands for useful details (e.g., secondary conditions or restrictions; what should also be taken into account)
- E stands for the recipient of the text (for whom the text is written)

Furthermore, it has proven useful to develop an understanding of the effects of prompts by trying them out for yourself. It is usually also important to take into account that language models such as ChatGPT take into account the previous context or course of the conversation, so that it makes sense to generate answers to a complex task step by step. This means, among other things, that the chat should be restarted when changing or starting a new task. In this context, it can also be helpful to use additional plug-ins such as “Text Blaze” or “Prompt Box” to efficiently save text snippets or prompts and quickly insert them into the input fields of ChatGPT or to extract and summarize texts from videos with the help of “Chrome” [1, 19].

### **3. Didactic concepts and requirements for competence-oriented examination planning**

A competence-oriented planning and design of examination arrangements that are appropriate in terms of the Bologna reform requires that this is based on learning outcomes which are formulated in a curriculum- and target group-oriented way [20, 21]. Corresponding learning outcomes for courses or course units are derived on the one hand from the overarching qualification objectives of the degree program and refer to the competences or sub-competences to be acquired during the course. On the other hand, they describe as specifically as possible the knowledge, skills, and abilities to be acquired in a course or associated teaching units in a defined subject domain, which should contribute to the development of the overarching competencies. On the basis of the learning outcomes, the teaching and learning activities as well as the associated content must then be planned in further steps, which not only aim to acquire knowledge, but also to initiate and practice skills, abilities and professional attitudes. The step of determining and developing the forms and tasks of the examinations is also carried out before or immediately after this. This must be done in a way that they

are suitable for observing and recording the knowledge and skills or competencies to be acquired under conditions of action and performance. It also includes the identification and description of assessment criteria and schemes in order to analyze and evaluate the extent of competence acquisition during the examination tasks. These criteria can also be used to provide informative and learning-promoting feedback to the learners. The next step is to check whether these didactic elements are sufficiently related or coordinated, which is referred to as constructive alignment [22]. This concept is the central didactic principle of competence-oriented teaching and examination design. ChatGPT or other generative language models can be used to support the design of the above mentioned didactic elements. Before we come to this, it should be clarified which design requirements these core elements of competence-oriented teaching and examination design should fulfill.

### **3.1 Definition and formulation of learning outcomes**

Learning outcomes describe the competence facets related to the relevant knowledge, skills, abilities and attitudes that have to be acquired in a course or course unit [20]. The outcomes should be formulated as specific as possible so that they can be operationalized for examination purposes. This is done in such a way that the description of objectives makes clear which behavior—especially in terms of cognitive performance—illustrates the application of knowledge or its mastery in certain situations [23]. On the one hand, reference must be made to the subject-specific content of the knowledge and application domain covered in the course, as well as to the tasks and requirements that must be mastered in this context in order to solve certain problems. However, the social-communicative, metacognitive and motivational-affective aspects that additionally motivate, control, and support professional action should not be neglected.

On the other hand, certain linguistic and conceptual principles must be taken into account when formulating learning outcomes in order to ensure that the learning outcomes provide a sufficient basis for further planning steps. The following aspects should be taken into account:

- Learning outcomes should describe actions to be learned, that is, they should refer to both a content component (What does the learning action relate to in terms of content?) and a behavioral component in the form of a verb (What is to be done? What are the requirements for dealing with the knowledge?)
- Learning outcomes should describe concretely observable modes of action so that they can be operationalized for teaching and assessment purposes; the criterion of concreteness and specificity refers both to the behavior to be demonstrated or the required cognitive activities and to the relevant knowledge concepts.
- It is also helpful if, in connection with the learning outcome, it is described which methods, instruments or procedures are required to implement the action to be learned (How is the learning outcome achieved?) and why the action to be learned is needed in a comprehensive sense.
- It is also advisable to use proven learning objective taxonomies to derive and formulate learning objectives in order to create a description of the learning content

that is based on learning theory and comprehensible to other participants. The taxonomy by Anderson and Krathwohl [24], which provides categories for the systematization and derivation of cognitive learning objectives or learning outcomes, has become widespread and proven its usefulness in the higher education context. For the formulation, categorization and analysis of cognitive learning objectives, a distinction is made between two dimensions: (1) the process dimensions, with which different cognitive processes in dealing with knowledge (remembering, understanding, applying, analyzing, evaluating, synthesizing/creating) are characterized, and (2) the knowledge dimension, which differentiates between different types of knowledge (factual knowledge, conceptual/contextual knowledge, procedural knowledge, metacognitive knowledge).

### **3.2 Construction of examination tasks**

The next step is to design the examination tasks on the basis of the learning outcomes and the learning content. The learning outcomes can be assessed in different formats, which can also be combined with each other. In principle, a choice or distinction can be made between written, oral and practical examination forms, which in turn can be implemented and methodically designed in a variety of ways [25, 26].

The further discussion is focused on written examinations, especially the more open formats. This is done because of space restrictions and in order to provide the most concrete advice possible for the use of ChatGPT in the generation of examination tasks.

Written examinations are the main examination format for many degree programs. In this context, test performance is achieved by answering or completing written tasks or requirements. With regard to the design of written examinations, a distinction is usually made between strongly pre-structured (e.g., in the form of multiple choice tasks) and more open forms (e.g., based on open questions on a topic) as well as different time periods that are made available (at a defined rather short timeslot in the form of written exams or tests vs. longer timeframes in the form of, e.g., term papers) [26]. The more structured formats are suitable for testing knowledge, whereas more open formats are also able to test more complex performance or competencies. In the more open forms of written examinations, a distinction is also made between restricted tasks (which can be answered with keywords or limited explanations and which relate more to requirements for knowledge reproduction and understanding or simple analysis and application requirements) and tasks that require a more detailed answer in the form of more complex statements, case analyses and solutions or requirements for more extensive conceptual drafts.

When formulating open written tasks, certain principles must also be considered [25, 27]. The tasks should be formulated as clearly, completely and structured as possible; that is, the examinees should understand exactly what is expected of them (e.g., with regard to the focus of the content, the scope and level of detail and the structure of the answers) as well as the criteria that the answers should meet. The questions or assignments should therefore clearly state what kind of knowledge is required to answer them (especially for less demanding learning outcomes) and what cognitive requirements are to be met when answering the tasks (especially for more demanding learning outcomes; e.g., describe, compare, justify, evaluate, develop).

Since the learning outcomes should relate to cognitive requirement levels based on learning taxonomies (e.g., the Anderson and Krathwohl taxonomy [24]), certain task forms and variants must also be taken into account when designing

appropriate tasks with reference to a specific requirement level (Schaper [28]). For the “Understanding” level, it is therefore particularly important to construct tasks that require the explanation or clarification of a theory or tasks in which it is necessary to justify why a certain method is particularly suitable for the analysis of certain facts, while for the “Applying” level, tasks such as the transfer of a theory to a specific situation should be set. At the “Analyzing” level, for example, tasks should be constructed in which two or more variants of a concept or case are compared or errors in an application description are to be identified. In connection with requirements at the “Evaluating” level, tasks are to be constructed, for example, in which a solution approach for a specific case is to be evaluated on the basis of various criteria or a case or a topic is to be viewed and evaluated from different perspectives. Finally, for the “Creating” level, tasks are required in which, for example, a complex plan for solving a specific problem must be designed using certain principles or heuristics or a concept or technical solution for a specific task or function must be designed or constructed.

In addition, the tasks must be designed with regard to difficulty-determining aspects (e.g., the number of aspects to be considered, the scope of the text to be analyzed, the contextual relevance of the analysis and the request for additional justifications at the “Analyzing” level). It should also be considered to what extent the tasks should be better illustrated or made more difficult by providing additional documents (e.g., statistics, illustrations, calculation examples, descriptions).

### **3.3 Determining and designing assessment criteria and schemes**

In a further design step, the focus is on the question of how examination performance can be evaluated and assessed. Basically, this step involves comparing the examination performance shown with the expectations that were formulated in advance of the examination with regard to certain requirements [26, 29]. According to the purpose of the examination, the type of performance expected and the examination format, an assessment scheme should be developed on which the assessment is based [30]. An assessment scheme requires the determination of assessment-relevant criteria that can be used for a transparent and objective assessment. In most cases, the individual tasks are presented in tabular form in the assessment scheme with response categories, their definition or characterizing description, anchor examples and the allocation of values (e.g., points) [31, 32]. For each response category, the characteristics that a response must fulfill in order to be assigned to the category are described. The descriptions therefore contain characteristics or indicators that allow different answers to be assigned without any doubt. In some cases, it is advisable to list all possible correct answers, in other cases, especially more complex questions, examiners should provide a generic description of characteristics for assessment purposes. The naming of anchor examples can also facilitate the assignment to a specific assessment category [32].

Furthermore, it is usually necessary to convert the assessments into points and grades; that is, the assessments of the individual aspects of an examination performance must be converted into a numerical value in the form of points. These points must then be aggregated and transformed into a grade using appropriate schemes. This requires that the assessment schemes should also specify how the individual aspects of the examination performance are to be scored and how the point totals are to be converted into grades. For more complex examination requirements (e.g., when assessing case analyses or more complex answer texts), where it makes little sense to refer only to individual aspects of the performance, but rather to assess the solution as

a whole on the basis of certain criteria, it is advisable to use so-called rubrics. Rubrics are assessment schemes that consist of a list of competence-related assessment criteria (including a definition of the criterion) and, for each criterion, a description of competence levels that reflect different levels of competence in relation to the criterion (e.g., excellent performance, satisfactory but improvable performance, unsatisfactory performance) [33].

Once the central methodological elements of an examination arrangement have been designed, the final step is to check the fit of the learning outcome, examination task and assessment scheme and adjust them if necessary. This corresponds to the construction alignment concept [22], in which the fit of the teaching/learning activities with the learning outcomes and the examination tasks and requirements must also be checked and ensured. Methodologically, the corresponding fit aspects can be checked with the help of learning objective taxonomies. Anderson and Krathwohl's approach is particularly suitable for this (see Universität Zürich—Arbeitsstelle für Hochschuldidaktik [34]). Essentially, this involves analyzing to which knowledge categories and requirement levels the learning outcome(s), the examination tasks and the assessment criteria and schemes can be assigned. After this step, a comparison is made as to whether the learning outcome, task and assessment criteria can be assigned to the same categories and levels or not (e.g., procedural knowledge and application for both the learning outcome, task and assessment schemes). If this is the case, a successful constructive alignment can be assumed. However, if there are deviating assignments, adjustments or modifications to the three components are necessary in order to achieve or guarantee constructive alignment. In addition, content-related and representation-related aspects (e.g., whether the content area is sufficiently represented by the tasks) must also be taken into account when assessing the fit.

The conceptual and design aspects described provide an overview of the key conditions that need to be taken into account when designing examination arrangements, particularly for written but also other examination forms. These aspects are also decisive in the instruction of ChatGPT for the generation of corresponding examination elements as well as in the evaluation of the elements generated by ChatGPT. The following section presents how to proceed when instructing or prompting ChatGPT for the generation of learning outcomes, examination tasks and assessment schemes for specific learning objectives.

## **4. Generation of a competence-oriented examination arrangement with the help of ChatGPT**

### **4.1 Generation of learning outcomes**

Teachers at universities—be they research assistants, academic assistants, professors or lecturers—often have little training in didactics and instructional psychology—with a few exceptions. However, they usually have a high level of professional and academic expertise in the subject matter they are teaching. When planning courses and teaching units, including the examination arrangements required in this context, they often approach this task from a subject-systematic, content-oriented perspective or are guided by traditional concepts of teaching design. It is therefore often difficult for them to determine learning objectives and the learning outcomes to be achieved for their courses and to formulate them in a didactically appropriate

way. This difficulty often results in learning objectives that only vaguely represent what is to be achieved. Or they are too knowledge-heavy in their objectives and do not adequately describe which cognitive and non-cognitive skills are to be acquired in the course. It is difficult to derive learning activities and examination requirements in an appropriate form on the basis of such deficient learning objectives respective learning outcomes.

In this context, a generative, AI-supported language model such as ChatGPT can provide helpful support in order to partially take on the task of formulating adequate learning outcomes for certain learning domains. In particular, ChatGPT is able to take into account the conceptual and linguistic aspects described in chapter 3. The more precisely and skillfully certain aspects of prompting are considered, the better the system is able to do this. Therefore, various aspects and levels should be addressed when generating learning outcomes for a course with the help of ChatGPT:

- The assignment for ChatGPT can be formulated as follows, for example: “Formulate learning outcomes for [specification of the overarching topic] with the learning content [keywords of the learning content and aspects to be covered].”
- Furthermore, the target group of the course should be stated (e.g., Bachelor’s students of Computer Science in the 3rd semester) and how the course or learning unit is integrated into the curriculum (e.g., the course builds on the introductory lecture of informatics)
- Another crucial aspect of prompting is to specify the taxonomic system according to which the learning outcomes are to be developed (e.g., “Base your formulation on the taxonomy of Anderson and Krathwohl.”). It is also advisable to specify the exact learning objective levels that you want to address in the course (e.g., understanding, applying, analyzing) or to specify each level individually using a separate prompt.
- It should also be specified what the overarching qualification objective of the course or teaching unit is (e.g., ability to carry out requirements analyses for specific issues) and also which format the course is based on (e.g., lecture, seminar, tutorial, project seminar) and which didactic principle or approach the course is based on (e.g., problem-oriented didactics).
- Didactic planning usually requires the consideration of different levels of planning, which refer to different levels of concretization of the instructional approach; at least two, if not three or more levels are to be distinguished (e.g., program, module, and course level). These different levels of planning also refer to different levels of goal formulation. For the prompting of learning outcomes, this means that these different levels should be addressed by specifying the respective curricular level.
- Last but not least, it may be useful to specify which additional aspects should be taken into account when formulating the learning outcomes (e.g., explain the why and wherefore of the learning outcomes).

Two examples of generating learning outcomes using ChatGPT are presented in **Tables 1** and **2**, which take the aforementioned aspects of prompting into account in

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The request for generating learning outcomes for this course unit was: “Formulate learning outcomes for a lecture with 10 sessions on the topic of personnel development based on personnel psychology with the following learning contents: definitions and objects of personnel development, methods for determining learning and training needs, approaches to promoting different areas of competence, evaluation of personnel development and approaches to enhance transfer. Participants in the lecture are Bachelor of Psychology students in their 4th semester. The overarching qualification objective of the lecture is to familiarize students with personnel psychology concepts and to enable them to develop solutions for practical problems in corporate personnel development on the basis of scientific concepts and findings. When formulating the learning outcomes, use Anderson and Krathwohl’s learning objective taxonomy as a guide.”

ChatGPT provided me with the following answer (this is limited to a selection of learning outcomes for reasons of space): “After completing the teaching unit ‘Psychology-based Personnel Development’, students should be able to achieve the following learning outcomes based on Anderson and Krathwohl’s learning objective taxonomy:

3. Applying:

- Students will be able to apply appropriate methods to determine learning and training needs in specific organizational contexts.
- Students can apply various approaches to promote different areas of competence in practice.

4. Analyzing:

- Students can analyze the evaluation of personnel development and select suitable evaluation methods.
- Students can analyze approaches to transfer enhancement and assess their effectiveness.

5. Evaluating:

- Students can evaluate the effectiveness of personnel development measures and make suggestions for improvement.
- Students can evaluate the effectiveness of transfer enhancement approaches and suggest alternative approaches.

These learning outcomes should ensure that students gain a sound understanding of personnel development based on personnel psychology and are able to apply and evaluate this knowledge in practical situations.”

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**Table 1.**

*Generation of learning outcomes for a lecture in personnel psychology by ChatGPT.*

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In a second trial the query was focused on a specific learning unit (approaches to enhance transfer in company training measures):

Inquiry: “Formulate learning outcomes at the Understand, Apply, Analyze, Evaluate and Create learning objective levels of Anderson and Krathwohl’s learning objective taxonomy for the teaching unit ‘Approaches to transfer enhancement for in-company training courses’. Approaches, influencing factors and methods of transfer enhancement in occupational psychology research are discussed with examples of operational application.”

ChatGPT provided me with the following answer (presentation is limited to excerpts):

- “Understanding: Participants will understand the basic concepts and theories of transfer enhancement. They will learn about the various approaches to promoting the transfer of training content into workplace practice and understand their importance to performance development and organizational success.
  - Apply: Participants will be able to apply the approaches and methods of transfer enhancement they have learned to specific in-company training programs. They will be able to identify suitable measures to promote transfer and integrate these into the design and implementation of training courses.
  - Analyze: Participants will be able to analyze the factors influencing the transfer of training content into operational practice. They will understand the individual, organizational and contextual factors that can influence the transfer process and will be able to evaluate these and derive appropriate measures to optimize transfer.”
- 

**Table 2.**

*Generation of learning outcomes for a learning unit of the lecture by ChatGPT.*

different ways. First, an example of generating learning outcomes with the help of ChatGPT for a lecture covering topics of “Psychology based personnel development” for psychology students in the 4th semester of their bachelor’s degree program and second learning outcomes of a lecture unit concerning the transfer of learning respective training results is presented:

*Comments on the first example (Table 1):* The learning outcomes generated by ChatGPT are consistently based on the cognitive process dimension of Anderson and Krathwohl’s taxonomy so that at least two learning outcomes are formulated for each of the learning objective levels. However, the knowledge dimension of the taxonomy is not taken into account. It is therefore not addressed which type of knowledge (declarative, conceptual, procedural or metacognitive) is to be acquired. It should also be noted that the learning objectives do not systematically refer to the various learning content areas addressed in the prompt. The formulated outcomes therefore only incompletely cover the breadth of the mentioned learning contents. However, the generated learning outcomes specify meaningful learning requirements of the HR development domain. They are therefore rather exemplary suggestions for relevant learning outcomes of this domain, although this is not made clear by the system. Overall, it should be noted that the specification of the taxonomy leads to a comprehensible addressing of cognitive learning requirements and relevant learning content in relation to the relevant knowledge and action domain.

*Comments on the second example (Table 2):* The first thing that is noticeable here with regard to the individual learning outcomes is that they are formulated more extensively than the learning outcomes for the overarching subject area. In addition to an introductory, rather general description of the learning outcome at the respective level, further sentences are used to specify what characterizes the cognitive activity or action at this learning objective level and with regard to which aspects of the action the learners should be enabled. Overall, it can be stated for this example that the three learning outcomes address important aspects of the respective learning objective level for the addressed content area. Also, the cognitive requirements of the content area are better and more completely covered than in the previous example. However, no reference is made to specific concepts of transfer enhancement. These may still need to be specified.

In both cases, there is a need to revise the learning outcomes generated by ChatGPT. The language model is therefore not able to provide readymade solutions for the formulation of learning outcomes for a course or teaching unit. However, the system provides useful suggestions as to the form in which the learning outcomes should be formulated and which content aspects should be addressed in the learning outcomes. It is also made clear how the learning objective levels differ in terms of specific learning requirements. In my opinion, this creates a good basis for further revision.

Therefore, in the next step you should revise the generated learning outcomes yourself (possibly in collaboration with colleagues or as part of an expert consultation). In a first step, this includes analyzing the learning outcomes generated for a specific case in terms of their strengths and deficits, in a similar way to that described in the comments. In further steps, depending on the initial situation, either minor additions or extensions (e.g., with regard to the mentioned concepts in the learning outcomes) should then be made. In some cases, however, it may also be necessary to formulate additional learning outcomes with regard to subject-specific content not yet covered or to significantly expand the description of the learning outcomes in

order to describe more specifically which aspects of acting and thinking the learners should be enabled to do.

Furthermore, it can also be recommended that ChatGPT should be used to optimize the learning outcomes—for example, through more limited and more specific prompts. For example, it is advisable to limit yourself to only one learning objective level in order to achieve a greater breadth of content in the generated learning outcomes. It is also possible to provide ChatGPT with a best practice example of a learning outcome for the learning domain and ask the system to generate learning outcomes for other content areas or learning objective levels in a similar way.

#### **4.2 Generating examination tasks on the basis of predefined learning outcomes**

On the one hand, examination tasks should cover the relevant learning area broadly enough in terms of subject matter content in order to test a representative cross-section of knowledge and skills in a domain. On the other hand, the tasks should address the cognitive and non-cognitive skills to be learned in the course, for example, with regard to different requirement levels. While most teachers can still meet the first requirement with relative certainty due to their subject matter expertise, many teachers are often unsure with regard to the second condition. That means they are unsure whether they are addressing more demanding learning objective levels appropriately with their examination tasks. This uncertainty or, in some cases, missing knowledge of how certain cognitive learning requirements can be specifically addressed with the help of certain tasks leads teachers to focus only on the requirements that they can confidently implement and assess (often tasks that only require knowledge reproduction and comprehension). As a result, certain requirement areas are not sufficiently addressed in the examination. Or tasks are constructed that lead to students being under- or overchallenged or that pose demands that are irrelevant in relation to the skills to be learned (e.g., by disproportionately emphasizing the fulfillment of formal requirements).

ChatGPT can also provide support with regard to the design of examination tasks. By specifying and prompting the relevant learning outcomes, ChatGPT is able to construct examination tasks that represent the relevant cognitive requirements of the addressed learning objective levels in a valid and appropriate manner. However, when generating examination tasks for a specific teaching area with the help of ChatGPT, certain aspects should be taken into account with regard to effective prompting:

- The assignment for ChatGPT can be formulated for example as follows: Suggest to me [number, e.g., 2] examination tasks for a [name the desired task or examination format; e.g., written exam] on the following learning outcome: [original formulation of the learning outcome]
- Furthermore, the target group for the examination should be specified and the prerequisites that the candidates have for the examination (e.g., whether they already possess skills to apply certain concepts or in dealing with certain tasks through exercises).
- It is also advisable to provide information on the framework conditions for the examination (e.g., the average amount of time available for a task or additional material/devices available for working on the task—e.g., reference books or calculators).

- Further information that may be relevant for the design of examination tasks relates to the relevant contextual reference or the degree of realism to be taken into account. Or it should be specified in which way certain aspects should be considered concerning the difficulty of the task (e.g., requesting a justification).

Three examples of how ChatGPT generates examination tasks are presented in **Table 3** to illustrate the potential that the bot has for creating examination tasks.

*Comments on the examples in Table 3:* In my opinion, the suggestions generated by ChatGPT for examination tasks on the topic of transfer enhancement address the cognitive requirements relevant to the respective learning objective level adequately. The tasks could certainly be adopted in this form. Nevertheless, they are more likely to be assessed as draft samples, as they are formulated rather vaguely with regard to certain aspects. These aspects that are not sufficiently addressed in the presented task examples I will discuss below for each of the three tasks:

- In the task for the Understanding level, it would be useful to specify the approach for classifying or systematizing the basic concepts to which the examinees should refer here, as various systematization approaches exist for this.
- In my opinion, the task for the Applying level should not only describe the measures for enhancing transfer but also explain why these are relevant for the stated training topic for enhancing transfer. If necessary, the overarching objective of

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1. Request: "Suggest examination tasks for a written exam on the following learning outcome (learning objective level Understanding): Participants will understand the basic concepts and theories of transfer enhancement in workplace training programs. They will become familiar with the various approaches for promoting the transfer of training content into operational practice and understand their significance for performance development and organizational success."

Answer: "Examination task (exemplary): Explain the basic concepts of transfer enhancement in in-company training measures and give an example of their application in each case. Also describe how these concepts can contribute to performance development and organizational success."

2. Request: "Suggest examination tasks for a written exam on the following learning outcome (learning objective level Apply): Participants will be able to apply the learned approaches and methods of transfer enhancement in training measures to specific in-company training programs. They will be able to identify suitable measures to promote transfer and integrate these into the design and implementation of training courses."

Answer: "Examination task (exemplary): You are working as a trainer for a company and are to carry out a training measure on the topic of 'Effective communication in a team'. Describe three specific measures that you would take to promote the transfer of what you have learned into the participants' everyday working life. Explain how these measures can be integrated into the design and delivery of the training."

3. Request: "Suggest examination tasks for a written exam on the following learning outcome (learning objective level Analyze): Participants will be able to analyze the factors influencing the transfer of training content into operational practice. They will understand the organizational, contextual and individual factors that can influence the transfer process and be able to evaluate these and derive appropriate measures to optimize transfer."

Answer: "Examination task (exemplary): Consider the organizational context and contextual factors that can influence the transfer of training content into workplace practice. Describe three organizational or contextual factors and analyze how they can influence the transfer process. In addition, evaluate what measures could be taken to optimize transfer in relation to these factors."

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**Table 3.**  
*Generation of examination tasks based on the learning outcomes by ChatGPT.*

the training measure should also be stated so that it is clear what the communication skills are specifically needed for or are to be improved.

- In the task for the Analyzing level, the task is somewhat general and is aimed rather at requirements of the knowledge reproduction and comprehension level. I would therefore make the application context more concrete or contextualize it with a specific training scenario so that the examinees are required to perform analytical tasks to a greater extent. In my opinion, the additional instruction in this assignment (“Explain how these measures can be integrated into the design and delivery of the training.”) also requires a correction: The examinee should first be instructed to create measures to adapt and optimize the context factors and then it should be asked for reasons why they lead to an improved transfer.

The comments make clear that there are several needs to optimize the task suggestions by ChatGPT. At best, the suggestions generated can be used as a basis for further elaboration. In my opinion, however, they are still useful as a source of ideas. They also substantially facilitate or support the conceptual work designing examination tasks. When generating examination tasks, ChatGPT draws relatively systematically on knowledge about suitable task formats for certain learning objective levels and contextualizes these in relation to the subject domains addressed. The bot thus provides valuable support in the construction of tasks tailored to learning objectives, as the consistent design of such examination tasks is often difficult to achieve on one’s own or without appropriate assistance, especially for teachers with little didactic experience.

However, it must also be stated that further revision steps are required in order to achieve a usable result. This requires also an analysis of which aspects already fulfill the proposed tasks, but where there are still deficits and a need for changes or additions. This can relate to technical aspects to make the task more specific and to better focus on the intended cognitive requirements or performance. Additionally, information should be provided in the task instructions with regard to the criteria used to assess the answers to the task. This gives the examinees information on what they need to pay attention to when answering the question or task and improves the clarity of the examination task. Furthermore, ChatGPT can be used to further develop and optimize examination tasks. For this purpose, it is recommended to provide the bot with the previous version of the task and ask it to specify certain aspects (e.g., generation of a suitable application scenario). The bot can also be used to generate additional tasks for a specific learning outcome in order to increase the covered breadth of content.

### **4.3 Generation of assessment criteria and schemes for examination tasks**

The assessment of examination performance should be as objective, reliable, valid, transparent and fair as possible. In addition to examination tasks that are geared toward learning objectives and the guarantee of standardized and fair implementation conditions, assessment criteria also essentially contribute to the examination being experienced as appropriate and fair and that the examination fulfills the above-mentioned quality criteria. Assessment criteria and assessment schemes support examiners in ensuring that the assessment of examination performance is not carried out arbitrarily or intuitively, but on the basis of comprehensible and content-appropriate standards, and that quality criteria of objectivity, reliability,

validity and fairness are fulfilled to a sufficient extent. If this is not the case, the result of the examination is not only questionable and distorted by uncontrolled assessment processes, but also legally contestable. Assessment criteria for evaluating examination performance—not only for written examinations—are therefore essential. They also provide examiners with certainty when evaluating examination performance, increase transparency with regard to how the examination result is arrived at and are helpful in providing detailed feedback on the strengths and weaknesses of performance. Incidentally, this applies not only to inexperienced examiners but also to experienced and didactically skilled examiners. In my opinion, assessment criteria for the tasks used in an examination that are appropriate in terms of content and requirements are therefore an indispensable part of the examination arrangement. For various reasons, appropriate assessment criteria should also be developed during the construction of the examination tasks, that is, parallel to or immediately after the task construction. On the one hand, they are necessary for a solid task design in order to avoid errors or ambiguities in the formulation of the task (e.g., to check whether the task is sufficiently focused on the skills and knowledge to be tested and whether this is also clearly stated in the task instructions for the examinees). Since the assessment criteria should also refer to a large extent to the learning outcome and the corresponding learning objective level as well as the knowledge required for this, they also ensure that the examination arrangement fulfills the principle of constructive alignment. In addition, the assessment criteria can be used to transparently communicate to examinees what is important in the examination and what standards their examination performance should meet.

In my opinion, ChatGPT can also effectively support examiners in this step. Various application tests show that the system is able to develop meaningful suggestions for determining and formulating assessment criteria and schemes for certain examination tasks. The bot is oriented toward common assessment dimensions in examinations and is also able to take into account specific methodological concepts of assessment schemes (e.g., the rubrics concept). When generating assessment criteria for a specific examination task or even a class/group of tasks with the help of ChatGPT, certain aspects of prompting should be taken into account:

- The core prompt for ChatGPT can be formulated, for example, as follows: “How should the answers to the following examination task be scored: [state the original wording of the exam task]. Also, give me a detailed evaluation scheme for scoring the performance.”
- In addition to stating the original task, it may be useful to state the learning outcome on which the task is based, which is also an important reference point for generating the assessment criteria.
- Additionally, it may be necessary to specify the type of assessment scheme required (e.g., whether this should take the form of a rubric). As described above, rubrics consist of an evaluation matrix in which the evaluation criteria relevant to a specific task or examination performance are named and defined on one axis. On the second axis, the type and number of quality levels for evaluating the individual criteria or dimensions are also specified (e.g., (1) good to very good, (2) satisfactory and (3) insufficient fulfillment of criteria). The cells of the matrix then describe notes and aspects for evaluating the respective quality level for each criterion. Another tested evaluation scheme refers to following aspects:

Evaluation category, definition/characterization of the level, anchor example, points. This scheme is particularly useful for tasks in which a distinction is made only between “correct” and “incorrect” or “partially correct.” In this way, a well-founded decision or assignment can be made on the basis of the definitions of each level and the anchor examples given in each case.

In the following (see **Tables 4** and **5**), two examples are presented in which ChatGPT was asked to generate suitable assessment criteria for two specific examination tasks. These in turn relate to the teaching unit “Enhancing transfer in in-company training measures” and include examination tasks for the learning objective levels “Understanding” and “Evaluating.”

*Comments on the first example (Table 4):* The assessment criteria for the “Understanding” level task refers to the various subtasks and proposes a scoring

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Question: “How should the answers to the following examination task be assessed? Explain the basic concepts of transfer enhancement in in-company training measures and give an example of their application in each case. Also describe how these concepts can contribute to performance development and organizational success. Give me a detailed assessment scheme for scoring performance.”

Answer: “The following criteria and a detailed scoring scheme could be used to score performance when evaluating responses to this assessment task:

1. Understanding of the basic concepts of transfer enhancement in workplace training programs (e.g., repetition, practical application, feedback, transfer climate):
    - Complete and accurate explanation of concepts: 3 points
    - Partially correct explanation of the concepts: 2 points
    - Superficial or incomplete explanation of concepts: 1 point
    - Missing or incorrect explanation of concepts: 0 points
  2. Exemplary application of the concepts:
    - Clear and relevant examples that illustrate the application of the concepts: 3 points
    - Partially appropriate examples that partially illustrate the application of the concepts: 2 points
    - Unclear or inadequate examples that do not clearly illustrate the application of the concepts: 1 point
    - Missing or incorrect examples: 0 points
  3. Description of the contribution of the concepts to performance development and organizational success:
    - Clear and comprehensive connection between the concepts and their contribution to performance development and organizational success: 3 points
    - Partially correct connection between the concepts and their contribution to performance development and organizational success: 2 points
    - Superficial or incomplete description of the link: 1 point
    - Missing or incorrect description of the connection: 0 points
  4. The evaluation scheme could then add up the points for each category and determine an overall score for the task. For example, a possible scale could be as follows:
    - 9–10 points: Very good performance
    - 7–8 points: Good performance
    - 5–6 points: Adequate performance
    - 3–4 points: Poor performance
    - 0–2 points: Insufficient performance”
- 

**Table 4.**  
*Generation of assessment criteria by ChatGPT for the task at the understanding level.*

Question: "How should the answers to the following assessment task be evaluated: Critically analyze the effectiveness of a particular approach to transfer enhancement in workplace training (e.g., collegial mentoring) and discuss its advantages and disadvantages. Assess in which workplace contexts this approach might work best and what factors might influence its effectiveness. Provide recommendations on how the approach could be improved to facilitate the transfer of training content into practice. Give me a detailed assessment scheme for scoring performance."

Answer: "A possible scheme for scoring performance in response to this examination task could be as follows:

1. Analyze the effectiveness of the transfer enhancement approach (max. 10 points):
    - Critically evaluate the effectiveness of the approach (e.g., using studies or case studies)
    - Consideration of advantages and disadvantages of the approach
    - Understanding of the underlying principles and mechanisms of the approach
  2. Discussion of the operational contexts and influencing factors (max. 10 points):
    - Identification of operational contexts in which the approach might work best
    - Analysis of factors that could influence the effectiveness of the approach (e.g., corporate culture, employee motivation)
  3. Recommendations for improving the approach (max. 5 points):
    - Creative and realistic suggestions for optimizing the approach
    - Consideration of the challenges and potentials in the implementation of the recommendations
  4. Structure and clarity of the argumentation (max. 5 points):
    - Logical and well-structured presentation of the arguments
    - Comprehensible and precise formulation of the statements
  5. References and use of specialist terminology (max. 5 points):
    - Citation of relevant sources to support the statements
    - Use of specialist terminology appropriately and correctly
  6. The maximum score is therefore 35 points. The assessment should be based on these criteria, with particular consideration given to the quality of the argument, the depth of the analysis and the originality of the recommendations."
- 

**Table 5.**  
*Generation of assessment criteria by ChatGPT for the task at the evaluating level.*

scheme for different levels of response quality for each subtask. However, the levels are characterized in relatively general terms (from "complete and precise" to "missing or incorrect explanation of concepts"), making it difficult to differentiate between the various levels or to assign a specific answer to a level. If this assessment scheme is to be used, it is therefore advisable to add more specific information to assign different answers and the delimitation of scoring levels. In particular, the insertion of anchor examples, that is, typical response examples for the respective level, could be helpful here. Also, the recommendation for the grading scheme is relatively generic and can or must also be adapted to specific application contexts (e.g., with regard to the point ranges selected for the respective grade).

*Comments on the second example (Table 5):* The assessment criteria for the task at the "Evaluate" level refer on the one hand to the various subtasks of the task and on the other to overarching aspects of the quality of the answer ("Structure and clarity of argumentation" and "Sources cited and use of specialist knowledge"). However, no levels of the response quality are described for the assessment of the individual subtasks, but rather specific criteria to which reference should be made in the response (e.g., "understanding of the underlying principles and mechanisms of the approach")

for the first subtask). In my opinion, this achieves a more detailed specification of the assessment criteria than in the first case. However, with regard to a concrete application of this assessment scheme, an additional concretization of these specific criteria is recommended (e.g., through sample solutions or anchor examples) in order to obtain even clearer indications for the evaluation of individual answers. Also, the scoring scheme should be defined more clearly. The indication of the maximum possible point totals for each criteria is not very comprehensible and primarily illustrates a different weighting of the subtasks. Overall, ChatGPT provides useful information on structuring the assessment and determining relevant assessment criteria and aspects, which, however, require further elaboration as described.

My comments on the two examples have already illustrated the potential, but also the need for revision, of the suggestions generated by ChatGPT for the assessment of examination tasks. For this step, it can also be stated that ChatGPT is able to generate useful suggestions for the assessment of examination performance for defined examination tasks. In this case too, ChatGPT's suggestions have the status of useful ideas and hints rather than readymade solutions. Suggestions for the independent revision of such proposals have already been mentioned and relate primarily to the specification of the assessment criteria through anchor examples and sample solutions as well as the clearer definition of the aspects for which points are to be awarded and how the points can be transformed into grades. Chat GPT can also be used in this context for the further development of assessment schemes, in particular by specifying certain forms of assessment schemes (e.g., rubrics or true/false assessment schemes).

Finally, in a further test step, it is advisable to analyze and evaluate the constructive alignment of the various elements. On this basis, adjustments can then be made between the elements and the fit between learning outcome, examination tasks and assessment criteria as well as the associated teaching/learning activities can be improved. This coordination of the various elements is not only important for reasons of successful didactic coherence, but also has an effect on the quality of the learning process and has been proven to promote motivation to learn. Various studies have shown that learning arrangements that follow the constructive alignment principle result in or effectively promote the use of learning strategies for more in-depth learning and greater learning effort as well as the achievement of more challenging learning goals [35–37]. However, attempts to determine the extent to which ChatGPT is also able to support teachers in checking constructive alignment proved to be less successful. Unfortunately, the language model was not able to make appropriate assessments of the fit between learning outcome, examination task and assessment criteria in relation to this didactic principle.

## **5. Conclusion and outlook**

In my opinion, the trial to use ChatGPT for the design of written examinations, in particular for the design of learning outcome and competence-oriented examination arrangements, has made clear that ChatGPT can indeed provide support for this task and the process in various ways. For example, the AI tool can be used to generate drafts and ideas for the appropriate formulation of learning outcomes, the learning outcome-oriented design of examination tasks and the construction of suitable assessment criteria and schemes. However, it also became clear that ChatGPT does not provide readymade solutions, but at best drafts and ideas that require further elaboration. It also became clear that ChatGPT creates errors and inaccuracies in

its proposals, which need to be identified and corrected through careful and critical analysis. In this context, it should be pointed out once again that the generative language models are not trained to produce true and correct solutions, but rather probable word sequences. The fact that these word sequences make sense and are true is to a certain extent only a by-product [1]. Although between 60% and 80% of the answers are correct in this way, conversely this means that 20–40% of the answers can also be or are incorrect [13]. ChatGPT therefore repeatedly presents answers that are partially incorrect or even invented. The providers and developers of generative language models will certainly work on increasing this rate of correct answers, but the fundamental problem will remain permanently, as it is inherent in the design of the language model. For the application context under consideration, this means that ChatGPT's proposals for the formulation of learning outcomes, the design of examination tasks and assessment criteria/schemes must be reviewed and revised in any case—it cannot be repeated often enough.

Finally, it should be pointed out that ChatGPT can be used to generate not only open response formats for exams, but also closed task formats or examination tasks. Reference should be made here to the presentations by Patel [12] or Workera [38], which show that ChatGPT can also be used to generate useful suggestions for multiple choice questions, cloze texts, true/false questions, matching tasks or open short questions for all possible subject areas. As described above, information is required not only on the content to be tested, but also on the target group, the level of difficulty or the type of cognitive demand, the style of wording, etc. when prompting. These descriptions also address what needs to be done and considered with regard to the revision of the proposals (in particular [38]). ChatGPT can also be used to check answers to exam questions. Examples of this can be found in Herft [39], where it is particularly pointed out that these reviews can be used for individual feedback to students regarding their performance in formative (exercise) tasks. Potential for change through ChatGPT in the area of examinations also arises from the fact that this tool can be used specifically when writing unsupervised examination formats (such as seminar papers and term papers) and when writing academic theses. ChatGPT thus becomes a partner in the writing process (in the sense of hybrid writing) and is therefore not only a relief for certain writing requirements, but also enables further learning processes through its support. However, in order to allow such hybrid processes in written examinations, clear framework conditions are also required that specify the form in which the bot may be used for the creation of such texts and what must be considered (e.g., that all passages in which ChatGPT or another generative AI was used in writing must be marked).

Let me resume with a statement of an experienced colleague in this field [1]: “I assume that sooner rather than later ChatGPT will become a tool that we use as a matter of course - especially at universities. We should understand this tool (with all its strengths and weaknesses), use it confidently and reflectively and be vigilant about the risks and side effects.”

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The book discusses the impact of artificial intelligence (AI) on education, exploring both the opportunities and challenges it brings. It aims to provide a comprehensive understanding of how AI is reshaping the educational environment, from personalized learning experiences and intelligent tutoring systems to administrative efficiencies and ethical considerations. The book also addresses the implications of AI on traditional educational models and the broader societal context, sparking a dialogue about AI's potential for enhancing learning outcomes and preparing students for an AI-driven world. Overall, it aims to inspire innovation and critical thinking in the field of education.

*Andries Engelbrecht, Artificial Intelligence Series Editor*

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