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Towards hybrid human-AI learning technologies

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Abstract

Education is a unique area for application of artificial intelligence (AI). In this article, the augmentation perspective and the concept of hybrid intelligence are introduced to frame our thinking about AI in education. The involvement of quadruple helix stakeholders (i.e., researchers, education professionals, entrepreneurs, and policymakers) is necessary to understand the opportunities and challenges of different educational use cases from an integrated point of view. To facilitate a meaningful dialogue, a common language about AI in education is needed. This article outlines elements of such a common language. The *detect-diagnose-act* framework is used to describe the core functions of AI in education. The *six levels of automation* model is introduced to develop our thinking about the roles of AI, learners, and teachers in educational arrangements. In this model, the transition of control between teacher and technology is articulated at different levels and related to the augmentation perspective. Finally, the future of AI in education is discussed using self-regulated learning as an example. The proposed common language will help to support a coordinated development of an interdisciplinary dialogue between quadruple helix stakeholders to strengthen meaningful application of AI for learning and teaching.

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1 | INTRODUCTION

We are currently in a new manifestation of Artificial Intelligence (AI), which is driven by trends in big data, increased processing power, and advances in machine learning techniques (Harari, 2018; Suguna et al., 2021). Great expectations about the future of AI exist in many application domains, such as the automobile industry (Awad et al., 2018), smart industry, energy, health (Topol, 2019), and education (Baker & Smith, 2019; Holmes et al., 2019; Tuomi, 2018). This article focusses on the use of AI to facilitate learning and enhance teaching. I argue that education is a unique application area for AI, with a different focus compared to other application areas where AI is often used for task automation. In order to position AI in education, the augmentation perspective and the concept of hybrid intelligence are introduced to describe the potential of AI for education. The main argument is that a critical evaluation of the use cases applying AI to support learning and teaching is needed to enhance education. A common language is needed for this, which can support the generation of novel transformative applications of AI among teachers, learners, researchers, entrepreneurs, and policymakers.

2 | AUGMENTATION PERSPECTIVE AND HYBRID INTELLIGENCE

Historically, the main focus of the research community that investigates AI in education (AIED)—and the International AIED Society, founded in 1993—has been to provide each student with a personal Intelligent Tutor (Woolf, 1991), envisioning the off-loading of teacher tasks to an AI-enabled computer system. This *replacement* perspective on AI in education has gradually shifted towards what is known as the *augmentation* perspective (Cukurova et al., 2019; Mavrikis et al., 2021). It emphasises the role of AI to support human teachers and learners in their quest to teach and learn. Learning is a key function of humans and—although conditions under which we learn will change—learning remains an essentially human activity. The central role of AI in education, therefore, is to facilitate learning and teaching processes (Chen et al., 2020; Selwyn, 2019 Williamson & Eynon, 2020; Woolf, 1991). AI is envisioned to enhance human intelligence with quick data collection, analysis, and translation into meaningful insights and actions (Kamar, 2016). Applying these strengths in diverse use cases, AI can enhance learning and teaching. This augmentation perspective is profoundly different from the replacement perspective which implicitly suggested substituting human teachers and optimising the guidance of learners with AI (Blikstein, 2018).

The augmentation perspective aligns well with the notion of *hybrid intelligence*, which aims to research and develop intelligent systems that augment rather than replace human intelligence (Akata et al., 2020). These systems are developed to leverage human strengths and compensate for human weaknesses. Humans and AI are regarded as equal team members solving tasks in cooperation (Siemon et al., 2019). Hybrid intelligent systems aim to optimise the complementary strengths of human intelligence and AI, so that the two together behave more intelligently than the two separately (Dellermann et al., 2019), and it envisions collaboration between human and artificial intelligence in a social, technological ensemble (Cukurova et al., 2019).

Yet, research on hybrid intelligence is still in a very early stage, and there are numerous challenges in conceptualising and developing such systems. Four challenges are set out by Akata et al. (2020): (1) how do we develop AI systems that work in synergy with humans, (2) how do these systems learn from and adapt to their environment, (3) how do we ensure ethical and responsible behaviour, and (4) how can humans and AI share and explain their awareness, goals, and strategies to each other? Developing collaborative, adaptive, responsible, and explainable hybrid intelligent systems is important across many application domains, but is especially useful for our thinking about the role of AI in education. The focus on the interplay between learners, teachers, and AI to optimise learning will be central to the successful application of AI in this field.

To summarise, the augmentation perspective and the concept of hybrid intelligence are introduced to guide our thinking about AI in education. In learning, AI and human cognition are intertwined and entangled. It is difficult

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to separate AIED from human cognition, and the system has to be viewed, developed, and researched as a hybrid *human-AI* system. This stresses the unique character of education as an application area of AI in which human-AI collaboration and vision on a combined strength of human and artificial intelligence is essential.

3 | DEVELOPMENTS TOWARDS HYBRID INTELLIGENT LEARNING TECHNOLOGIES

There are generally thought to be three critical elements that have recently emerged in western countries for AI in education to develop. First, students now have personal devices and computers, available both in the classroom and at home. Second, there is an improved understanding of how data can help explain learning in the field of learning analytics and learning sciences (Gašević et al., 2015; Mangaroska & Giannakos, 2018). Third, the availability of intelligent learning technologies using learning analytics and AI techniques at scale for schools (Molenaar, 2021). Moreover, the digitalisation of education accelerated during the COVID-19 pandemic, driven by many initiatives to support education at home during school closures (Cone et al., 2021). Until recently, most learning technologies have focused on delivering educational content and/or managing educational arrangements (Holmes & Tuomi, 2022; Tabuenca et al., 2021). Although these technologies were mostly unintelligent, they do provide a solid foundation for developments towards more intelligent learning technologies.

Recent digitalisation efforts have led to a new generation of intelligent learning technologies that use artificial intelligence to support specific tasks (Baker, 2021). In addition to computer-assisted learning technologies (CAL) often used for remediating individual students' skills, and Intelligent Tutor Systems (ITS) developed to optimise individual learners' learning trajectories (Baker, 2021), Adaptive Learning Technologies (ALTs) focus on supporting individual learners according to their needs (Martin et al., 2020). Computer-assisted learning technologies, intelligent tutor systems and Adaptive Learning Technologies generally focus on interaction with individual learners. There is a new type of adaptive learning technologies that are instead developed within classrooms, in close collaboration with teachers (Molenaar & Knoop-van Campen, 2016). These ALTs are considered as a first step towards hybrid intelligence with combined responsibility between the system and the teacher (Molenaar, Knoop-van Campen, & Hasselman, 2017; Molenaar et al., 2017). The focus on task division and reciprocal interaction between teacher and adaptive technology has been central in developing these technologies. The quick uptake of these hybrid adaptive learning technologies may be explained by the explicit role for teachers in these educational arrangements (Kerssens & Dijck, 2021). In the Netherlands alone, estimations are that 60% of students in primary education work with such a technology daily for maths, spelling, and grammar (Molenaar, 2021).

Positioning itself in the augmentation perspective and following the well-established understanding that co-creation will support innovation in education (Prahalad & Ramaswamy, 2000), this paper argues that a coordinated dialogue will be useful to support the development of hybrid intelligence in education. Especially because pedagogical and didactical innovations need to be aligned with technical innovation (Molenaar, 2021). Such alignment is likely to take advantage of a dialogue between different quadruple helix actors (researchers, educational professionals, entrepreneurs, and policymakers) in order to further develop and conceptualise forms of hybrid intelligence. The following section outlines such a language to advance the dialogue about opportunities and threats posed by AI in education.

4 | A COMMON LANGUAGE TO COORDINATE DIALOGUE AROUND AI IN EDUCATION

The aim of developing common language in this article is to support a coordinated development of a dialogue between researchers, education professionals, entrepreneurs, and policymakers. It is intended to support the

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development of hybrid human-AI learning technologies. This common language should fuel a basic understanding of AI, also referred to as an AI mindset (Luckin, 2021). As discussed above, the current state of digitalisation in education provides a shared common ground for this dialogue. A clear distinction between *digital technologies* that mainly transfer and manage content and *intelligent technologies* that apply a certain level of artificial intelligence, provides the main distinction between the current state at scale and the future state of the art. Where the augmentation perspective and hybrid intelligence frame the dialogue, the *detect-diagnose-act* framework and the *six levels of automation* model are presented for guiding the discussion of hybrid intelligence in learning technologies.

4.1 | Detect-diagnose-act framework

The *detect-diagnose-act* framework describes the basic functioning of AI in education (Molenaar et al., 2021; Tabuenca et al., 2021). Detect stands for the input for AI, the data that is used to observe the educational arrangement and its context. The input data determine how much AI can capture the context and *observe* the learner and teacher. Typically in learning technologies, clickstream data are used to assess learners' behaviour, and learners' answers to questions are instrumental to measuring their current knowledge (Bannert et al., 2017; Joksimović et al., 2019). More advanced input data are physiological data such as skin conductivity, behavioural data such as eye tracking, and contextual data such as voice recording (Bannert et al., 2017). These allow a more comprehensive view of a learner and the learning environment, which enhances the functioning of the AI.

Next, the collected data are diagnosed to determine a learners' current state and anticipate future development. AI uses different algorithms to diagnose a relevant learner state (Baker, 2021). Learner knowledge and skills are assessed effectively by AI in structured subjects such as maths and science (VanLehn, 2011). Although less developed, progress is also being made in determining learners' knowledge in less structured subjects (Baker, 2021). Predictive techniques are also used to forecast longer-term future developments, such as determining how successful a student might be in a particular course (Ranjeeth et al., 2020). In addition to generic algorithms to diagnose students' knowledge, specific algorithms are used to assess specific skills, such as the ability to read or write (Asselborn et al., 2020), or dyslexia (Rauschenberger et al., 2020). Hence, AI is used both for diagnosing where a student is in terms of having learned subject matter content, and to anticipate future developments.

The last step is to translate the diagnosis into meaningful pedagogical-didactical actions that support learners and teachers. These actions are divided into two types. First, actions to *inform* the user (teacher or learner) of the diagnosis, where actual enactment is left to the teacher or the learner. Typically, dashboards are used to communicate this information (Bodily et al., 2018; Jivet et al., 2018). Even though AI in this educational arrangement does not take any action, dashboard information can profoundly alter the pedagogical and didactical actions of teachers (Knoop-van Campen et al., 2021) as well as learning actions of learners (Molenaar et al., 2020, 2021).

Second, there are adaptive actions in which AI performs activities. There are different types of adaptive actions such as step, task, or curriculum adaptivity (VanLehn, 2011). Step adaptivity gives feedback on learners' actions within a problem to help them solve problems accurately and efficiently. Task adaptivity selects the next task for a student that fits with the student's current knowledge or skill development. Curriculum adaptivity determines the learning objectives or topics students can progress in—or subjects that a student has not yet acquired sufficiently are foregrounded—to ensure future progress (Narvekar et al., 2020). In current practices, these different forms of adaptivity are primarily used in isolation in learning technologies. Typically, learning technologies are good at *one* type of adaptivity, whereas educational professionals often request combinations of different types of adaptivity. Further progress in applying AI in education therefore lies in combining these different forms of adaptivity (Molenaar, 2021).

The detect-diagnose-act framework can be used to understand the functioning of AI in educational use cases. It is also helpful to discuss the current limitations of AI, which are dependent on three critical elements, namely: (1) our ability to follow learners and track their environment (detect), (2) our ability to diagnose

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learners' current abilities and anticipate their development (diagnose), and (3) our ability to consequently determine the most appropriate action to optimise learning (act) (Molenaar, 2021). While this framework is helpful for describing the functioning of AI educational use cases, it does not help us to understand the relationships between different actors. The *six levels of automation* model of AI in education can help here by focusing on those actor relationships.

5 | SIX LEVELS OF AUTOMATION OF AI IN EDUCATION

The *six levels of automation* model is inspired by similar models used in the automobile industry (Parasuraman et al., 2000) and the medical field (Topol, 2019). It helps to analyse the role of AI in education and explains relations among the actors in educational use cases. In this model, the *transition of control* between teacher, learner, and technology is articulated at six different levels. The model is useful for outlining the current state of the art in AI in education, and supports a dialogue about the future of AI in education use cases.

Central in this model is the division of control between teacher, learner, and AI (see Figure 1). The input of different data streams is visualised at the bottom. The assumption is that more and more diverse data streams are needed to increase automation with AI. On the upper level of the model, teacher and learner monitoring (eyes) and control (hands) are shown for each level of automation, indicating the expected level of monitoring and control. The interaction between human and artificial intelligence increases with the level of automation.

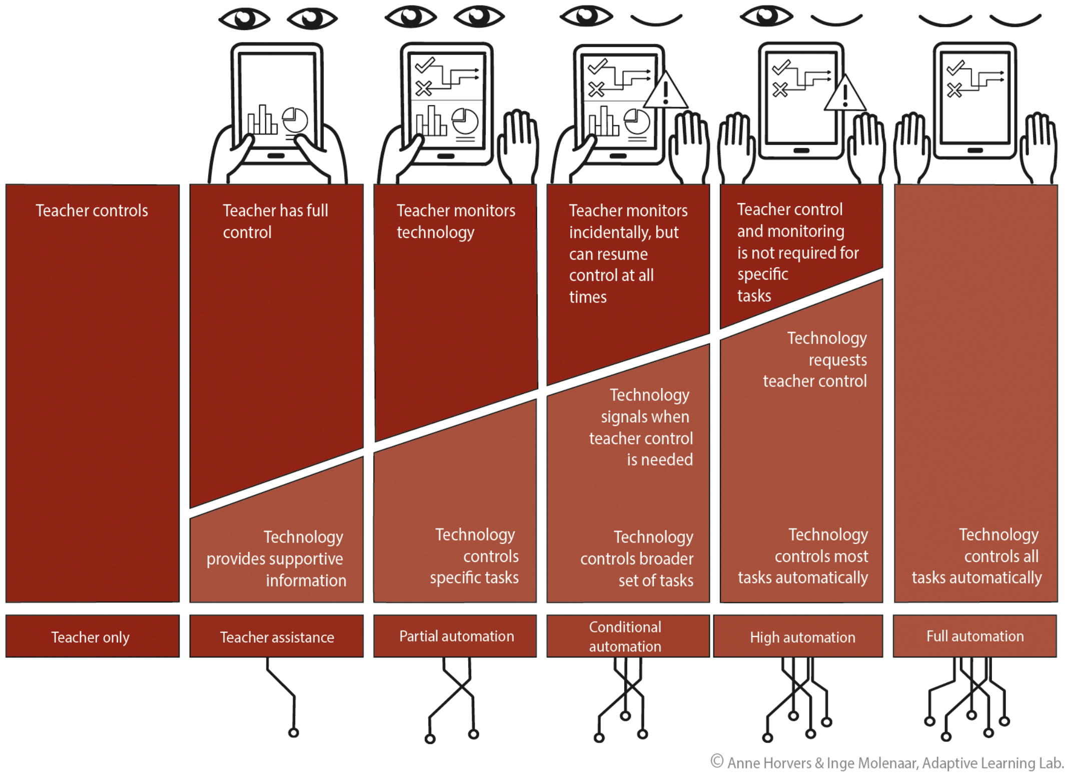

FIGURE 1 Six levels of automation model of personalised learning. *Source*: Figure constructed by Anne Horvers and Inge Molenaar. Illustration—Anne Horvers and Inge Molenaar, Adaptive Learning Lab. https://www.ru.nl/bsi/research/group-pages/adaptive-learning-lab-all/. [Colour figure can be viewed at wileyonlinelibrary.com]

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Starting in the *conditional automation level*, the warning triangle indicates the critical importance of AI communicating to human actors. Mutual understanding and reciprocity is essential for both forms of intelligence to truly augment each other (Dellermann et al., 2019). Different interfaces can be used to facilitate this interaction. Today, two-dimensional dashboards are mainly used, but augmented reality (AR) dashboards are currently being developed to integrate real-world vision with additional information (Holstein et al., 2018). These AR dashboards empower teachers and learners with analytics based on artificial intelligence embedded in their real-world vision (Holstein et al., 2019). As such, AR dashboards could function as an interface between human and artificial intelligence in classrooms.

These interfaces are essential to facilitate hybrid intelligence between teachers and AI. There is a tendency to think in a one-directional way: AI informing the teacher or the learner. However, these actors also have valuable insights and knowledge to inform AI. Two-directional interaction between AI and learners or teachers is essential to further develop the augmentation perspective on AI in education. In Figure 1, the white line between AI and human intelligence depicts this perspective.

For example, AI can provide teachers with information based on diagnosis of data gathered in the classroom context. Investigating teachers' actions in response to this information allows for the enhancement of AI in selecting pedagogical actions. Hence, going beyond the current restricted use of in-system data, integrating contextual data from the classroom, observations, and teacher assessments improves detection and enhances diagnosis. In this way, essential insights from teachers can improve the detection and diagnosis from AI and optimise the selection of pedagogical actions.

Teachers need an interface to share their professional knowledge with AI to develop reciprocal relationships (Van Leeuwen et al., 2021). This reciprocal relationship between teacher and AI further elaborates the vision of hybrid human-AI systems to improve learning and teaching. Facilitation of the communication between human and artificial intelligence is central to this model.

In level one of the model, the *teacher only* level, teachers (or learners) control the whole educational arrangement. AI is first introduced in level two, the *teacher assistance* level. Here, the teacher controls and monitors the educational arrangement and receives supportive information from AI. AI detects data and diagnoses this data, deriving important information about learner behaviour, progress, current abilities, and communicates this to the teachers as appropriate. The teachers can use the additional information to act and inform pedagogical actions that fit within the educational arrangement. Some may argue that this is not an application of Artificial Intelligence in education as the AI does not enact any actions, but although AI does not enact tasks at this level, it does influence teachers' behaviour. Research investigating the effects of teacher-faced dashboards on teachers' professional routines and actions has shown that dashboard information changes their pedagogical actions (Knoop-van Campen et al., 2021; Van Leeuwen et al., 2021). Research indicates that more task-related feedback is given to students, and that teachers change the allocation of feedback due to the additional information (Knoop-van Campen & Molenaar, 2020), and students who need assistance receive more help (Holstein et al., 2020). In a similar vein, student-faced dashboards have been shown to help students improve their practice behaviour in maths classes (Molenaar et al., 2019). Student maths practice became more effective and efficient when they had dashboards that showed their progress and insights into their learning development (Molenaar et al., 2021). Hence the potential of AI to assist teachers and learners should not be underestimated.

The teacher monitors the educational arrangement on the third level, the level of *partial automation*, but some control is handed over to AI. AI now executes specific tasks to support teachers. AI detects, diagnoses, and acts in the arrangement, but the enactment is restricted to specific tasks, whereas the teacher continues to carry out most tasks at this level. Typically, AI executes one type of learning adaptivity: step, task, or curriculum adaptivity (see description of the detect-diagnose-act framework). For example, in adaptive learning technologies, the selection of the following problem that fits well with the knowledge development of the student is selected by AI (Molenaar, Knoop-van Campen, & Hasselman, 2017). The teacher does not have to align problems to the needs of the students and can spend more time giving instruction or additional feedback to students.

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Research has shown that partial automation educational use cases, such as adaptive learning technologies, improve maths achievements (Faber et al., 2017). These solutions successfully supported educational progress during school closures during the COVID-19 lockdown by connecting teachers and students remotely (Meeter, 2021). Partial automation in which AI takes over specific tasks from the teacher operationalises the augmentation perspective of AI in education. Meaningful communication from AI to the teacher was essential for these use cases to develop.

Teachers can transfer part of the monitoring of the educational use cases to AI in level four, the level of *conditional automation*. Beyond control over specific tasks, monitoring is now also taken over by AI. The AI should include more advanced communication methods to notify the teachers if students need additional support. The core responsibility of monitoring is transferred to AI, including additional communication to the teachers. AI detects, diagnoses, and enacts a broader set of tasks, and the interface with the teachers is extended to ensure the teacher remains well informed to resume control at any time.

The broader set of tasks generally combines different types of adaptive actions. For example, advanced Intelligent Tutoring Systems often combine step feedback within a problem with curriculum adaptivity, determining when a learner has mastered a particular learning objective (Fang et al., 2019). There are only a few examples of learning technologies in which different types of adaptivity are combined for use at scale in schools, (Faber et al., 2017). The combination of types of adaptivity is quite challenging to design while maintaining transparency for the teacher. For example, task adaptivity is often combined with curriculum adaptivity so that predictive analytics—which predict a student's progress on a learning object—determine the time a learner should spend on a topic, in making curriculum decisions. This combination of adaptive actions is hard to make transparent for teachers, and therefore the ability to control the functioning of such a learning technology is at stake.

Most learning technologies combining multiple types of adaptivity have focused on a bidirectional relation between learner and technology without taking the role of the teacher into account. A notable exception is the work of Holstein et al. (2018) that developed an augmented reality dashboard for teachers on top of an Intelligent Tutor System. He showed that providing teachers with additional information to help students who face challenges induced an equalising effect and reduced unequal development in ITS classrooms (Holstein et al., 2019). This again emphasises the importance of the teachers' role in classrooms and shows that the augmentation perspective on AI in education can outperform the replacement perspective.

Teacher control is further reduced in the transition to level five, the *high automation level*. AI now controls most tasks automatically. In complicated cases, AI can request teachers to step in and take over control. This reduces the teacher's task of monitoring specific elements in the learning arrangement to observing the signals from AI to take over control when needed. There are, to my knowledge, no examples of such a system. Some systems, dedicated to one specific learning task do exist, such as the presentation trainer that supports learners' development of presentation skills such as posture and tone of voice (Schneider et al., 2017). Teachers, however, remain responsible for evaluating the presentation's content in this educational arrangement. There is quite a high level of automation concerning behavioural presentation skills. These are detected by multiple data streams (audio and video) and diagnosing posture and tone of voice, and they give feedback to the presenter supporting improvements. Content evolution is assigned to the teacher, but the collaboration between teacher and AI is not yet fully developed in this learning arrangement.

In envisioned high automation systems, all types of adaptivity are combined: AI detects multiple data streams, diagnoses a broad range of learner characteristics, abilities, and progress features, and adapts at the step, task and curriculum level. Ideally, it does this in close collaboration with human teachers. This means that the system is fully transparent in its interactions with the learner and the learning process, and it allows teachers to add observations and resume control when needed. Such systems are yet to be developed and evaluated in education (Molenaar, 2021; Vincent-Lancrin, 2021).

Finally, the sixth level of *full automation* entails situations in which no human actor is in the loop to supervise the educational arrangement. This is a highly unlikely prospect in formal education, but it may be a future use case

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in informal educational settings. We see these fully automated use cases under development for AI-supported language learning. These systems autonomously steer learning in particular learning domains or areas. Many data streams are needed to diagnose the learner's development and adjust the educational actions accordingly. These systems provide feedback on learners' performance, adjust tasks to their needs and plan the learning curriculum according to their progress and performance. There are few fully automated systems for education, but as indicated for specific language learning activities, the ALELO system is an example of a system that steers second language learning (Kim et al., 2020).

In formal educational settings, we may conclude that conditional automation is the best form for combining human and artificial intelligence and ensuring enough human control. In medicine, Topol (2019) has expressed the view that it is unlikely that developments will surpass the level of conditional automation without taking humans out of the loop. There is a risk that humans will end up *on* or even *out* of the loop in these automated systems (Cornelissen et al., 2022). Ongoing dialogue between educational professionals, researchers, and developers is needed to keep humans *in* the loop and evaluate the augmentation perspective's functioning.

To conclude, the six levels of automation model helps to articulate the division of control between humans and AI in different use cases. It provides a model to position current AI practices in education, evaluate future practices, and drive the dialogue about ideal use cases. The model is especially useful for the emergent augmentation perspective on AI in education—by developing hybrid intelligence including reciprocal interaction between humans and AI as a social-technical system. Once educational use cases with learners, teachers, and AI are conceptualised, the role of AI can be described using the detect-diagnose-act framework and the roles of the actors can be made explicit with the six levels of automation model. Until now, most applications of AI in education are diagnosing student knowledge, yet research indicates that broader types of diagnoses are within future reach and this will be discussed below.

6 | TOWARDS THE FUTURE

6.1 | Hybrid human-AI regulation

In most current use cases, AI assesses student knowledge (Aleven et al., 2016). Most examples described above are intelligent technologies that adjust the learning content to the student's performance, progress, or knowledge (Baker, 2016; Kulik & Fletcher, 2016). Although, few examples go beyond this cognitive focus on personalisation of learning, more advanced educational use cases are expected to diagnose beyond measuring student knowledge and skills. Artificial intelligence can help detect and diagnose other learner characteristics and progress features during learning. For example, important emerging research areas include self-regulated learning (SRL; Fan, Lim et al., 2022; Järvelä & Bannert, 2019), emotion (du Boulay, 2018; Horvers et al., 2021), motivation (Duffy & Azevedo, 2015; Rodrigo et al., 2008), engagement (Pedro et al., 2013), and collaboration (Olsen et al., 2014: Onan et al., 2019). Developments around SRL are outlined below as an example of these novel developments. The resulting future vision of AI in education is described in the following.

Increasingly, attention is given to developing SRL skills, i.e., the ability to monitor and control one's learning effectively (Azevedo & Gašević, 2019; Molenaar & Chiu, 2017; Winne, 2017). When students self-regulate, this contributes to deep learning, connecting prior knowledge to new knowledge and transferring knowledge and skills across domains (Molenaar et al., 2020, 2021). Students need to apply these skills throughout their lives in lifelong learning and the importance of these skills is increasingly being realised (Järvelä & Bannert, 2019).

In addition, there is growing awareness that current learning technologies are taking over regulation from learners (Molenaar et al., 2021). This off-loading of self-regulated learning may harm the development of cognitive and meta-cognitive skills that drive the application of SRL during learning (Molenaar et al., 2019). Researchers have called for caution in how adaptivity is developed and the need to be alert to the consequences of AI taking over critical tasks from students (Bodily et al., 2018).

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Fortunately, novel research has shown that this potential pitfall of AI-supported learning technologies can also be used to solve this problem. Hybrid intelligence can support learners by combining control over regulation between learners and AI. Fluctuating control between the two actors depends in this approach on the ability and skill of the learner (Molenaar, 2022). This use case can be described using the detect-diagnose-act framework and the six levels of automation model. Concerning detection, there is growing awareness of opportunities provided by multiple data streams to detect self-regulated learning (Azevedo & Gašević, 2019). Clickstream data, mouse, keyboard movement, eye tracking, and physiological data all reveal specific elements of SRL (Järvelä & Bannert, 2019). Although researchers are still learning to combine different data streams to detect SRL, two main approaches are currently distinguished.

The *horizontal approach* focuses on relationships between events in one data stream and learning. For example, van der Graaf et al. (2022) analysed which SRL activities and sequences of events were associated with learners' essay scores. In the *vertical approach*, events in multiple data streams are related. For example, log data and eye-tracking data are combined to measure episodes of orientation during learning (Fan, Van der Graaf et al., 2022).

Advancement in SRL detection during learning supports accurate diagnosis, which forms the basis for more advanced forms of enactment. Examples of diagnostics are the moment-by-moment-learning curves that can interpret student self-regulation (Baker et al., 2013). The curves provide insights into self-regulation of behaviour in practice and the ability of learners to apply strategies to improve accuracy (Molenaar et al., 2021). Another approach is to use advanced action and pattern libraries that detect sequences of learner behaviour across data streams to diagnose SRL during learning (Fan et al., 2020; Saint et al., 2018). Diverse AI techniques are used to optimise these libraries and apply them during learning (Fan et al., 2020).

These diagnostics can be translated into different pedagogical actions to support learners with SRL. Humans and technologies can provide scaffolds to elicit SRL activities (Azevedo et al., 2006; Bannert & Mengelkamp, 2008; Molenaar et al., 2012). Scaffolds are increasingly becoming personalised, taking into account the diagnosis of SRL during learning (van der Graaf et al., 2021, 2022). Dashboards have also been used to make learners aware of their regulation and provide them with information to improve their control (Jivet et al., 2021; Molenaar & Knoop-van Campen, 2018). Learners can improve regulation if they are given accurate cues about their progress and performance during learning. Ultimately, the learning technology can also control the learner and externally regulate the learning process.

Although offloading control is widely practised, there is currently little understanding of where this is justified (Molenaar et al., 2019). Depending on the roles of learner, teacher and AI, educational use cases can be positioned somewhere on the *six-levels-of-automation* model. Currently, dashboard and scaffolding, examples of learner assistance or partial automation, are most widely used. This example of SRL shows how AI could also support learning beyond knowledge development. The detect-diagnose-act framework can be used to describe the role of AI in educational use cases supporting SRL. The six levels of automation model can be used to specify the division of control between learners and AI and to understand how to advance the augmentation perspective for supporting SRL with AI. Hybrid human-AI regulation conceptualises this perspective by emphasising the importance of the transfer of control between AI and human learners—referred to as forward adaptive support (Molenaar, 2022). Scaffolds, dashboards, and external regulation can all support SRL with different levels of automation between AI and learners. Appropriate interfaces that support reciprocal interaction between AI and learners in this context are still underdeveloped.

The traditional focus of AI in education on content delivery and support for cognitive development is diversifying. Co-creation processes involving researchers, learners, teachers, and developers are helpful for developing the augmentation perspective and hybrid human- AI solutions. In the future, it is important to understand how intelligent learning technologies can be integrated to education. In particular, for tasks that go beyond knowledge and content and support diagnoses of broader learner features, such as SRL, metacognition and emotion, to advance use cases of AI in education.

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7 | CONCLUSION

In this article, I argued that education is a unique area for the application of artificial intelligence (AI). There are multiple use cases in which AI could improve teaching and learning. The augmentation perspective and the concept of hybrid intelligence were discussed for framing analyses of hybrid Human-AI use cases. To facilitate a dialogue between quadruple helix stakeholders, researchers, education professionals, entrepreneurs, and policymakers, it is essential to have a common language about AI in education. This article outlined such a common language to accommodate a fruitful discussion and support the development of hybrid Human-AI learning technologies. The detect-diagnose-act framework was used to describe the functioning of AI in education. The six levels of automation model develops our thinking about roles of AI, learners, and teachers in educational use cases. The common language introduced describes how new pedagogical models with different values can be articulated and helps to support a coordinated development of an interdisciplinary dialogue between quadruple helix stakeholders, to build on the combined strength of human and artificial intelligence. This is critical for efforts to envision future practices in which these technologies are used, develop the augmentation perspective and understand the role of hybrid human-AI use cases, and envision accompanying roles for learners, teachers, and AI.

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