LEARNING, TEACHING & TRAINING IN THE ERA OF ARTIFICIAL INTELLIGENCE

What does the recent AI push mean for our education and training institutions? How do we reinforce the nexus between AI technology and teachers/trainers?

At itec, we believe that the future of AI in education and training lies at the intersection of human intelligence and technological intelligence. In this positioning paper, we want to further unravel this idea together with the reader. We call for a nuanced point-of-view in the AI debate, wherein machines empower educational stakeholders and vice versa, ultimately strengthening education together. To do so, it is important to acknowledge limitations and risks that come along the way.

We provide insight into how AI in education is being researched at itec, an imec research group at KU Leuven, thereby contributing to the accelerating research domain of Artificial Intelligence in Education (AIED).

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VERSION 2024

Positioning Paper itec, an imec research group at KU Leuven

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Challenges and opportunities for evidence-based educational research

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Version 2024

First edition: 2024

Published by
Acco cv, Sluisstraat 10, 3000 Leuven, Belgium
E-mail: uitgeverij@acco.be – Website: www.acco.be

The Netherlands:
Acco Uitgeverij, Westvlietweg 67 F, 2495 AA Den Haag, The Netherlands
E-mail: info@uitgeverijacco.nl – Website: www.accouitgeverij.nl

Cover design: Frisco
Typesetting: Xpair

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You can refer to this report as follows:
Itec (2024). *Learning, teaching & training in the era of Artificial Intelligence: Challenges and opportunities for evidence-based educational research.* [Positioning paper: coordinated by Rani Van Schoors and Ann Fastré]. Kortrijk: itec, an imec research group at KU Leuven.

D/2024/0543/164 NUR: 984 ISBN: 978-94-64149-98-2

Content

Foreword

In recent months, the spotlight on Artificial Intelligence (AI) has intensified, fueling discussions across various domains. Nowhere is this more evident than in the domain of education, where the promise and potential of AI has generated significant speculation about the future of learning, teaching & training. Is the learner taking more control of his learning process? Might AI replace the teacher or the trainer? Will AI systems determine a learner's study success or professional upskilling or reskilling? Has the time come when learners no longer need to write papers, with advanced language models like ChatGPT at their disposal?

The domain of AI in education has sparked a lot of questions, with various stakeholders actively engaging in the pursuit of answers. Educators, edtech companies, researchers, innovators, government bodies, learners, and parents all have their part to play in the future of AI in education. In formal education as well as in lifelong learning.

Collaboration becomes key, and imec Smart Education enjoys playing a role in bringing these diverse voices together to innovate in order for AI to have a positive impact on education. AI is not a distant concept but a reality, sure to play a defining role in our society, education included. The responsibility now rests on our shoulders to collaboratively shape the trajectory of the role of AI in education. This is the reason why imec Smart Education fully focuses on the global AI research strategy of imec with a strong emphasis on trustworthy and explainable AI.

This positioning paper offers insights into the nuances of AI in education—what it is, what it is not, the challenges it poses, and the potential implications. Moreover, we explain the role itec, an imec research group at KU Leuven, plays as a key stakeholder in this field.

We hope this paper offers you valuable insights about educational AI in all its facets. And since you are a stakeholder in this field, just as we the writers of this paper are, we hope you reach out so we can collaborate on shaping the future of AI in education.

Lien De Bie
Programme manager imec Smart Education

About itec and imec Smart Education

itec

Itec is an imec research group at KU Leuven, located at KU Leuven Kulak in Kortrijk (Belgium). We conduct fundamental and applied interdisciplinary research on personalized and adaptive digital technologies, with applications primarily in the domain of education & training, and in the domain of healthcare. The mission is to carry out excellent research in the field of data science and artificial intelligence (AI) as well as instructional effectiveness, and produce valorisable research results that can inform the design of digital technologies in the above mentioned domains in order to achieve impact both at the level of the end user (e.g. learner or patient, trainer or medical expert) and at the level of their organizations (e.g. school, training institution, hospital). More specifically, the research group advances the state of the art in data science and artificial intelligence (multilevel statistical modeling, machine learning, and language technology), with a strong focus on explainable AI methods. In addition, we advance the state-of-the-art in theory-informed research on learning effectiveness, leveraging the latest methods in data science and AI (quantitative and qualitative methods for behavioral research, multimodal learning analytics, and meta-analysis).

imec Smart Education

Imec is the world's leading research and innovation hub in nanoelectronics and digital technology.

As a result, Imec is active within several application domains: such as smart health, smart energy or smart mobility but also smart education. The mission of imec's Smart Education program is to design, develop, and evaluate beyond state-of-the-art digital technologies such as artificial intelligence, sensors and actuators in order to tackle societal challenges related to teaching, training and lifelong learning. Through co-creation with industry and schools, it also aims to incubate novel solutions and services, and accelerate their adoption in the market. As such, it aims to contribute to evidence-based and sustainable digital transformation of education and training in today's knowledge society. The strategic pillars of the program focus on personalized learning, empowering teachers and trainers, enabling the learning of 21st century skills through open-ended tasks, and hybrid and flexible learning. The program comprises activities across a wide range of technology readiness levels, including fundamental and strategic basic research on new methodologies for data analysis as well as efficacy studies, technology development driven by industrial needs, the creation and maintenance of research infrastructure, and the co-creation of prototypes with schools and companies in Flanders. To realize its ambitions, the program brings together imec researchers at KU Leuven, UGent and VUB from a wide range of scientific disciplines and domains, such as instructional psychology & technology, statistics, machine learning and artificial intelligence, language technology, engineering sciences, neurosciences and social sciences. It has also forged a strategic alliance with the local industry through the startup accelerator program imec.iStart and EdTech Station, the Belgian community of EdTech companies.

Executive summary

Driven by the process of digitization and datafication, innovative technologies are increasingly finding their way into educational research, policies and technology development efforts (Nowotny, 2021; Knox, 2023; Holmes et al., 2019). Within this context, Artificial Intelligence (AI) is established as a timeless and intriguing issue for educational practitioners and researchers around the globe (du Boulay, 2019; Salomon, 2002; Selwyn, 2017). The field of AI is characterized by rapid progression and several technology pushes (Selwyn, 2017).

These developments also find their way into education and training. However, when it comes to changes in the educational domain, decisions are made at many levels, thus embedded in a complex and multilayered context. Most often, this is accompanied by heated debates about what our education stands for and how it should evolve (Knox, 2023; Selwyn, 2017).

But what does the recent AI push mean for our education and training institutions and how do we reinforce the nexus between AI technology and teachers/trainers?

At itec, we believe that the future of AI in education and training lies at the intersection of human intelligence and technological intelligence. In this report, we want to further unravel this idea together with the reader. We call for a nuanced point-of-view in the AI debate, wherein machines empower educational stakeholders and vice versa, ultimately strengthening education together. To do so, it is important to acknowledge limitations and risks that come along the way.

In this report ***'AI in Education and Training'***, we provide insight into how AI in education is being researched at itec, an imec research group at KU Leuven, thereby contributing to the accelerating research domain of Artificial Intelligence in Education (AIED). This report is referred to as a 'positioning paper'. Its purpose is to illuminate the perspectives and efforts of our research group regarding the main subject of AI in education and training.

In part one, the report begins with an overview of the status, challenges and perspectives of AI in learning, teaching and training. summarizing findings and conclusions from the already wide-ranging field of AIED.

In part two, the different research expertises within itec are outlined to describe our current AI related research projects as well as the concrete use cases we are working on. The implications, recommendations and challenges for the future are brought together in an overall conclusion that can inspire future research and design efforts.

The contents of this first report of 2024 are not static, but can – and will – be dynamically updated over time, in tandem with the rapid revolutions within AI, new initiatives within the itec research group and shifts within the broader educational landscape. Updates regarding subsequent reports can be found on the website: www.kuleuven.be/itec .

If you want to learn more about the role of AI in education after reading this report, we warmly recommend our online e-learning environment launched by our team in January 2024. It is accessible to everyone for free after registration. You can find it on the aforementioned website, under 'AI training'. (https://kulak.kuleuven.be/e-learning-ai/register.php)

PART ONE

AI in learning, teaching and training: status, challenges and perspectives

1. Artificial Intelligence (AI) in learning, teaching & training: why should we consider it and what do we understand by it?

There is a growing interest in AI shared among educational researchers, policy stakeholders, and educational technology developers, both public and private (Maslej et al., 2023; Miao et al., 2021; U.S. Department of Education, 2023). This interest emanates from many presumed benefits. Studies concerning AI systems often indicate a positive impact on cognitive and non-cognitive learning outcomes (Holmes & Porayska-Pomsta, 2023; Zhang & Aslan, 2021; Zhai et al., 2021). Many praise AI for taking into account the heterogeneity of learners and their needs through appropriate technology-driven personalisation of exercises, scaffolds, or assessments (Holmes et al., 2019). Moving away from the traditional 'one-size-fits-all' learning approach, it is believed that AI tools hold the promise to remediate learning gaps, especially in the post-pandemic context (Breines & Gallagher, 2020; Knox, 2023; OECD, 2021; U.S. Department of Education, 2023; UNICEF, 2022; Zhai et al., 2021). Furthermore, AI is seen as a valuable means to provide ample support to teachers and trainers, for example through intelligent dashboards, making teaching and coaching more efficient (Breines & Gallagher, 2020; Knox, 2023; OECD, 2021; U.S. Department of Education, 2023; Zhai et al., 2021; Zhang & Aslan, 2021; Zimmerman, 2018). It is said that AI can take over routine tasks (e.g., automated grading and testing), allowing teachers and professors to focus on more personalized, didactic and emotional aspects of the learning process (Breines & Gallagher, 2020; U.S. Department of Education, 2023; Zimmerman, 2018). Considering such promising prospects, advocates predict that AI is bound to stay and may even change the educational ecosystem (Holmes et al., 2019; Holmes & Porayska-Pomsta, 2023; Knox, 2023; U.S. Department of Education, 2023).

Defining AI is a complex task (Holmes et al., 2022; Lameras, 2022; Luckin et al., 2016; Zimmerman, 2018). As Zimmerman (2018, p.2) explains: "Advances in AI raise the bar for AI, which makes it more difficult to pin down what counts as AI."

> In 2016, Luckin and Holmes (2016, p.14) defined AI from a technological and affordance point-of-view as:
> ***"Computer systems that have been designed to interact with the world through capabilities (for example, visual perception and speech recognition) and intelligent behaviours (for example, assessing the available information and then taking the most sensible action to achieve a stated goal) that we would think of as essentially human."***

> In 2021 a more systemic definition was put forward by UNICEF (p.16):
> ***"AI refers to machine-based systems that can, given a set of human-defined objectives, make predictions, recommendations, or decisions that influence real or virtual environments. AI systems interact with us and act on our environment, either directly or indirectly. Often, they appear to operate autonomously and can adapt their behavior by learning about the context."***

Holmes and colleagues (2022) believe this definition is noteworthy as it highlights the broader scope of AI and emphasizes that AI systems can and should not exist independently. It is noteworthy to state that AI is different from ***human intelligence***: AI systems do not "learn" in a manner comparable to humans and they lack emotional intelligence as well as consciousness (Holmes & Porayska-Pomsta, 2023). When human intelligence remains positioned at the core and is supplemented by AI, numerous authors refer to ***augmented intelligence*** (Holmes et al., 2019; Holmes & Porayska-Pomsta, 2023; Molenaar, 2022, U.S. Department of Education, 2023; Zheng et al., 2017).

When it comes to AI in learning, teaching, and training, technology and pedagogy are intertwined. However, both domains have their complexities. In the following section, we will briefly focus on the technology to gain a clear understanding of 'AI' within this paper. A plethora of different technologies and applications come together under the umbrella term of AI (Luckin et al., 2019; Luckin et al., 2016; Zimmerman, 2018). To clarify different conceptualisations (see figure 1, 2 and 3), it is best to start with the very basis of AI: ***algorithms***. These are computer programs made out of lines of code that render instructions to the computer (Holmes et al., 2019).

In the early days of AI, the primary focus was on pre-programmed algorithms that remained static (fixed set of rules, systems do not learn from new data) and were intended for specific, often repetitive tasks. As depicted by Figure 1, AI from that earlier era is referred to as **rule-based systems** (Holmes et al., 2019; Luckin et al., 2019; Miao et al., 2021; Miao & Shiohira, 2022; Zimmerman, 2018). **Expert systems** (around 80-90s) serve as excellent illustrations of a rule-based approach. The concept 'expert' refers to simulating the behavior of human experts. They consisted of computer programs operating on if-then rules and were often considered one of the first commercially deployable forms of AI (Buchanan & Smith, 1988).

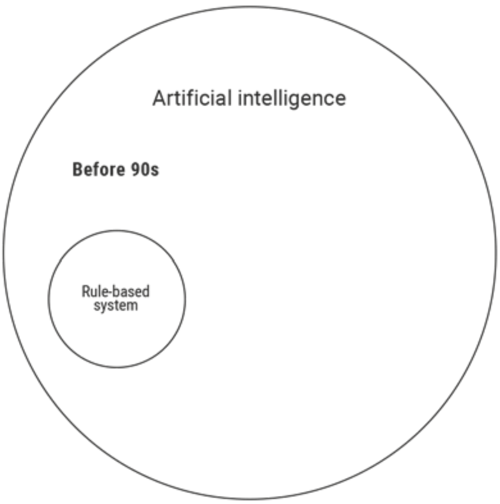

Figure 1: AI Before 90's - rule-based systems

In recent years, systems have become more dynamic (systems that are capable of adapting and learning from data) due to the improvement of engineered algorithms and computational power, but also the availability of more data. As depicted by Figure 2, This led to a gradual shift from rule-based AI to data-driven AI or **Machine Learning** (**ML**).

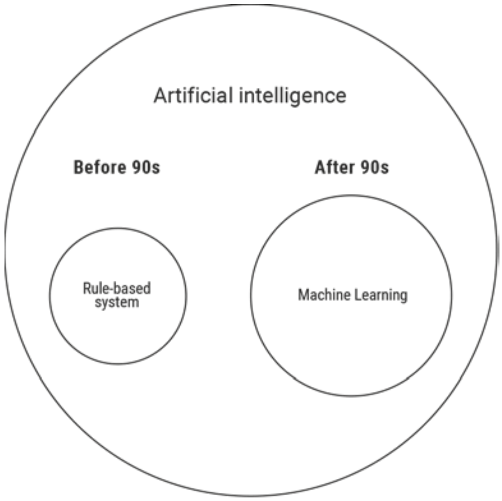

Figure 2: AI after 90s - Machine Learning

The difference with rule-based AI is that ML algorithms can gradually update themselves and enhance their accuracy as they learn from the data they are presented with (Holmes et al., 2019; Luckin et al., 2022; Miao et al., 2021; Zimmerman, 2018). Via ML algorithms, extensive data sets can be analyzed to identify patterns (for example: the visual characteristics of a dog) and even make predictions about new instances it has not previously encountered (for example: recognizing an animal as a dog, even if no expert has taught the machine before that the specific animal that is currently being presented is a dog) (Holmes et al., 2019; Miao et al., 2021; Zimmerman, 2018). As described by Miao and colleagues (2021), there are three main approaches when it comes to ML: (1) When the algorithm models are trained on labeled data to make predictions or discover patterns, which is referred to as ***Supervised Learning***. (2) ***Unsupervised Learning*** relates to algorithm models that find structure in unlabeled, often larger amounts of data (Miao et al., 2021; Miao & Shiohira, 2022). In the cases of supervised and unsupervised learning, the data is fixed in advance. If the data changes, analyses must be repeated. When the underlying models learn and update themselves over time – often based on initial human feedback – this is referred to as (3) ***reinforcement learning*** (Miao et al., 2021).

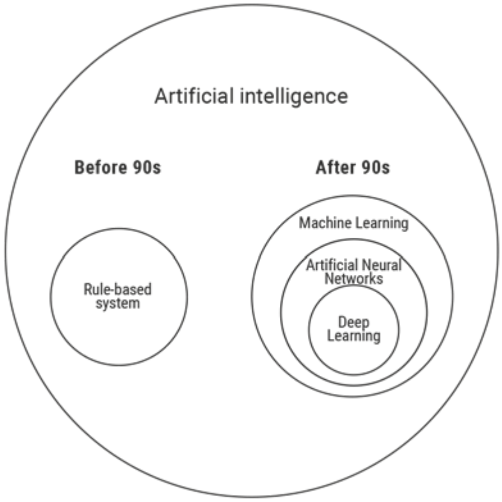

Figure 3: Specific branches of Machine Learning.

Figure 3 illustrates different branches of ML. One specific branch is ***Artificial Neural Networks***. This AI approach often entails three layers. The input layer, followed by a more "hidden" intermediary multilayered network of data structure, followed by an output layer. This approach can be used for classification, regression, pattern recognition, and more (Miao et al., 2021; Miao & Shiohira, 2022).

Another branch of ML which encompasses multiple intermediary layers of Artificial Neural Networks is called ***Deep Learning***, employed for elevated data analysis and processing. However, a challenge within the domain of deep learning lies in comprehending the operations within these multiple intermediary "hidden" layers, often described as a black box. Recently, a counter movement emerged advocating for ***Explainable AI (XAI)***: a technique that involves describing models and algorithms in a way that users can understand what happens behind the scenes and hence overcome distrust and make informed decisions (Rai, 2020).

In the strict divide between rule-based AI and ML outlined above, it's important to note a couple of nuances. It's not always the case that these exist entirely independently of each other. In various domains, tools are designed that leverage both rule-based AI and ML. For instance, data-driven AI is often complemented with logic to achieve better performance. Therefore, it's worth noting that the Figures (1, 2, and 3) serve as visual representations aimed at providing structure to a complex domain. However, it's important to bear in mind that these figures oversimplify in order to enhance clarity.

AI finds applications in various domains, including language processing, speech, and image recognition/processing (Miao et al., 2021; Miao & Shiohira, 2022). To enhance comprehension, other prevalent concepts are briefly touched upon. For example, within language processing, there exists a subdomain called ***Natural Language Processing (NLP)***, which focuses on algorithms to analyze and produce human language (Holmes et al., 2019; Miao et al., 2021; Miao & Shiohira, 2022). In the context of image applications, the subdomain ***Computer Vision*** focuses on the analysis and interpretation of visual information such as face recognition (Miao et al., 2021; Miao & Shiohira, 2022). Moving on from 'analyzing' to 'generating' , ***Generative AI (GenAI)***, refers to AI tools capable of generating new data, such as images, text, music, and videos (Miao & Holmes, 2023). A well-known example of a generative AI tool is ChatGPT (Miao & Holmes, 2023).

In this paper, we primarily report insights on AI in the context of education and training, also referred to as AIED (du Boulay, 2016; Luan et al., 2020; Tuomi, 2023). AIED was initially rooted in computer science, but later merged with educational sciences. As a distinctive research domain, the focus now encompasses diverse educational and training settings, reflecting broader perspectives on AI in learning environments including formal learning as well as lifelong learning. With an increasing interest in AI within the field of education, many new research initiatives emerge such as critical reflections on traditional educational objectives, the exploration of ethical, technical and implementation challenges as well as the design and development of new algorithms to further enhance the field (Luan et al., 2020; Tuomi, 2023). In sum, AIED is a very broad domain that focuses on a variety of AI systems and examines their potential impact on everyday teaching, training and learning practices (du Boulay, 2016; Holmes et al., 2019; Luckin et al., 2016; Zhang & Aslan, 2021).

2. AI in education and training: a brief history

AI has already played a significant role in education and training for quite some time (Holmes et al., 2019; Lameras, 2022; Luckin et al., 2022; Miao et al., 2021; Miao & Shiohira, 2022; Tahiru, 2021; U.S. Department of Education, 2023). While John McCarthy, an American computer scientist, first introduced the concept of AI during a 1955 Dartmouth College workshop, AI finds roots in education and training even further back in time (Knox, 2023; Miao et al., 2021; Tahiru, 2021). Early initiatives started around the 1920s, when researchers experimented with personalized learning. Noteworthy outcomes of these early efforts were the teaching machines (see Sidney Pressey around 1920 and Skinner around 1930), which were grounded in the science of behaviorism (Skinner, 1958). While mechanical in nature and non-digital, their design was compatible with the if/then-logic that is typically used in computer algorithms. Skinner claimed that his teaching machines would allow learners to progress through the learning process at their own pace (Skinner, 1958). The impact of the teaching machines was mostly found in the academic field as many educational scientists could easily imagine the opportunities programmed learning would bring, soon leading the topic to be hyped immensely (Holmes et al., 2019; Tuomi, 2023). As Tuomi, 2023 (p.1) describes it most eloquently: "Data-driven AI stands on the shoulders of Skinner".

Another important character within the history of AI is the English mathematician Alan Turing who wrote a paper called 'Computing Machinery and Intelligence' (Turing, 1950). He posed one central question: can machines think? As thinking is a difficult concept to grasp, Turing developed a test called the imitation game – later to be known as the Turing test – in which a person was challenged with the task to distinguish a machine from a human simply through the use of conversation (Holmes et al., 2019; Lameras, 2022; Miao et al., 2021; Zhang & Aslan, 2021; Zimmerman, 2018). Turing believed that around 2000 the distinction between human and machine could no longer be made (Holmes et al., 2019, 2022; Zimmerman, 2018). With ChatGPT's 3.5 version launching in 2022, Turing's prediction seemed one step closer to being realized.

As it goes with every promising technological innovation, AI was expected to transform the educational and training context in ways that were never seen before. With governments quick to provide funding, lots of research was conducted in the field during those early years (Breines & Gallagher, 2020; Holmes et al., 2019). From the 60s until the 70s, several educational technologies were invented. For example, the University of Illinois launched a computer-based system for programmed and automated instruction called PLATO that would later become an online community avant la lettre (Smith & Sherwood, 1976).

Between 1990 and 2000, computing power grew spectacularly which led to a new era of expectations for AI. High-performance computers allowed the analysis of large datasets, unveiling complex patterns that previously remained hidden. Technological advancements enabled a shift from simple, old-fashioned rule based AI to a self-learning systematic approach of deep learning AI. With the emergence of ML, e-learning tools and intelligent tutoring systems could meet learners' needs in a more advanced way (Holmes et al., 2019)

From 2000 to 2020 and beyond, AI in education experienced significant growth. Today, AI is increasingly embedded in numerous types of educational technologies, which were designed and developed to support and enhance the educational process (U.S. Department of Education, 2023; Miao & Shiohira, 2022). The release of certain AI tools was groundbreaking, with ChatGPT as the primary example. It was released by OpenAI on November 30, 2022 and played a pivotal role in advancing the discussion of AI in education and training.

3. Putting to use AI in the current context of education and training

While AI in formal education and professional training was once perceived as belonging to a distant future, it is now undeniably becoming a reality (Holmes et al., 2019; Knox, 2023; Lameras, 2022; Miao & Shiohira, 2022; Nowotny, 2021; Selwyn, 2019; U.S. Department of Education, 2023). According to Holmes and colleagues (2022), there are four key perspectives between AI and the broader educational field (K12 and higher education, lifelong learning/training, on the-job learning/training, formal and informal professionalization initiatives…): (1) preparing for the AI driven future, (2) learning about AI, (3) learning and training with AI and (4) the use of AI to learn about learning and training.

First, an important aspect of AI in education is ***preparing learners for the impact of AI*** on our daily lives. This involves learning about the opportunities that AI presents, while also considering the challenges, implications and risks it involves (Luckin et al., 2022; Miao & Shiohira, 2022). The ability to make informed decisions and engage in critical reflections concerning the evolving AI technology is also referred to as 'AI Literacy' (Luckin et al., 2022; Miao et al., 2021). In line with this, the U.S. Department of Education (2023) advocates a strong focus on integrating AI literacy comprehensively, empowering individuals to effectively interact with and use AI. A second essential aspect is ***learning about*** *AI*, including understanding AI techniques, models and algorithms (Zhai et al., 2021; U.S. Department of Education, 2023; Miao & Shiohira, 2022). Such AI understanding serves as a strong foundation for learners and trainees to develop skills in areas like data analysis, problem-solving and computational thinking, all of which are considered skills needed for the 21st century (Lameras, 2022; U.S. Department of Education, 2023; Luckin et al., 2016).

A third dimension involves ***learning with AI***, where AI tools facilitate personalized learning experiences (Lameras, 2022; Luckin et al., 2016; Luckin et al., 2022; Miao & Shiohira, 2022; Zimmerman, 2018). These tools include for example intelligent tutor systems, chatbots, immersive simulations with personalized feedback and assistive technologies that were specifically developed to support learners or trainees with disabilities or learning difficulties. From the perspective of teachers, trainers and school administrators as well as policymakers, AI can also alleviate administrative tasks, such as planning, scheduling, and communication (Miao & Shiohira, 2022; U.S. Department of Education, 2023; Luckin et al., 2016).

Connected with the third dimension, the fourth dimension involves ***the use of AI to gain insights into the learning progress***. Through dashboards, valuable insights about the learning process can be obtained, serving as a complementary source to teachers' and trainers' observations. Dashboards facilitate the collection, measurement, analysis, and reporting of learner data via learning analytics. In doing so, it aims to understand and improve the learning experience (Holstein et al., 2020). For example, teachers/trainers can identify at-risk learners/trainees and provide timely data-informed interventions (Luckin et al., 2016; Luckin et al., 2022; U.S. Department of Education, 2023; Zimmerman, 2018). By applying AI methods, the identification of patterns and trends within large datasets becomes feasible, particularly in higher education where thousands of learners may enroll in the same course (Luckin et al., 2016; Luckin et al., 2022; Zimmerman, 2018). Additionally, some AI tools encompass dashboards that provide guidance, recommendations, and actionable insights. Furthermore, routine tasks and basic activities can be delegated to AI tools, enabling educators to focus on areas where human interactions, empathy, and socio-emotional skills remain irreplaceable (Luckin et al., 2016; Luckin et al., 2022; U.S. Department of Education, 2023; Zimmerman, 2018).

These four key perspectives illustrate how AI can contribute to modern education, training and work. However, it should be noted that AI's role extends further. As Luckin and colleagues (2022) describe, the implementation of AI in education should not be narrowed down to the adoption of AI technology in an educational context of immediate teacher-learner interactions. It extends to the broader idea of implementing AI to empower the educational ecosystem as a whole (Luckin et al., 2022).

4. AIED Applications: from a global taxonomy to concrete cases

Over the years, numerous AI applications (e.g., intelligent tutor systems, simulations, chatbots, …) have entered the educational field (Breines & Gallagher, 2020; Holmes et al., 2019; Holmes & Porayska-Pomsta, 2023; Knox, 2023; Luckin et al., 2016; Zhang & Aslan, 2021; Zimmerman, 2018). To get a grip on the great variety, many authors developed different frameworks. For example, Holmes and Tuomi (2022) developed a taxonomy of AIED systems (see Figure 4). They distinguish three different categories:

1. Student-focused AIED. This category includes AI systems specifically designed and developed to support students and their learning process.
2. Teacher-focused AIED. This category includes AI systems specifically designed and developed to support teachers in various processes, from assessment to management.
3. Institution-focused AIED. This category includes AI systems specifically designed and developed to perform administrative and management-related tasks on institution level.

Within these three categories, they describe various AI applications that are speculated, researched, or available in the current AIED debate. A note on the taxonomy is that the described tools may not be fully integrated in education and training, or might even be considered controversial such as tools for admission (Holmes and Tuomi, 2022).

Student-focused AIED
Intelligent Tutoring Systems (ITS), AI assisted Apps (e.g., math, text-to-speech, language learning, AI assisted Simulation (e.g., games-based learning, VR, AR), AI to support Learners with Disabilities, Automatic Essay Writing (AEW), Chatbots, Automatic Formative Assessment (AFA), Learning Network Orchestrators, Dialogue-based Tutoring Systems (DBTS), Exploratory Learning Environments (ELE), AI assisted Lifelong Learning Assistant
Teacher-focused AIED
Plagiarism detection, Smart Curation of Learning Materials, Classroom Monitoring, Automatic Summative Assessment, AI Teaching Assistant (including assessment assistant), Classroom Orchestratio
Institution-focused AIED
Admission (e.g., student selection), Course-planning, Scheduling, Timetabling, School Security, Identifying Dropouts and Students at risk, e-Proctoring

Figure 4: Refinement of the AIED systems taxonomy

In what follows, three examples from within this taxonomy – also widely researched within itec – will be explored to illustrate the possibilities and outcomes they can yield in education and training: (1) chatbots, (2) digital personalized learning tools and (3) learning analytics tools. Note that 'Digital Personalized Learning (DPL) tools' and 'learning analytics tools' as concepts are not explicitly included in Holmes and Tuomi's taxonomy. However, as Holmes and Tuomi acknowledge, reality is more intricate than any framework can encompass. While the concepts align with concepts from the framework such as 'intelligent tutor system' and 'classroom monitoring', we focus on a broader scope. Therefore, we have chosen the terms DPL tools and learning analytics tools. Another note is that, within these three examples, we only focus on the learner- and teacher-focus AIED. At itec, one of our main aims is to empower both the teachers/trainers and learners. With research regarding chatbots and DPL tools, we highlight one perspective of learning: from the student to the teacher. With research on learning analytics tools, we highlight another perspective of learning: from teacher to student. Hence, we do not cover an example of institution-focused AIED.

It is important to note that tools within the taxonomy of Holmes and Tuomi (2022) are not exhaustive; they merely serve as a set of examples. It is also noteworthy that here may be overlap within these categories. For instance, there are chatbots equipped with adaptivity features and dashboards with built-in chatbot functionalities.

4.1 | Chatbots

Chatbots are designed and developed to imitate human conversations. These systems receive human input through text or voice commands which require clear prompts. Chatbot systems are often powered by NLP machine learning algorithms to determine what to say, and how to say it. Initially, chatbots found their primary use in specific contexts like customer service chats for businesses (Zimmerman, 2018). However, there's a growing trend of deploying chatbots in broader contexts, including education and training. They can be used for conversational practice in a foreign language, assessment of writing, development of (critical) information literacy skills, ... An illustrative example of a chatbot is ChatGPT, which gained significant attention upon the release of its 3.5 version in late 2022 (Miao & Holmes, 2023; Vaswani et al., 2017). Some view ChatGPT as a disruptive change within education and training, others may have different views on its innovative potential. For instance, the digital personalized learning platform Khan Academy recently incorporated an AI tutor featuring GPT-4 (Khan Academy, 2023).

Thanks to the advancement of chatbots, opportunities arise to utilize them for language development, communication skills, and open-ended tasks. This leads to more powerful learning environments, particularly in complex domains like communicative language learning. For instance, chatbots allow to tackle one of the main challenges in second language acquisition and language learning: the training of open-ended communicative tasks (Bibauw et al., 2022a; Bibauw et al., 2022b).

4.2 | Digital personalized learning tools

Digital personalized learning (DPL) is part of a research field that is both old and recently established (du Boulay, 2019). In today's society, the demand for personalized learning is ever-present (Groff, 2017; Lee et al., 2022; National research council, 2011; Schmid et al., 2022). Heterogeneity of class groups increases and brings forth great diversity in learners' background, knowledge, interest and abilities (Deunk et al., 2015; OECD, 2021). Teachers are expected to be perceptive and responsive to these differences by providing personalized goals for every learner and adjusting teaching practices accordingly (Deunk, et al., 2015; Grant & Basye, 2014). However, due to time constraints, it is not always feasible for teachers to facilitate personalized learning (Holmes et al., 2018). In this regard, the interest in personalization shares a reciprocal relationship with the growing digitisation (Baker, 2021; Major & Francis, 2020; Molenaar, 2021; Plass & Pawar, 2020; Schmid et al., 2022). Many AI tools have surfaced, which create opportunities to personalize learning (U.S. Department of Education, 2023; Luckin et al., 2016; Zhang & Aslan, 2021). These tools are often referred to as 'adaptive', 'intelligent', 'personalized' or 'individualized' (Van Schoors, 2021). Based on a systematic review, Van Schoors and colleagues (2021, p.19) define digital personalized learning as follows:

> ***"Unlike conventional learning, digital personalized learning (DPL) takes place in a digital learning environment that adapts to the individual learner in function of optimizing individual and/or collaborative learning processes focussing on cognitive, non-cognitive and/or efficiency outcomes. Adaptations: (1) can take into account cognitive and non-cognitive characteristics of the learner; (2) can relate to all aspects of the learning environment, more specifically the (nature, number, and sequence of) learning tasks, the content as well as the instruction and support provided by the learning environment; (3) can be the result of information provided by the teacher or the learner himself/herself, but also information collected by the digital environment; and (4) can be enhanced by the teacher through the effective use of data derived from DPL tools."***

This definition is based on earlier published work within itec by Vandewaetere & Clarebout (2014), who developed a typology to describe adaptivity. The scholars focus on four elements: *(1) Source:* the source of adaptation can be either based on learner parameters or learner-system parameters. *(2) Target:* Three possible targets can be the content (e.g., difficulty level of tasks), the presentation (e.g., hiding or highlighting elements) and the support or instruction (e.g., increasing/decreasing direct guidance). *(3) Method:* the method of adaptation refers to how the adaptation is carried out. They distinguish between learner-, program- and shared- control (combination of program and learner), *(4) Time:* The time of adaptation refers to the moment that the adaptation takes place. Three possible moments can be distinguished: before interaction with the system (static), during interaction with the system (dynamic) and a combination of both (dual pathway).

In sum, DPL encompasses a broad range of tools designed to recognize both the unique needs of learners and the variations among them (U.S. Department of Education, 2023). AI algorithms can assess individual learners' strengths and weaknesses, delivering adaptive and personalized content (Luckin et al., 2016). As the U.S. Department of Education (2023, p.18) describes it, "AI can be an especially strong toolkit for expanding the adaptivity provided to students."

4.3 | Learning analytics tools

Some technologies include learning analytics. They measure, aggregate, analyze and visualize learner data (Maseleno et al., 2018; Schwendimann et al., 2017; Teasley, 2017). Such visualizations are generally presented through real-time visual interfaces, also called data visualization tools or dashboards. Specific learning activities are displayed in a meaningful way through graphs, gauges or maps (Schwendimann et al., 2017). Examples of data visualizations are completed learning content/exercises, amount of time spent on learning content/exercises, results on exercises/tests, analyses of failed tasks, progress over months/weeks/years, feedback from the system and/or the teacher, achieved goals and agendas with personal schedules or deadlines (Maseleno et al., 2018; Schwendimann et al., 2017; Teasley, 2017).

Teacher dashboards, or dashboards designed for teachers, serve multiple purposes such as creating awareness, facilitating data-informed reflection, and supporting evidence-based decision-making related to classroom management and instruction. Additionally, learner dashboards aim to empower learners by providing insights into their own learning processes, ultimately enhancing engagement and self-regulation (Knoop-van Campen & Molenaar, 2020; Luckin et al., 2016; Maseleno et al., 2018; Miao et al., 2021; Schwendimann et al., 2017; Teasley, 2017).

Recently, there is evolution in LA, as well as in the type of data we analyze. More dashboards provide not only descriptive (reporting on what happened) but also predictive (reporting on what will happen) and even prescriptive (reporting on what should be done) information. For example, a relevant research avenue is the investigation of tools that incorporate prescriptive learner feedback (e.g., remedial advice or human-readable prescriptive feedback as referred to by Susnjak (2022)) instead of automated or descriptive learner feedback. Van Leeuwen and Rummel (2020) discuss the benefits of DPL tools comprising teacher dashboards that not only provide information (mirror) but also alert the teacher to groups in need of support (advising). To establish such advanced feedback, more sophisticated learning analytics are needed (Baker, 2016; Groff, 2017; King et al., 2016; Susnjak, 2022).

Another example of advanced LA is that in higher education parameters can be selected to identify learners that are at risk of dropping out of a course (Chen et al., 2020). An example includes the work of Van Petegem and colleagues (2022), who investigated pass/fail predictions in a programming environment through measurements of data on learner behavior. In doing so, analytics identify at-risk learners early on in the semester. Van Petegem and colleagues (2022) argue that there are benefits (timely remediation, deeper insight into the learning process of learners), yet they also raise some questions that need to be considered (if and how should such information be communicated to learners, risk of negative influence on learners' motivation, risk on errors in the systems' algorithm…).

Data forms the central focus of AI, with current technologies allowing for rapid real-time collection and processing of extensive and diverse datasets (Luan et al., 2020). Various algorithms enable the transformation of raw data into refined and understandable data by facilitating both data gathering and analysis. This process, in turn, leads to the generation of knowledge (Luckin et al., 2016). For example, visualized data can serve as the foundation for pedagogical actions (Cukurova et al., 2019; Luan et al., 2020; Luckin et al., 2016; U.S. Department of Education, 2023). There are many algorithms and techniques used in AIED tools. Notable examples are DKT (deep knowledge tracing) to evaluate and predict learners' progress with deep learning techniques, matrix factorization techniques underlying recommender systems, ML-based survival analysis to predict dropout, and many more.

Through such algorithms and techniques, it is possible to examine complex variables (such as learners' proficiency, motivation, anxiety, engagement, etc.), their evolution, and suggest effective instructional interventions. To do so, the use of ***multimodal data*** analysis is increasingly being employed (Cukurova et al., 2019). Multimodal data refers to the integration of various types of data sources to obtain a more comprehensive understanding of complex realities. The data sources rely on different modalities, such as textual data, visual materials, audio recordings, sensor data, and so on (U.S. Department of Education, 2023; Cukurova et al., 2019). To gather multimodal data, a range of diverse technologies can be utilized such as wearable devices or eye tracking (Cukurova et al., 2019). One notable benefit of collecting data through these technologies is the ability to do so unobtrusively. This type of data collection is commonly known as unobtrusive data collection. By combining multiple types of data, models and algorithms can achieve higher levels of accuracy compared to using only one type of data (Cukurova et al., 2019). This can lead to an augmentation of human intelligence. Based on different data sources, teachers can make more well-informed decisions, enhance reflections, and provide substantiated assessments and feedback (Cukurova et al., 2019).

5. Challenges and implications: towards trustworthy AI

Notwithstanding the wide array of expected benefits, successful implementation of AI in education and training can be more challenging than expected (Luckin et al., 2016; Tahiru, 2021; U.S. Department of Education, 2023; Zhai et al., 2021). To obtain trustworthy AI, it remains essential to conscientiously, methodically, and securely evaluate every AI application before its implementation in education, prioritizing social and educational benefits (Luckin et al., 2022; Nowotny, 2021). Evidence shows that teachers' and trainers' trust in technology can influence the implementation process (Holmes & Tuomi, 2022; Ertmer & Ottenbreit-Leftwich, 2010; Kim et al., 2013; Vanderlinde & Van Braak, 2010). To foster trustworthy AI it is crucial to acknowledge not only the potential, but also the challenges and constraints that come along with AI in education and training (Nazaretsky et al., 2022; Vereschak et al., 2021).

Therefore, in the subsequent section, we will discuss three categories of challenges related to trustworthy AI: (1) technological challenges, (2) ethical and legal challenges, and (3) educational challenges. It is worth noting that these challenges are not exhaustive, as there are numerous other challenges that do not fall within the scope of this paper (e.g., ecological challenges linked to sustainability issues). Moreover, most challenges are interconnected. For instance, technological challenges may cause ethical dilemmas.

5.1. | Technological challenges

Hindrances can be situated at the technological level. Concerning ***software***, it is common that the inner workings of AI systems remain largely invisible (Rai, 2020). This lack of transparency can make it difficult to interpret how an AI system arrived at a specific conclusion. Furthermore, it is essential to keep in mind that the data used in AIED applications are prone to contamination, inaccuracies, or incompleteness due to sparse or erroneous inputs (Kolchenko, 2018; Miao & Holmes, 2023; Tahiru, 2021). For instance, learners who work at a higher pace deliver more data, which makes the algorithm smarter. The opposite happens for learners who have a slower learning pace, as the algorithms generate less suitable data to enhance the personalisation of learning experiences (Kolchenko, 2018). The imbalance in the dataset due to learning pace also creates risks of bias (see further 6.2.2).

Furthermore, it should be noted that models can only offer an approximation of reality and may not provide an accurate fit (U.S. Department of Education, 2023). This challenge is exacerbated by the fact that the majority of AI technologies presently employed in education lean towards rule-based systems, lacking dynamic adaptability (Baker, 2016; Groff, 2017; Murphy, 2019; Van Schoors, 2021). As a consequence, numerous tools continue to overlook learners' strengths, weaknesses, and contextual factors, thus failing to holistically adapt learning experiences to individual learner needs (Baker, 2016; Basham et al., 2016; Kolchenko, 2018). Limitations persist, such as difficulties in comprehending commands or inaccuracies in responding to queries. For example, facial recognition misinterprets a smile as frustration, leading to learners receiving exercises that may not align with their actual requirements (Zimmerman, 2018).

In addition to software, there are also some challenges related to the ***hardware*** of AI systems. Many schools lack the necessary technological infrastructure to fully embrace AI in education, a contrast to the sophisticated tools found in research settings (Baker, 2016; Zimmerman, 2018). For instance, as Baker (2016, p. 601) states: "there is a disconnect between the vision of what intelligent tutoring systems could be, and what they are; a disconnect between the most impressive examples of what intelligent tutors can do, and what current systems used at scale do." In this respect, Zimmerman (2018) stresses that – while in absence of state-of-the-art technology – learners can already be prepared by engaging in discussions about ethical and privacy-related aspects.

5.2. | Ethical and legal challenges

In addition to technical challenges, there are numerous ethical challenges associated with the use of and trust in AI systems in education (Miao & Holmes, 2023; Zimmerman, 2018). In the following section, three ethical challenges will be discussed: (1) the impact of inaccurate information, (2) bias and (3) privacy. Again, it should be noted that there are many more ethical challenges, such as plagiarism, integrity and so on.

As it is widely known, AI systems can generate inaccurate information (U.S. Department of Education, 2023). For instance, chatbots can provide information that sounds plausible but is factually incorrect upon closer examination, also known as 'hallucinating' (Miao & Holmes, 2023). Additionally, misinformation output can result from erroneous data (Kolchenko, 2018; Miao et al., 2021; Tahiru, 2021; U.S. Department of Education, 2023). Despite the risk of misleading information, AI systems often have a persuasive nature due to their sophisticated human-like design, which can influence both teachers and learners (Holmes & Porayska-Pomsta, 2023; U.S. Department of Education, 2023). Hence, a central ethical question arises concerning the extent to which AI should be allowed to impact teaching and learning (U.S. Department of Education, 2023). For example, in case of predictive analytics that identify at-risk learners early on in the semester, the question could be posed if and how such information should be communicated to learners. Not only the risk of negatively influencing learners' motivation should be mitigated but even more so the risk of errors in the systems' algorithm should be considered (U.S. Department of Education, 2023; Van Petegem et al., 2022). Recognizing the significance of this ethical issue, various calls to action have emerged, including initiatives at our own university of KU Leuven, such as the Open Letter addressing 'Manipulative AI' (Smuha et al., 2023). This letter sheds light on the ethical concerns surrounding AI technology, emphasizing the need for accountability and trustworthy systems, as stated: "The AI playtime is over: it's time to draw lessons and take responsibility" (Smuha et al. 2023).

5.2.1 Bias

As described by the UN (2015), an important sustainable development goal is the pursuit of quality in education. This encompasses equal access to high-quality education and promoting lifelong learning opportunities for every learner. However, the emergence of AI introduces certain ethical challenges (Miao et al., 2021; U.S. Department of Education, 2023).

Many AI systems are inherently biased, which can aggravate discrimination, widen inequalities, or preserve injustices such as racism and sexism (Holmes & Porayska-Pomsta, 2023; U.S. Department of Education, 2023). Bias in AI can manifest in various ways. Holmes and colleagues (2022) raise the issue of historical inequalities being embedded in training data, which can lead to algorithmic decisions perpetuating discrimination, for example related to gender (Holmes et al. 2022; Miao et al., 2021; U.S. Department of Education, 2023). Zimmerman (2018) points out that minority groups are often uninvolved in developmental or design cycli. Furthermore, big data and machine learning are not flawless. Take for example an algorithm that fails to recognize African-American faces, resulting in discriminatory outcomes. Gender neutrality in AI also remains a concern, as the industry is still predominantly male-dominated (Holmes et al., 2022; Zimmerman, 2018). Another ethical concern, described by Reich (2020), is the 'EdTech Matthew Effect,' which implies that new technologies disproportionately benefit already affluent learners. Therefore, involvement and pedagogical responsiveness of teachers remains of utmost importance so that the risk of extrapolating underrepresented (offline) learners is mitigated (Holmes & Porayska-Pomsta, 2023).

In summary, when implementing AI in education, careful consideration is essential to ensure equitable access while avoiding biases, stigmatization, or harmful stereotypes. Overlooking these aspects can unintentionally worsen existing inequalities. Since eliminating bias in AI is not always achievable, it is critical that we evaluate how AI might affect our learners (U.S. Department of Education, 2023; Zimmerman, 2018).

5.2.2 Privacy

With regard to rights, rules and regulations, it is evident that AI learning applications aiming to offer any level of adaptivity must necessarily capture and use personal data (Holmes et al., 2019; Nowotny, 2021). Such an inevitable reliance on data collection poses an ongoing challenge for anyone involved in education to search for the optimal balance between personalization on the one hand and privacy on the other hand (Holmes et al., 2019; Nowotny, 2021). Policy makers, tool providers, school leaders, teachers, learners and their parents all need to be aware of the potential risks and take proactive measures to address them. Consequently, AI introduces new challenges concerning data access and privacy (Holmes et al., 2019; Luckin et al., 2016; Miao et al., 2021; Nowotny, 2021; U.S. Department of Education, 2023). As AI systems not only capture personal data, but also detailed information of individual learners' learning process, transparency is imperative in this context (U.S. Department of Education, 2023). Additionally, it is crucial to ensure that this data remains safeguarded against unauthorized access and misuse (Miao et al., 2021).

To address ethical and legal concerns, a clear and urgent need for a comprehensive legal framework emerged (U.S. Department of Education, 2023). In December 2023, the EU finalized the AI Act, which provides clear guidelines and rules for trustworthy AI, aimed at minimizing risks to individuals and society. This framework, in addition to the General Data Protection Regulation (GDPR), aims to regulate AI technology's development and deployment. Furthermore, it should ensure the protection of human decision-making and judgment, maintain data quality for the accurate functioning of AI systems, investigate their impact on equity, and mitigate associated risks. Therefore, the AI Act foresees transparency requirements and classifies applications based on the risks they pose to citizens, with stricter rules for higher potential impact.

> *"The AI Act is a global first. A unique legal framework for the development of AI you can trust. And for the safety and fundamental rights of people and businesses. A commitment we took in our political guidelines - and we delivered. I welcome today's political agreement."*
> (Platform X - Ursula von der Leyen, European Commission President).

Next to the need for legal frameworks, it is equally important to acknowledge the Digital Divide, which implies that many people are unable to comprehend the complexity of AI technology and associated risks. Therefore, basic data literacy becomes essential to recognize and address in compulsory education (Luckin et al., 2022; U.S. Department of Education, 2023).

5.3. | Educational challenges

In addition to the many problems at level of the technologies and tools, some issues are situated at the level of context (school, teacher and learner related) which is linked to important preconditions of successful adoption (Christodoulou, 2020; FitzGerald et al., 2018; Salomon, 2002). It is important to approach implementation thoughtfully rather than rushing into it, as emphasized by the UK government's AI council (Luckin et al., 2022). A clear example is the 2020 grading fiasco which occurred during the COVID-pandemic: algorithms were used to decide on students' A level grades while the exams itself were canceled. It was unclear how these grades were calculated and widespread controversy resulted in numerous protests pointing out unfairness and inaccuracy. This event brought negative attention to algorithmic decision-making, leading to skepticism about solely relying on AI in decisive matters within education (Luckin et al., 2022).

One question in this respect, is the role AI should play in education (Miao et al., 2021; Zimmerman, 2018). Many aspects of teaching and learning can be augmented by AI, yet our current educational system often falls short in this regard, treating AI as a threat instead (Selwyn, 2019; Zimmerman, 2018). As Kent & du Boulay (2022, p.7) describe it: "The sweet spot in AI system design is the moment at which AI systems stop mimicking humans and take advantage of how different the unfair advantages of humans and AI are."

This issue should be addressed by educational policy stakeholders (Selwyn, 2019). For example, the International Society for Technology in Education (ISTE) has taken steps to support educators in the integration of AI. They have developed new guidelines to help educators make informed choices about how to use AI and what learners should learn in this new AI era (Zimmerman, 2018). Next to educational policy stakeholders, research should also reflect on the design and efficacy of AI tools, as well as inform the teachers about this (Selwyn, 2019; Zimmerman, 2018). Another question is whether the existing educational curriculum should be reevaluated. As Holmes and colleagues (2019, p.3) state: "if you can search, or have an intelligent agent find anything, why learn anything?". Reflection is needed on the extent to which certain aspects of current jobs may potentially be automated by algorithms (Holmes et al., 2019).

In education and training, two stakeholders may influence the implementation of AI: teachers/trainers and learners. One of the teacher/trainer-related issues is that the use and integration of tools can be hampered by negative teacher/trainer perceptions such as distrust or frustration (e.g., as a result of non-useful and non-user-friendly tools) or shortcoming of teacher/trainer knowledge as a result of limited professional development (Davis, 1989; Ferede et al., 2022; Vanderlinde & Van Braak, 2010). As a result, their initial implementation approach (e.g., overreliance) can have a negative impact on the eventual impact of the tool (Nowotny, 2021; U.S. Department of Education, 2023; Zhai et al., 2021). Learner-related issues can be, for example, insufficient ICT skills that hamper independent use of technology (Christodoulou, 2020; Reich, 2020). Another learner-related issue is the induced cognitive load inherent to using digital tools (Christodoulou, 2020).

To engage both teachers/trainers and learners in the implementation challenge, an emphasis on trust and agency is needed (Brod et al., 2023; Holmes et al., 2019). As Nowotny (2021, p.1) states: "There are widespread feelings of ambivalence: we trust AI as a bet on our future, but we also realize that there are reasons for distrust". To enhance trust, Brod and colleagues (2023) advocate for enhancing teachers'/trainers' and learners' agency, which involves granting them a sense of control and active involvement. Related to this, teachers/trainers and learners should have more influence over personalization efforts (Van Schoors, 2020) as well as data processing (Brod et al., 2023).

6. Perspectives on the future of AI in education and training

Reflecting on a future vision for AI in education and training is not straightforward due to the constantly shifting landscape of AI hypes and winters. The **enthusiasts** about AI's potential in education and training believe it will have a pivotal role. Per contra, **skeptics** point out various challenges (including technical, ethical, and implementation issues as previously described) which temper optimistic claims. In the final section of this literature review, we aim to provide insights into the beliefs of both enthusiasts and skeptics. Taking into account both perspectives, we introduce an alternative approach to reflect on the future of AI in education and training. In doing so, we contemplate (1) the role of the teacher, as well as (2) the collaboration among educational stakeholders, to ensure a sustainable implementation of AI in education and training.

6.1. | The perspective of the advocates: "the replacement movement"

During the COVID-19 pandemic, in which large numbers of schools and training institutions made a rapid shift to hybrid learning and online education, a "technology push" occurred in which technological tools became necessary to continue the learning process (Holmes et al., 2019). Enthusiasts pushed the naive idea that technology could be a solution to many education-related problems, such as teacher shortages and addressing differences between learners. In this respect, many enthusiasts praise AI for its ability to take into account individual needs of learners through technology-driven personalization of exercises, scaffolding, assessments, and more (Breines & Gallagher, 2020; Holmes & Porayska-Pomsta, 2023; Knox, 2023; U.S. Department of Education, 2023; UNICEF, 2022; Zhai et al., 2021). Additionally, it holds potential for assisting teachers in various tasks, including planning, monitoring, coaching, designing, orchestrating, and consolidating personalized learning experiences tailored to learners' needs (FitzGerald et al., 2018; Grant & Basye, 2014; OECD, 2021).

> As described by Roberts-Mahoney and colleagues (2016, p.405):
> ***"Advanced by powerful venture philanthropies, educational technology companies, and policy-makers, it is suggested that big data, cloud computing, learning analytic software, and adaptive learning systems hold the potential to fundamentally 'reinvent education for the twenty-first century' through the 'customization of education' and the 'personalization of teaching and learning."***

Some proponents even argue that AI has the potential to completely replace teachers in the future, thanks to its ability to emulate the expertise of any subject matter specialist. This perspective has given rise to a "replacement movement", as described by Molenaar (2022). Neil Selwyn (2019) conceptualized such an approach of substituting teachers by tools as "Technological Singularity". In short, technological singularity is a hypothetical scenario in which artificial intelligence develops itself to such an extent that it surpasses human understanding and control, resulting in a potentially unpredictable and uncontrollable future.

6.2. | The perspective of the skeptics: "the banning movement"

The replacement movement was countered by a disillusionment, as skeptics not only unraveled many implementation challenges but also stated that DPL is not suitable as a standalone tutor (Miao et al., 2021; Molenaar, 2022; Zhai et al., 2021). As FitzGerald and colleagues (2018, p. 1) state: "For many people, personalized learning is an ambiguous and even loaded term that promises much but does not always deliver." Reasons can be found on various levels, for example on tool-level (e.g., failing algorithms, poor personalisation) and context-level concerning the school, teachers and students (e.g., unreliable infrastructure, negative teacher perceptions, limited ICT skills) are identified by skeptics (Bulger, 2016; Groff, 2017).

Due to the many risks and challenges involved, some skeptics advocate for the banning of AI in education (Kishore et al., 2023). This stance is often referred to as the 'banning' movement. However, the decision to ban AI is not straightforward. It requires careful consideration concerning the balance between embracing innovation and preparing for it, while also addressing the risks of misuse and abuse (Kishore et al., 2023).

Failing to adequately address AI-related challenges can result in unrealistic promises which could lead to disappointment and subsequent integration failures (Christodoulou, 2020; Reich, 2020). Miao and colleagues (2021) urge caution in the face of overly optimistic assertions by advocates, particularly the belief that AI will one day exceed human intelligence. This caution is particularly relevant in the field of education, where the role of human tutors remains indispensable (Zimmerman, 2018).

6.3. | A future perspective: "the augmentation movement"

Today, a new enlightenment can be noticed in prevailing AI research – also referred to as the augmentation movement – in which the focus is examining if and how AI tools can augment teachers while also recognizing the complexity of AI (Holmes & Tuomi, 2022; Molenaar, 2022). In light of the augmentation movement, it is important to examine an innovation by its potential to comprehensively capture and interact with the intricate realities of the educational context (Reich, 2020). Short-term expectations should be avoided, rather attempts should be made to improve the design of an innovation over a considerable period of time together with relevant stakeholders in a real-life setting (Reich, 2020). The augmentation movement is clear: AI tools are no panacea. They are, if anything, best used as a supplement to empower teachers instead of replacing them (Cukurova et al., 2019; Mavrikis et al., 2021; Molenaar, 2022). As Salomon (2002, p.75) states: "It is not the medium that makes the difference, it is the pedagogical way in which it is used that makes the difference".

6.3.1 AI and the role of the teachers/trainers

The role of the teachers and trainers in AIED should be recognised as they additionally influence any potential outcomes (Cukurova et al., 2019; Molenaar, 2021). Therefore, teachers' and trainers ' needs, perceptions and experiences cannot be ignored when pursuing the successful implementation of AI in education. As Reich (2020) mentioned in the wider context of online learning:

> *"Online learning won't be an effective replacement for our old system. Rather, the best possible future will be one where we recognize the incredible importance of our formal education system to the social order, and we provide these systems with adequate funding, support, and respect. Our learning technologies are only as strong as the communities of educators who guide their use."* (p.xi)

It is clear that AI cannot operate in isolation but its true potential lies in complementing and enhancing the existing educational framework (Cukurova et al., 2019; Miao et al., 2021). Consequently, a notable shift in current AIED research centers around the collaboration between technology and educators in the design and evaluation of AI tools (Cukurova et al., 2019; Holstein et al., 2020; U.S. Department of Education, 2023). The emerging focus on hybrid human-AI learning and teaching has been explored in various scientific studies, albeit differently conceptualized. Examples include *distributed scaffolding* (Puntambekar & Kolodner, 2005), *synergy* (Tabak, 2004), *AI-assisted decision-making* (Vereschak et al., 2021), *Human-AI hybrid adaptivity* (Holstein et al., 2020), *hybrid intelligence and the six levels of automation* (Molenaar, 2022) and *the Teacher-Technology Nexus* (Van Schoors, 2023). The latter concept pertains to the dynamic interaction between teachers/trainers and technology in the context of personalization. Shared adaptivity control adds significant value to personalization that would be unattainable if teachers/trainers and technology operated independently. The nexus is often dynamic, as various forms of teacher-technology interactions can be observed in different scenarios (Van Schoors, 2023).

6.3.2 AI and the broader educational community

The future of AI in education lies in co-creation: to ensure a meaningful implementation of AI in education, a strong partnership among four key stakeholders is needed: research, policy, educational practice, and EdTech software providers (see also 'quadruple helix' as conceptualized by Molenaar, 2022 and 'golden triangle' as referred to by Cukurova and colleagues (2019)). This collaborative approach allows for mutual learning and knowledge exchange among these actors (Cukurova et al., 2019; Luckin et al., 2016; Molenaar, 2021; 2022; Vanbecelaere et al., 2023).

Teachers and trainers are at the frontline when it comes to implementing AI in education. They face significant demands since they are required to demonstrate a high level of flexibility to keep up with the rapid changes and the continuous development of new AI tools (Zimmerman, 2018). Often, teachers and trainers experience feelings of uncertainty as they lack the necessary technical knowledge and skills for the sustainable integration AI tools and for safeguarding learner data (Luckin et al., 2022; Zimmerman, 2018).

6.3.2.1 The role of educational policymakers and school leaders

To support, guide and motivate teachers and trainers, policymakers and school leaders play a primary role to provide professional development initiatives and training programs aimed at improving AI literacy (Luckin et al., 2022; Miao et al., 2021). A recent study within the Flemish i-Learn project showed that teachers are particularly willing to engage in professional development and training, as they found several support initiatives important for digital personalized learning interesting (Van Schoors, 2023). Further exploration of teachers' specific needs related to AI implementation can help refine and optimize these support initiatives.

Through effective professionalization support, teachers and trainers can be equipped with knowledge and skills to comprehend complex AI systems and manage associated risks (Luckin et al., 2022; Miao et al., 2021; Nowotny, 2021; U.S. Department of Education, 2023). In considering these support measures, it may be beneficial to shift focus towards pedagogical support rather than purely technical assistance, emphasizing the integration of AI into classroom instruction (Van Schoors, 2023). In this respect, it is interesting to focus on the growing potential of dashboards. When it comes to using teacher dashboards, the challenge is going from 'visualizations of learner data' to 'evidence-based instructional actions'. This gap could be bridged with appropriate pedagogical support enhancing data literacy (Ndukwe & Daniel, 2020; Wise & Jung, 2019).

Miao and colleagues (2021) delivered a report commissioned by UNESCO, shedding light on policymakers' role not only in fostering professional development initiatives but also in providing guidance on the ethical use of AI tools, particularly regarding data protection (Luan et al., 2020). This is rather challenging as AI innovations often outpace political discourse (Miao et al., 2021). Miao and colleagues (2021) recommend EdTech companies to work towards a shared vision for AI in education, serving as a guiding principle for educational institutions and stakeholders. This vision should prioritize safe, inclusive, and equitable AI implementation.

6.3.2.2 The role of research

Research institutions also play an important role in the sustainable implementation of AI in education (U.S. Department of Education, 2023). For example, academic findings could help educational policymakers set the tone when creating new support initiatives regarding AI in education, instead of focusing solely on the potential of the tool. Based on research findings (e.g., empirical evidence, needs-analysis) it can be identified what works and what does not in different contexts. Moreover, research aimed at advancing educational technology can enhance personalization within learning environments.

Research could also enhance the path of "co-creation and collaboration". One research approach that embodies these values is design-based research (DBR), as outlined by McKenney and Reeves (2012). They describe this approach as iterative and typically involving collaboration between researchers and practitioners. McKenney and Reeves (2012) outline three primary phases: (1) 'analysis and exploration', (2) 'design and construction', and (3) 'evaluation and reflection'. The DBR approach yields two main outcomes: (1) the development of interventions aimed at improving practice and (2) contributions to theoretical understanding (McKenney & Reeves, 2012).

6.3.2.3 The role of EdTech companies

When striving for the sustainable integration of AI in education, it's crucial to consider the role of EdTech companies. In this respect, itec heavily invested in three main objectives: (1) to map the EdTech landscape and foster strong interaction between the many EdTech companies in Flanders. (2) we wanted to internationalize itec and put it on the map as a knowledge institution. (3) we sought to merge insights from research with the technological advancements of EdTech companies, enriching lifelong learning opportunities within companies through various academies. To achieve these aims, <edtech/station> was established.

<edtech/station> is a networking organization that links from EdTech companies to both research groups, users and policy makers. Of the 350 companies active in this segment in Belgium, over 150 are now members of <edtech/station>. Besides building the network and supporting companies in both domestic and international growth, the organization also has an explicit role towards strengthening research and innovation in the sector. <edtech/station> does not conduct research itself, but acts as the connector between companies and research groups, facilitates collaboration, and plays a role in disseminating research results.

In a survey of <edtech/station> (December 2023), 95% of EdTech members were found to be actively integrating AI into the solutions they create. We can therefore say that the implementation of AI in EdTech is at full speed. The way AI is integrated into different applications is very diverse.

Returning to the four key perspectives as by Holmes and colleagues (2022) (see also section 3), companies are mainly working on two dimensions. Firstly, **learning with AI.** AI is being integrated to promote personalized learning. Personalized feedback and assistive technology, both in learning as in assessment tools, are seen not only towards learners with learning disabilities, but equally well to promote self-regulated learning, and to engage with learners' personal motivation (e.g. by personalizing the context of exercises to learners' interests). The discussions around the stress on teachers, where administrative workload and the shortage of teachers are often heard topics, also translate into the AI applications being built. Planning, actionable feedback for teachers, signaling functions towards specific learner problems are being co-addressed by various companies through AI. Let teachers get back to doing their core job is the motto here.

Secondly, very current in innovation projects and research within companies, is **the use of AI to gain insights into the learning progress.** The various EdTech solutions integrate AI to improve the use and interpretation of data in order to enhance learning processes and organizational impact.

An important evolution is also the trend towards interoperable collaboration and aggregation of data from different solutions (sometimes from different companies). Through AI, the stream of data generated by the various applications is collated, enriched with other information, and transformed into tools for learners, teachers, as well as management and policymakers.

Want to know more about <edtech/station>? Take a look at the website:
https://www.edtechstation.be/

7. Conclusion

As this positioning paper aligns with the augmentation perspective, it becomes apparent that establishing a robust partnership among teachers/trainers, policymakers, researchers, and EdTech companies is essential when integrating AI into education.

These stakeholders not only mutually influence one another but also significantly impact the effectiveness of AI tools, including their implementation in the classroom. Teachers/trainers and researchers both play essential roles by offering valuable insights and contributing to the collaborative design of AI tools as developed by EdTech companies, aiming to enhance their user-friendliness and utility. Furthermore, when teachers/trainers, researchers and software providers collaborate, it enhances the validity of their findings, especially when innovations are evaluated by teachers/trainers within the authentic context of a classroom. This in vivo approach allows for a deeper understanding of the impact of AI tools on teaching and learning, taking into account the rich and complex dynamics of the classroom environment. Additionally, government-led initiatives can provide essential support to provide guidelines and professionalization opportunities with regard to design, development and implementation.

In sum, the collaboration between educational stakeholders holds significant value and is highly regarded: by sharing knowledge, designing interventions together, and engaging in ongoing dialogue, more evidence-based AI-tools can be developed which are relevant, applicable and valorized in real-world educational settings.

Currently, an international trend towards collaboration is already noticeable. An example is the EDUCATE project from the University College London. They want to invest in evidence-informed educational technology by bringing actors of the 'golden triangle' together: (1) educational technology designers, (2) educational practitioners and (3) academia (Cukurova et al., 2019). Another example is the National Education Lab AI (NOLAI), a recently founded lab funded by the Dutch ministry, to foster the integration of AI in education. NOLAI also focuses on collaborations between educational practitioners, researchers and software developers. Additionally, it involves policy makers throughout its projects in order to foster structural innovation. Such multiperspective collaborations are also referred to as the 'quadruple helix'. At itec, we firmly believe in a collaborative approach and will continue to create strategic partnerships that can leverage complementary expertise. As illustrated before, imec's Smart Education @ Schools projects develop new educational technology solutions in close cooperation between research and industry. Our affiliation with <edtech/station> also allows us to directly engage with EdTech companies. Several events, such as the Learning Bytes Festival (LBF), specifically aim to connect all stakeholders within the educational ecosystem.

While this review paper delves into a small segment of the complex AIED field, it seeks to offer key facets of the contextual framework in which our research group operates. Our aspiration is to continue contributing to the ongoing puzzle that builds over time, i.e., the intersection of AI and education, which is a timeless and intriguing area of research and practice for educational practitioners and researchers around the globe as it shapes the future of teaching and learning.


Thay vì lan toả nghiệp chướng,
hãy lan toả yêu thương!
BRAND FOR YOUR ENEMIES

PART TWO

Evidence-based educational research on AI: The contribution of itec, an imec research group at KU Leuven

8. Itec's general roadmap for Smart Education

Central to itec's mission is to seek an optimal synergy between fundamental and strategic basic research on the one hand and applied research in realistic settings that will positively affect the fields of education/training and medicine on the other hand. In the field of education and training, itec has identified ***three research tracks that are main drivers behind our research roadmap***:

1. **Instructional design and effectiveness** of AI-based learning environments. Focuses are complex learning and personalized decision support.
2. AI-based natural l**anguage processing in (language) learning environments**. Focuses are grounded AI-based language processing as well as on communicative competences in language learning environments .
3. **Explainable AI for learning, teaching & training**. Focuses are on measuring and tracking (learning) variables, explainable machine learning methods for personalized decision support, meta analysis and single-case experimental designs.

As can be noted in their explanations, the three research tracks are methodology-driven. Zoals opgemerkt kan worden, zijn de drie research tracks methodologie gedreven. The following section presents a snapshot of research projects related to AIED currently being conducted at itec, following the three research tracks. These projects highlight the opportunities for impactful AI innovation as well as the expected challenges that might surface in future AI research.

8.1. | Instructional design and effectiveness of AI-based learning environments

The focus within this research track is twofold: On the one hand, **complex learning**. On the other hand, the **effectiveness of personalized learning support**. The combination of these two foci generates the following overall objectives: evaluating designed technology-enhanced and AI-based learning environments and instructional design principles, investigating the advantages of various tools in terms of supporting teachers/trainers, enhancing teaching quality and impacting cognitive, noncognitive and efficiency outcomes. Additionally, the impact on different transversal skills is being explored.

STUDY EXAMPLE

The potential of educational games

AIED topic? Adaptive digital games may enhance children's learning process. Recently, we developed a game to foster fraction understanding in the fourth grade of elementary education (see Figures 5 and 6). The adaptivity was operationalized by providing adapted explanatory feedback to students based on process measures within the learning environment.

Figure 5: adaptive digital game for fraction understanding

To examine the impact of the game, we assessed cognitive and noncognitive learning outcomes, such as fraction knowledge, math self-concept, motivation, and anxiety. To do so, various data sources were collected such as product data (tests and questionnaires) for assessment and process data (logs and sensor data) to gain deeper insights into students' process through the game.

Figure 6: Students using the game in the classroom.

AI value? The current operationalization of adaptivity is rule-based. The AI value lies in enhancing adaptivity in digital games through more advanced machine learning techniques, offering personalized experiences based on multimodal data, including log data (e.g., click behavior, mouse movements, responses, reaction times) within digital learning environments. This can lead to more effective and personalized learning experiences.

Challenges? The use of AI in personalization requires the collection and analysis of large amounts of data, such as student learning achievements. It is important to handle this data carefully and ensure that student privacy is protected. Properly managing, storing and securing this data is crucial. Related to this challenge, it should be carefully considered which variables are relevant to include in the data collection process. Furthermore, it must be noted that Teacher Support and Involvement are important. While AI can enhance personalization, human teacher support remains crucial. Balancing technology with human interaction is a challenge to maintain the role of teachers and tutors. Finally, AI systems can struggle to provide effective personalized recommendations when there's little or no information available about new users or situations, potentially leading to suboptimal learning experiences for newcomers.

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STUDY EXAMPLE

Supporting Teamwork in Technology-Enhanced Learning Spaces (TELS): Assessing and improving optimal learning experiences in computer-supported collaborative problem solving by means of multimodal classroom analytics

AIED topic? Technology-Enhanced Learning Spaces is a topic that we have focused on for quite some time now. One of the aspects that we are currently investigating is how to optimize the quality of learning environments and how to assess this through data analytics. For example, in several studies we focused on using audio data to analyze collaborative problem solving, using Automatic Speech Recognition (ASR) to convert spoken conversations into text for further analysis. AI has significant potential for advancing this research, including semi-automated content analysis and integrating audio data analysis with other data types like video. The goal is to explore how group composition based on factors like personality and previous performance can optimize performance, with future AI applications enhancing data analysis and identifying crucial factors for optimal group composition (see Figure 7).

Figure 7: A lesson in which the group composition is being research

AI value? AI streamlines data processing, enabling the analysis of combined data types like audio and video to uncover correlations with collaborative learning outcomes. This enhances performance assessment and a comprehensive analysis of collaborative learning factors. In the field of computer-supported collaborative learning, AI can identify variables for ideal group composition and offers real-time teacher and learner recommendations based on student and context-related aspects.

Challenges? ASR performs well for languages with ample data but encounters limitations with certain languages and dialects. Training a model to handle language variability is challenging. Additionally, extracting meaningful insights from diverse data sources in this research domain necessitates advanced algorithms that can manage variability and contextual nuances, considering potential data imperfections like unclean or noisy data.

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STUDY EXAMPLES:
Research on an AI buddy for instructional feedback

AIED topic? Within itec, we focus profoundly on AI tools that – either directly or indirectly – foster 21st century skills. One exemplary study is the use of AI to monitor students' progress in computational thinking within an open-ended learning context. Input from diverse sources (images, code fragments, audio, ...) are being used, as well as diverse models to process these sources to find the underlying concepts defining computational thinking. The results are visualized on a dashboard with feedback on the students' progress (see Figure 8).

Figure 8: Dwengo Simulator - programming tool

AI value? The automation of the instructional feedback provides relevant support for teachers as they can divide their attention more to other aspects of the teaching process. AI also provides efficiency as it allows for comprehensive (e.g., based on multiple types of data) and timely feedback.

Challenges? Challenges include finding methods to accurately interpret and evaluate computational thinking using a variety of input sources, ensuring algorithm transparency for teachers to establish trust. Additionally challenging is understanding how AI assessment aligns with teachers' assessments, as they often consider more aspects. In this specific study, teachers' assessments are multifaceted, suggesting a potential avenue for examining the correlation between AI assessment and these diverse dimensions, including the possibility of predictive capabilities.

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STUDY EXAMPLE
Study examples: Research on Learning analytics (LA) dashboards

AIED topic? A related research topic involves researching Learning Analytics (LA) dashboards with a dual purpose: (1) enhancing teachers' professional competencies and (2) promoting personalized learning in primary schools (see example Figure 9). These dashboards offer personalized, data-driven feedback to teachers as well as insights into the learners' individual learning progress.

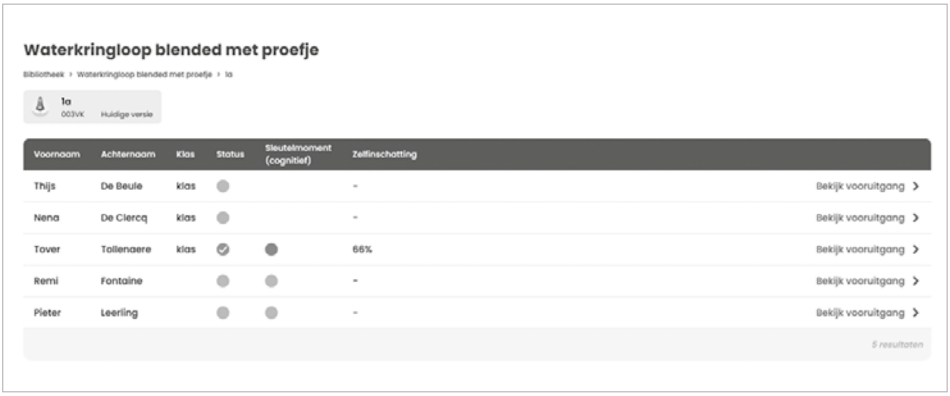

Figure 9: example of the a teacher dashboard on the i-Learn platform

AI value? Advanced by LA dashboards, teachers and trainers are supported in various tasks such as planning, monitoring, coaching, designing, orchestrating, decision-making and consolidating personalized learning experiences according to students' needs. In doing so, teachers can (1) personalize tasks or instructions according to each learner's needs and (2) can initiate early diagnosis of learning difficulties and prompt intervention.

Challenges? Challenges involve investigating how teachers interpret data and how we can support and train them to interpret data effectively in the classroom for further personalized instruction. Additionally, we need to explore ways to optimize the design and development of dashboards to ensure they offer actionable insights, empowering teachers to effectively utilize both tools and dashboards.

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STUDY EXAMPLES:
Design, development and implementation of a digital personalized learning tool for programming in secondary education.

AIED topic? Possibilities for digital personalized learning (DPL) tools are rising given recent AI developments. DPL is a major focus within our research group. To give an example, during a recent study we developed a DPL track for programming in collaboration with teachers and EdTech providers. Based on students' answers on tests, they were presented with personalized tasks which they could complete at their own pace. The track also supported teachers in the delivery of programming education with relevant learning materials. As a follow-up study, a multiple case study was established, in which teachers implemented the track (and accompanying teacher dashboard) in the classroom (see Figure 10). Various forms of interaction between teachers and technology were observed, which led to the development of a teacher-technology interaction model and concept to refer to this interaction: "teacher-technology nexus".

Figure 10: An adaptive learning track for programming is being implemented in the classroom.

AI value? The teachers felt supported and empowered in their teaching practices. For example, the track took over repetitive tasks (e.g. personalized feedback, personalization of tasks). Based on the teacher dashboard, they could make well-informed didactical decisions (additional teacher-driven personalization for specific students).

Challenges? These studies highlighted the necessity of teacher training for effective use of AI tools and a stronger AI teacher nexus. In addition, the need for more sophisticated algorithms became apparent with regard to accurate student profiling and personalization of the learning process. In this respect, ensuring data privacy is crucial.

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8.2. | AI-based natural language processing in (language) learning environments.

The focus of this research track is twofold: On the one hand, the topic **grounded natural language processing** is being examined. The goal is to design and develop a new generation of human-machine interfaces that incorporate various modes of communication, such as speech, images, and psychophysiological information. These interfaces aim to be context-aware, robust, flexible, adaptive, dynamic, and explainable.

On the other hand, the focus lies on **communicative competence in language learning environments**. This involves (1) effectively integrating natural language technologies (NLP/AI) into interactive learning and assessment tasks, covering text, speech, and dialogue; (2) developing language technologies for analyzing and adaptively generating language; (3) creating valid methods to evaluate both technology-mediated and human communicative interactions; and (4) measuring the effectiveness of these technologies in the realms of language learning and assessment.

STUDY EXAMPLES

Automatic analysis and adaptation of language in written communication

AIED topic? Within itec, we share a focus on Educational Natural Language Processing (NLP). Illustrative studies (Figure 11) involve (1) computational modeling of language complexity in texts read/written by learners (feature-based models, neural language models), (2) automatic analysis and adaptation of language difficulty for a specific user (personalization, simplification, generation, ...) and (3) automatic evaluation methods for generative AI in educational contexts (e.g. adequacy of teacher language).

In a recent study, we use NLP to enhance the efficiency and validity of comparative judgment assessments in education (see Figure 12). Through this method, teachers are supported in comparing pairs of student works to decide which one is better, establishing a rank order. It also supports students as informative feedback is being generated.

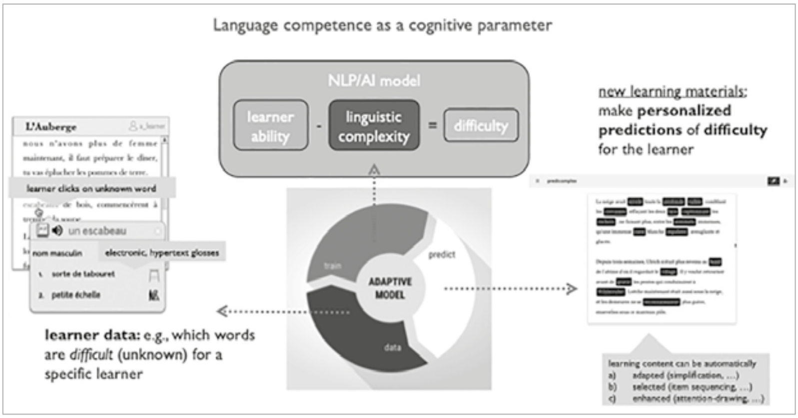

Figure 11: An AI application within the education NLP domain

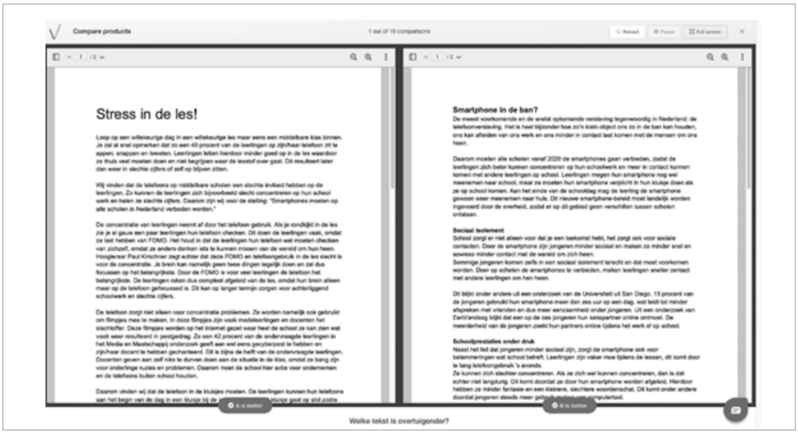

Figure 12: A comparison of two essays of students in the tool Comproved.

AI value? By incorporating educational NLP technology, we introduce richer information and context that can be used in psychometric models and data analysis. Moreover, the real-time analysis and feedback capabilities enable a dynamic and responsive learning environment. As a result, the workload and cognitive burden on teachers can be reduced (e.g., in case of the comparative judgment example, teachers can make a fast and reliable comparison). Furthermore, the latest generative AI models represent an enhanced force in generating tailored learning content.

Challenges? In addition to the benefits within the field of educational NLP, there are also several challenges. One difficulty is personalization, as existing language models often represent a general "average" language speaker. Addressing this requires effective adaptation mechanisms to ensure personalized learning experiences. Additionally, evaluating generative language models through benchmarks poses a challenge, as assessing the adequacy of generated text and overall model quality proves to be complex. In this respect, developing valid assessment techniques for AI methods becomes essential. Another critical aspect is dialogue, with existing models often specialized for either receptive (e.g., readability assessment) or productive tasks (e.g., essay grading). Bridging this gap necessitates technology that adeptly handles both, recognizing the dynamic interaction between reception and production within a single task. Finally, when implementing NLP systems in an educational context it is important to find synergy between the NLP tool and the teacher. For example in the comparative judgment case, a human-centered approach should be maintained, where teachers' input remains integral to the assessment process (to guarantee fairness and reliability, account for bias).

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STUDY EXAMPLES:
Automatic analysis and adaptation of language in written communication

AIED topic? One of the research tracks within itec is the evaluation of open tasks. An example of a study in this research track is the focus on the automatic evaluation of open dialogue tasks for (French) language learning. In order to facilitate teachers' evaluation process of spoken language, it is important to know what aspects should be taken into account for evaluating that type of language.

AI value? Generative AI could (1) help identifying the different parameters that are important when evaluating learner language generated in open speaking tasks as well as (2) generate different open tasks that are adapted to the student's level. It could also (3) provide intelligent feedback, which helps learners to advance more quickly in their learning process.

Challenges? There are many challenges in the implication of generative AI within this domain. First, in order to identify the parameters that are making up the evaluation of spoken learner language, large data samples of French learner language need to be available. Further, the system clearly needs to be adaptive and personalized in order to correspond to the learners' needs and should thus provide appropriate content and support. Finally, it is challenging to provide accurate and constructive feedback on spoken language. Generative AI systems should be able to offer feedback on different aspects that are important when learning to speak a language (e.g., vocabulary, grammar, pronunciation).

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STUDY EXAMPLES:
Modeling human-like language emergence, acquisition and processing in situated environments

AIED topic? Another specific topic that we investigate within itec, is how machines can acquire natural languages in a human-like manner, i.e. through meaningful and intentional situated communicative interactions that are grounded in everyday environments. As opposed to the techniques that currently dominate the field of natural language processing, we focus on flexible and adaptive language models that are grounded in the environment and communicative needs of the agents.

AI value? The computational modeling of language emergence, evolution, acquisition and processing has been a central topic in the field of artificial intelligence since its inception in the 1950s. At itec, we are contributing new methods and techniques for finding abstract linguistic patterns through syntactic-semantic generalization. As such, we work towards a next generation of language models that are more human-like and grounded in real-world environments.

Challenges? The main challenge resides in combining subsymbolic AI techniques that are excellent for low-level pattern recognition – in particular neural networks – with symbolic (logic-based) AI techniques that are excellent for higher-level reasoning and planning operations.

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8.3. | Explainable AI for learning, teaching & training

This research track consists of two parts: One part includes advanced statistical and psychometric techniques for measuring and tracking (learning) variables, meta-analysis and automatic evaluation of learning environments. Another part includes explainable machine learning methods for personalized decision support.

8.3.1 Statistical and psychometrical techniques to measure learning

In this field, three main focuses are outlined: (1) **Measuring and Tracking Learning Variables:** The objective is to develop methods for accurately, unobtrusively, and comprehensively capturing student variables, including complex latent variables such as computational thinking, creativity, and collaborative skills. This also involves tracking and describing progress and evolution. Additionally, the aim is to develop and validate tools to measure various student variables. (2) **Meta-analysis**: The goal of a meta-analysis is to combine and compare data from multiple studies that studied a similar research question in order to get a more accurate and detailed answer to that question. We develop, propose and evaluate further models and techniques for meta-analysis, including for the meta-analysis of Single-Case Experiment Designs (SCEDs) , these are experiments with one or a few participants. (3) **Automatic Evaluation of Learning Environments:** The goal is to provide a continuous, automatic, person- and context-dependent evaluation and optimization of learning environments. As a first step, this includes exploring, further developing, and illustrating the use of SCEDs for evaluating Technology-Enhanced Learning (TEL).

STUDY EXAMPLES:
Data analytics and predictive modeling: personalized recommendations

AIED topic? In the field of data analytics and predictive modeling, AI can be very helpful to analyze large data sets to identify patterns, trends and insights. For example, by analyzing log data, AI algorithms make it possible to draw inferences on the (change in) proficiency, motivation, …, and factors that affect these, and hence to provide recommendations towards learning materials, pace instruction, as well as targeted feedback. Such recommendations could lead to more effective and efficient learning outcomes as they can help educators and trainers to make data-driven decisions. In addition to recommendations, predictions of student performances can be made, which can enhance timely teachers feedback and improve educational outcomes. One study example within this field is the design and development of a recommender system for primary and secondary school contexts, in which we focused on using data to help teachers design more easily personalized learning tracks in their classrooms (see Figure 13).

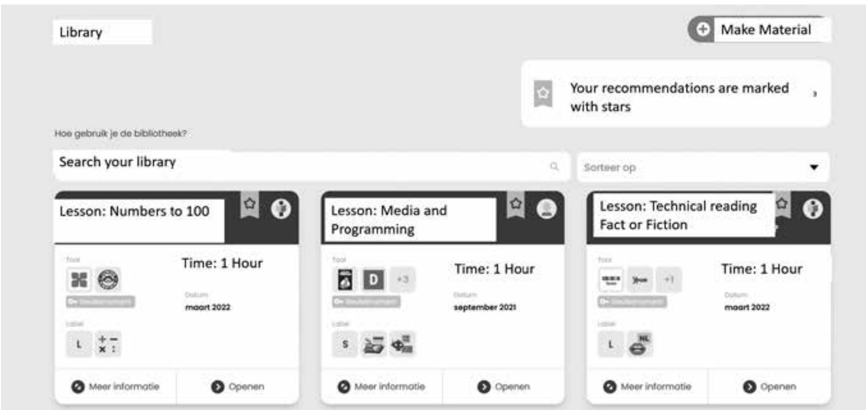

Figure 13: Yellow bookmark stars identify recommended adaptive learning tracks that teachers can use in their classroom.

In another study, we examined the effects of courses on students' soft skill proficiency. In doing so, we try to model and predict the students' soft skill proficiency in different stages of the academic program (e.g. Master's program). Next to that, we use AI (specifically genetic algorithms: stochastic optimisation algorithms), to find the most suitable set of courses for postgraduate students based on their current soft skills proficiency, the modeled course effects over soft skills, and the minimum standards (minimum soft skill proficiency) we expect from them at the end of the academic program.

AI value? Using AI in the field of data analytics and predictive modeling can provide new insights and applications based on educational data. For example, by the use of genetic algorithms, we are able to develop a system that maximizes the soft skill proficiency of the students based on all the possible combinations of courses they could follow. This maximization attempts to allow the students to surpass the minimum standards on each of the soft skill dimensions (problem-solving, stress management, leadership, communications, etc).

Challenges? When making predictions based on AI, we take into account several challenges in our research. First, one of the main concerns with AI enhanced psychometric assessments is the potential for algorithmic bias. If the algorithms used to analyze the data are biased, the conclusions will be flawed. Therefore, identifying bias in AI models is of utmost importance to guarantee accurate outcomes. Second, AI models (or parameters) may function well on particular datasets but struggle to generalize to other contexts or populations. AI models need to be validated across different populations to ensure their accuracy. Third, when providing predictions through AI algorithms, we should always account for optimal human-AI collaboration: AI should complement rather than substitute for human expertise in psychological measurement. If a teacher estimates a flaw in the prediction, it should be possible to adjust the prediction. In this respect, when developing a recommender system, it is important to enhance interpretation. Some recommender systems act like black-boxes and provide few to none explanations regarding the relation of the users and items. This imposes a huge constraint if part of the objective is to analyze the academic program's curriculum to remove, add or change the courses' pedagogical design so that they could sufficiently foster soft skills

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STUDY EXAMPLES:
Meta-analysis

AIED topic? Meta-analyses combine and compare the results of several studies. For instance, by combining the data from multiple studies that evaluated the effect of the use of technology in education, we can get a more accurate estimate of the overall effect, but we can also get a closer insight into what exactly works, for whom and under what circumstances. Although meta-analytic methods were already proposed in the 1970s, methods and models are still (or again) under full development.

AI value? Advanced statistical modeling makes it possible to account for various complexities in the data. These complexities include ubiquitous dependencies, for instance because studies may assess the effect of different variations of interventions, on multiple outcome variables, or in multiple samples. We have done much research on the use of multilevel (or mixed) models in meta-analysis to account for such dependencies. We also studied the use of multilevel models for meta-analyses of Single-Case Experimental Design (SCED) data. SCEDs are designs in which one or a few cases are measured repeatedly under different conditions in order to assess the effect of the condition. Because of the multilevel structure of the data (measurements are nested in cases, which in turn are nested in studies), the use of multilevel models is indeed helpful.

Challenges? The use of multilevel models for meta-analysis requires more research. As an example of a study: we currently explore the use of multilevel models for network meta-analyses of SCED studies. In theory, these meta-analyses can give valuable insight in the relative performance of several interventions based on a set of SCED studies on these interventions, but it is not immediately clear how models should be adapted to account for the peculiarities of SCED data, nor how well the techniques perform given the small sample sizes that are common in SCED research.

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STUDY EXAMPLES:
Psychometric modeling and multidimensionality measurement for adaptive learning

AIED topic? Several of itec's research projects are located in the area of psychological and educational measurement. In recent years, with the exploration of online learning and testing, the performance (e.g., stability) of traditional psychometric methods has been challenged due to the new data features, such as the large number of items, the high latent dimensions, sparsity, and so on. Researchers (also at itec) started studying combining AI methods (e.g., machine learning) with traditional psychometric methods (e.g., exploratory factor analysis) to address the new challenges. Also because of the availability of new data, such as log data and content data, which are different from traditional psychometric data (e.g., students' response matrix), researchers have tried to use AI methods (e.g., natural language processing and deep learning) to complement traditional psychometric methods. In doing so, richer input can be provided for AI systems to personalize the learning environment.

One example within this field is our research project with Linguineo in which we investigate adaptivity in complex language learning tasks. We are working to achieve adaptivity in open, productive language tasks in computer-assisted language learning (chatbot conversations) both for autonomous learning and classroom contexts. The goal in this project is to (1) predict whether a task will be too difficult for a learner and consequently and (2) offer the appropriate support (see Figure 14).

Figure 14: The chatbot that provides adaptive learning experiences.

By analyzing learner metrics in productive language tasks we are developing profiles. In addition, we analyze unstructured language data from learner production and we try to convert it into sensible structured data based on the literature of Second Language Acquisition and Task-Based Language Teaching to get an idea of learners' underlying language proficiency, which can form the basis of adaptivity.

AI value? The additional input and support of AI systems helps us make more accurate, unobtrusive and dynamic adaptations. For example, in another study we examine how an AI system can automatically adapt the level of instructional support of learners given the time or duration they require to complete items. This duration can be quite informative in helping to match the learner's skill level with the item's difficulty in terms of time. In another study, we focus on the improvement of rating systems in adaptive learning environments where we aim to adapt item selection based on the ability levels of the learner. The idea is to personalize the learning process by allowing learners practice at their own pace and level. In order to select appropriate items for each learner, estimates need to be made of learner ability and item difficulty levels. To do so, we focus on the

Elo rating system (ERS) as a method for tracking both learner and item parameters in adaptive learning environments so that estimation can happen on-the-fly.

Challenges? While AI models and algorithms might enhance the adaptation of learning environments, they can still suffer from some problems. For example, when relying on the ERS in adaptive learning environments, there were still some difficulties such as the cold start problem and scale instability issues which we further investigate in present and future research. In addition, it is good to acknowledge that, although AI technologies have the capacity to generate data of various modalities related to user behavior (e.g., text, video, audio, logfile, or sensor data), handling such multimodal data poses also challenges as decisions have to be made regarding which and how many variables to include in the analyses. Moreover, it is necessary to note that existing statistical models may not always be able to handle certain types of data. Therefore, it is crucial to acknowledge the irreplaceable role of teachers in education. Not all educational decisions should be delegated entirely to algorithms and models. Instead, automated measurements may support and empower teachers in creating an optimal learning environment.

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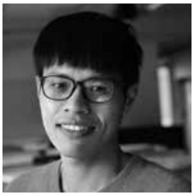



STUDY EXAMPLES:
Single-case experimental designs - the case of virtual reality (VR)

AIED topic? Single-Case Experimental Designs (SCEDs) can be adopted for the evaluation of Technology-Enhanced Learning (TEL) and the recommendation of evidence-based practices. Insights from the broader field of TEL can inform the potential utilization of AI. For example, ongoing research projects within our group explore the application and impact of (nudges in) virtual reality (VR). One study explores VR as an innovative tool for evaluating individual competency levels in the domains of communication and collaboration. Situated in a dyadic VR setting, the research aims to reduce reliance on external evaluators by examining the feasibility of VR for objective competency assessment (see Figure 15). The study leverages two main applications of Artificial Intelligence (AI) in education: Automated Evaluation and Natural Language Processing (NLP). AI integration enhances the efficiency of competency assessment by providing consistent evaluations and enabling continuous learning through feedback loops.

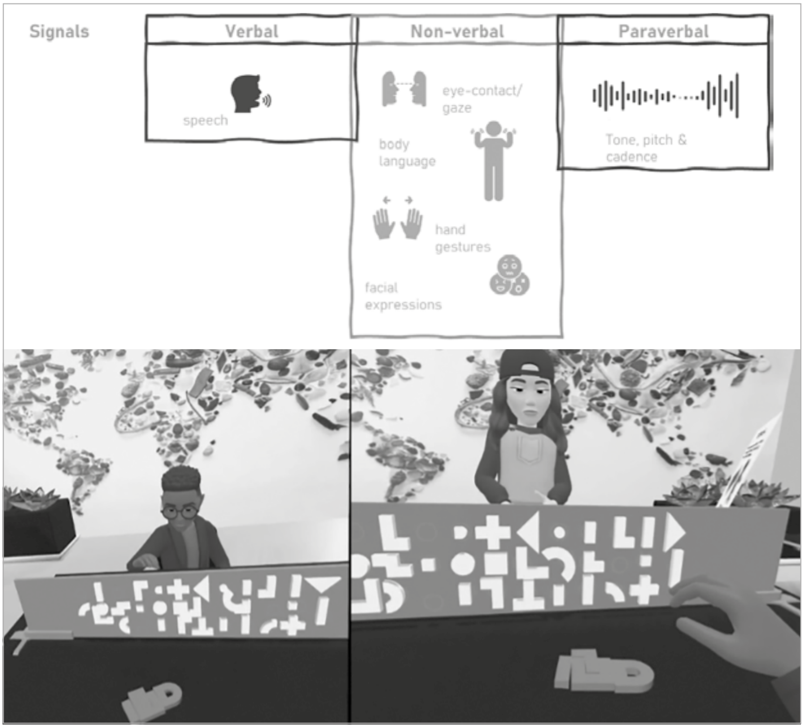

Figure 15: Task in a VR environment.

Another study focussed on VR based intervention to enhance learners' spatial reasoning. Despite being distinct technologies, AI and VR can synergize to improve immersion, interaction, virtual characters, and personalized elements. The research involves measuring the effects of VR on spatial reasoning and collecting psychological data (e.g., facial/emotional recognition, heart rate, galvanic skin response, eye tracking, electroencephalography). This comprehensive dataset enables the assessment of VR effectiveness for learners, with physiological data used to detect anomalies, such as stress or anxiety, allowing for adjustments to the learning environment.

AI value? When the components of repeated measures of SCEDs are assisted with AI enabled features (which help in collecting physiological variables) the impact of TEL can be understood in greater depth with the help of performance metrics, and multimodal data. By harnessing the power of AI algorithms in a virtual learning environment, learner specific (uniqueness, a key characteristic of SCEDs) spatial reasoning lessons can be designed. Furthermore, AI algorithms which help in designing VR characters can interact and respond to learners' actions. In terms of statistical analysis, AI helps in automatic data collection, monitoring and analysis which ultimately reduces researchers' workload and helps in getting a comprehensive view of data by integrating machine learning techniques to detect patterns, trends and meaningful insights out of repeated data collected in SCEDst.

Challenges? The development of AI algorithms which can correctly respond and interpret individuals actions is a continuous and challenging process. Related to VR, collecting various continuous and discrete data types adds complexity to creating an AI algorithm capable of simultaneous processing and analysis.

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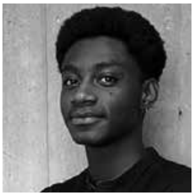

8.3.2 Explainable machine learning for personalized decision support

Our objective in this field is to maximize probability of successful outcome by making long term outcome predictions, adaptive over time and identifying key factors contributing to these predictions, resulting in actionable insights.

STUDY EXAMPLES:

Course recommendations in MOOCs based on relevance and dropout

AIED topic? We already highlighted that one of itec's key focuses is personalized learning experiences and recommender systems. In a recent research project, we're exploring advanced machine learning methods to further enhance personalized recommendations, such as course recommendations in MOOCs using survival analysis and collaborative filtering (see Figure 16). High dropout rate is one of the main challenges in MOOCs and therefore should be considered to provide more relevant recommendations. The main idea is to model time-to-dropout from courses using survival analysis and consider its predictions as additional signals to rank courses for users. The survival analysis method, which is trained based on the dropout and completed courses of each user, predicts a risk score for each user-course pair that can be coupled with collaborative filtering relevance scores to recommend courses to the users.

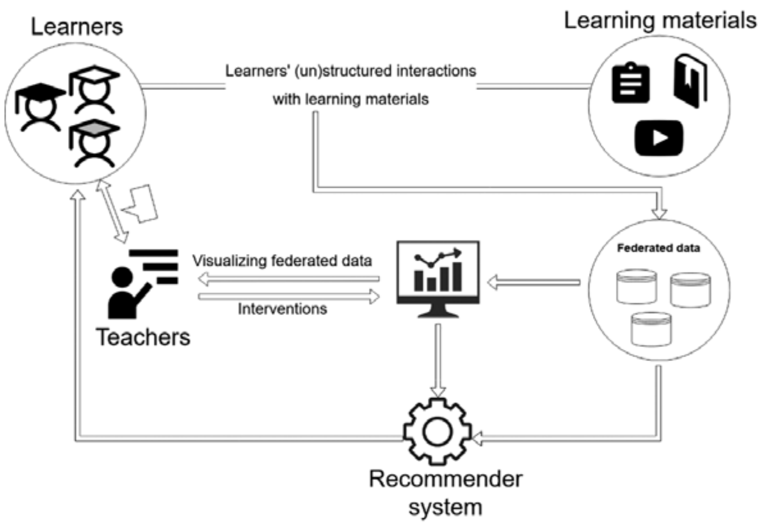

Figure 16: Behind the scenes of recommender systems

AI value? Advanced and personalized recommendations offer numerous benefits. By tailoring learning experiences instead of adopting a one-size-fits-all approach, recommendations are crafted based on learners' preferences and needs. This approach not only considers the likelihood of dropout and disengagement from the learning system but also provides dynamic predictions that adapt to learners' current contexts, offering recommendations accordingly.

Challenges? While there are notable benefits to advanced and personalized recommendations, there are also challenges. One lies in the validation of proposed approaches, requiring real learner involvement. There are very few publically available datasets that can be used to further validate the findings of the research project and the available ones lack descriptive features of the courses.Additionally, it might be complex to integrate pedagogical learning methods into AI based personalization approaches.

MORE INFORMATION ABOUT THIS TOPIC?

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9. Specific use-cases: four larger AIED-projects

In conclusion, we would like to emphasize that, across the three aforementioned research tracks, we consistently aim for larger interdisciplinary projects run at itec. In the following part, four larger projects are presented that have been successfully concluded in the past years.

9.1. | Personalized learning and training

One of the crucial research ambitions of itec is to shift from a one-size-fits-all approach towards **personalized learning and training**. Leveraging state-of-the-art adaptive and personalized learning technologies, it aims to create a learning context that is maximally tailored to each learner's unique talents and needs.

PROJECT LEAPS:
Learning analytics for adaptive support

Adaptive learning and performance support systems are considered superior to human trainers in monitoring user behavior and providing personalized support and feedback. However, the process of their development is complex and expensive, and they are typically not transferable to domains other than those for which they were intended (e.g. from math to reading). Moreover, their adoption is barred by a lack of didactical integration. LEAPS tackled these challenges by investigating and implementing an approach that combines behavioral data with learning analytics, machine learning, and learning dashboards.

This approach was evaluated in three demonstrators for four very specific populations: training of number sense in pre-school children, training of initial reading for primary school children, compensatory support in writing for people with dyslexia, and on-the-job development of written language skills. The interdisciplinary consortium brought together expertise in statistics, computer science, educational sciences, cognitive science, human-computer interaction design, software engineering, and thorough knowledge of user populations in the markets of school education and professional training.

9.2. | Hybrid and flexible learning and training

itec is also committed to broaden the perspective on when & how learning should take place. With a seamless integration of virtual and non-virtual learning environments, moving towards more **hybrid and flexible learning and training** solutions will eventually foster a lifelong learning attitude in today's rapidly evolving society.

PROJECT LECTURE
Effective LEarning in remote Classrooms through Technology-enhanced UseR Engagement

Pedagogical evolutions towards more interactive and collaborative teaching and learning, individual demand for more flexible training and education, and an evolution towards multicampus teaching in higher education require solutions for remote and asynchronous learning that are as interactive and effective as face-to-face training, and do not introduce technological or psychological barriers. Current solutions such as WebEx and video conferencing tools either do not meet these requirements or are too expensive for the

average higher education institution or corporate training. On top of the ongoing development of a cloud-based and bring-your-own-device-ready platform for interactive learning, LECTURE+ aimed to research, design, and evaluate a data-driven and evidence-based platform for decision support for teachers, room operators and learners in higher education and corporate training, geared towards improving learner engagement in face-to-face, remote, and recorded lectures. Objectives included modeling and enhancing learner engagement through behavior tracking and audiovisual processing, improving the cost-efficiency and scalability of real-time video direction, and demonstrating the added value of interactive technology-enhanced learning in three living labs (face-to-face learning, remote groups, remote individuals).

9.3. | Complex open-ended tasks

A third focus in itec's research projects is to incorporate data from complex **open-ended tasks** instead of allowing technological advancements to reduce the learning process to simple cognitive outcomes that fail to consider context, skills, motivation and other crucial indicators of progress.

PROJECT COSMO
COgnitive Support in Manufacturing Operations

The manufacturing industry is experiencing increased product diversification, requiring effective on-the-job training and support. Augmented reality (AR) and virtual reality (VR) technologies, along with digital work instructions, hold promise, but empirical research

is needed to demonstrate their added value. The COSMO project aimed to accelerate the entry of these technologies into the market by personalizing training solutions, reducing content creation costs, and expanding their application. Collaborating with industry players and research partners, COSMO focused on making immersive technologies in assembly environments more personalized and scalable. The project aims to develop technologies for real-time adaptation of cognitive support to operators' evolving abilities and well-being, as well as semi-automated creation of training content. The effectiveness of these solutions were studied, with testing and adaptation in Flemish school contexts for societal valorization.

9.4 | Empowered teachers/trainers

As a fourth and final guiding principle, the research group strives to contribute to a future that **empowers teachers/trainers** rather than overloading them. Innovative learning systems can and should support them in their day-to-day roles, aiding in planning, monitoring, coaching, designing, decision-making and so forth.

PROJECT I-LEARN:
digital personalized learning in Flemish primary and secondary education

The main goal of i-Learn was the creation of an online portal to help teachers with personalized digital learning in the classroom. September 2020 marked the start of the testing phase: the project team consisting of employees from the three lead partners

(imec, KU Leuven and itec) designed a prototype of the portal to start testing in primary and secondary schools. After a thorough needs assessment (large scale survey and focus group interviews with teachers) and months of intensive interaction with 12 pilot schools, priorities were defined concerning topics and target groups. Platform features were developed in co-creation with teachers and more than 50 educational tools were selected to be integrated into it, encompassing over 500 000 learning activities for teachers to choose from when creating personalized learning tracks for their students. i-Learn also encompasses an Academy, which has the goal to support teachers through videos, tool manuals, visualizations, learning sessions, detailed e-learning modules and an online community. Currently, almost 2500 teachers and over 10 000 students are interacting with i-Learn, as more than 750 schools were registered in the project.

Conclusion: going digital, staying human

While the field of AIED unfolds, we must continue to strive for optimal synergies between all stakeholders. Although it is impossible to predict exactly what the future will hold, we can maximally prepare ourselves by leveraging the entire educational ecosystem. Fostering collaboration between schools, companies, researchers and policymakers will become increasingly important for sustainable growth. Only within a shared vision and constructive dialogue about responsible AI use, teachers/trainers and learners can be empowered to actively shape their educational paths in education and training contexts.

Throughout this paper, we have outlined some of the main challenges for each stakeholder group within the quadruple helix. With many new exciting technological advancements awaiting us in the years to come, we hope this paper has inspired everyone to contribute to their respective recommendations.

Above all, we want to appeal to a realistic approach with regards to AIED. Neither naivety nor skepticism will futureproof our attitude towards innovation. AI is here to stay, with every risk and opportunity in full effect immediately upon release. The only truly impactful way will be forward!

Moving ahead, we need to raise awareness and empowerment about privacy and ethics concerning the use of AI, demand main actors' agency within the teaching/training and learning environment (i.e. teachers/trainers and learners) and incentivize explainability within artificially intelligent systems that can be used in both formal and informal educational settings. Only then will we be able to go digital while simultaneously staying human.

Outreach:

Our research group wants to play an active role in facilitating innovation, by bringing together different domains of expertise (see research tracks 'instructional design and effectiveness', 'AI-based natural language processing in learning environments', 'explainable AI for learning, teaching and training') and incorporating various perspectives to tackle 'real' challenges within today's education. The many research projects outlined in the second part of this paper illustrate how, already today but even more so as time progresses, we should combine efforts in order to strive for evidence-driven educational technology that holds a strong valorization potential. Are you a research group with complementary expertise, a company seeking opportunities for cooperation, a teacher with an innovative idea, a school's policymaker in search of a feasible vision for the future…? Contact us!

Our website: http://www.kuleuven.be/itec

Call to action:

Are you curious to find out more about AIED? Sign up for our free e-learning course and unlock 5 to 7 hours of theoretical insights, accessible overviews, practical tips and tricks and above all a bright outlook on AI's possibilities within education.

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