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ORIGINAL RESEARCH

Artificial Intelligence in Education: Implications for Policymakers, Researchers, and Practitioners

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Abstract
One trending theme within research on learning and teaching is an emphasis on artificial intelligence (AI). While AI offers opportunities in the educational arena, blindly replacing human involvement is not the answer. Instead, current research suggests that the key lies in harnessing the strengths of both humans and AI to create a more effective and beneficial learning and teaching experience. Thus, the importance of 'humans in the loop' is becoming a central tenet of educational AI. As AI technology advances at breakneck speed, every area of society, including education, needs to engage with and explore the implications of this phenomenon. Therefore, this paper aims to assist in this process by examining the impact of AI on education from researchers' and practitioners' perspectives. The authors conducted a Delphi study involving a survey administered to $N=33$ international professionals followed by in-depth face-to-face discussions with a panel of international researchers to identify key trends and challenges for deploying AI in education. The results indicate that the three most important and impactful trends were (1) privacy and ethical use of AI; (2) the importance of trustworthy algorithms; and (3) equity and fairness. Unsurprisingly, these were also identified as the three key challenges. Based on these findings, the paper outlines policy recommendations for AI in education and suggests a research agenda for closing identified research gaps.

Keywords Artificial intelligence · Adaptive learning · Ethics · Privacy · Data protection · Policy recommendation · Algorithmic bias · Stakeholders · Human-AI-Alliance · Delphi study

1 Introduction

Artificial intelligence (AI) is finding its way into people's everyday lives at breathtaking speed and with almost unlimited possibilities. Typical points of contact with AI include pattern, image and speech recognition, auto-completion or correction suggestions for digital search queries. Since the 1950s, AI has been recognised in computer science and interdisciplinary fields such as philosophy, cognitive science, neuroscience, and economics (Tegmark, 2018). AI refers to the attempt to develop machines that can do things that were

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previously only possible using human cognition (Zeide, 2019). In contrast to humans, however, AI systems can process much more data in real-time (De Laat et al., 2020).

AI in education represents a generic term to describe a wide collection of different technologies, algorithms, and related multimodal data applied in education's formal, non-formal, and informal contexts. It involves techniques such as data mining, machine learning, natural language processing, large language models (LLMs), generative models, and neural networks. The still-emerging field of AI in education has introduced new frameworks, methodological approaches, and empirical investigations into educational research; for example, novel methods in academic research include machine learning, network analyses, and empirical approaches based on computational modelling experiments (Bozkurt et al., 2021).

With the emerging opportunities of AI, learning and teaching may be supported in situ and in real-time for more efficient and valid solutions (Ifenthaler & Schumacher, 2023). Hence, AI has the potential to further revolutionise the integration of human and artificial intelligence and impact human and machine collaboration in learning and teaching (De Laat et al., 2020). The discourse around the utilization of AI in education shifted from being narrowly focused on automation-based tasks to the augmentation of human capabilities linked to learning and teaching (Chatti et al., 2020). Notably, the concept of 'humans in the loop' (U.S. Department of Education, 2023) has gained more traction in recent education discourse as concerns about ethics, risks, and equity emerge.

Due to the remaining challenges of implementing meaningful AI in educational contexts, especially for more sophisticated tasks, the reciprocal collaboration of humans and AI might be a suitable approach for enhancing the capacities of both (Baker, 2016). However, the importance of understanding how AI, as a stakeholder among humans, selects and acquires data in the process of learning and knowledge creation, learns to process and forget information, and shares knowledge with collaborators is yet to be empirically investigated (Al-Mahmood, 2020; Zawacki-Richter et al., 2019).

This paper is based on (a) a literature review focussing on the impact of AI in the context of education, (b) a Delphi study (Scheibe et al., 1975) involving $N=33$ international professionals and a focus discussion on current opportunities and challenges of AI as well as (c) outlining policy recommendations and (d) a research agenda for closing identified research gaps.

2 Background

2.1 Artificial Intelligence

From a conceptual point of view, AI refers to the sequence and application of algorithms that enable specific commands to transform a data input into a data output. Following Graf Ballestrem et al. (2020), among several definitions related to AI (Sheikh et al., 2023), AI refers to a system that exhibits intelligent behaviour by analysing the environment and taking targeted measures to achieve specific goals using certain degrees of freedom. In this context, intelligent behaviour is associated with human cognition. The focus here is on human cognitive functions such as decision-making, problem-solving and learning (Bellman, 1978). AI is, therefore, a machine developed by humans that can achieve complex goals (partially) autonomously. By applying machine learning techniques, these machines can increasingly analyse the application environment and its context and adapt to changing conditions (De Laat et al., 2020).

Daugherty and Wilson (2018) analyse the interaction between humans and AI. They identified three fields of activity: (a) Human activities, such as leading teams, clarifying points of view, creating things, or assessing situations. The human activities remain an advantage for humans when compared to AI. (b) Activities performed by machines, such as carrying out processes and repeating them as required, forecasting target states, or adapting processes. The machine activities are regarded as an advantage when compared to humans. In between are the (c) human–machine alliances. In this alliance, people must develop, train, and manage AI systems—to empower them. In this alliance, machines extend the capabilities of humans to analyse large amounts of data from countless sources in (near) real time. In these alliances, humans and machines are not competitors. Instead, they become symbiotic partners that drive each other to higher performance levels. The paradigm shift from computers as tools to computers as partners is becoming increasingly differentiated in various fields of application (Wesche & Sonderegger, 2019), including in the context of education.

2.2 Artificial Intelligence in Education

Since the early 2010s, data and algorithms have been increasingly used in the context of higher education to support learning and teaching, for assessments, to develop curricula further, and to optimize university services (Pinkwart & Liu, 2020). A systematic review by Zawacki-Richter et al. (2019) identifies various fields of application for AI in the context of education: (a) modelling student data to make predictions about academic success, (b) intelligent tutoring systems that present learning artifacts or provide assistance and feedback, (c) adaptive systems that support learning processes and, if necessary, offer suggestions for learning support, and (d) automated examination systems for classifying learning achievements. In addition, (e) support functions are implemented in the area of pedagogical decisions by teachers (Arthars et al., 2019), and the (f) further development of course content and curricula (Ifenthaler, Gibson, et al., 2018).

However, there are only a few reliable empirical studies on the potential of AI in the context of education concerning its impact (Zawacki-Richter et al., 2019). System-wide implementations of the various AI application fields in the education context are also still pending (Gibson & Ifenthaler, 2020). According to analyses by Bates et al. (2020), AI remains a sleeping giant in the context of education. Despite the great attention paid to the topic of AI in educational organizations, the practical application of AI lags far behind the anticipated potential (Buckingham Shum & McKay, 2018). Deficits in organizational structures and a lack of personnel and technological equipment at educational organizations have been documented as reasons for this (Ifenthaler, 2017).

Despite its hesitant implementation, AI has far more potential to transform the education arena than any technology before it. Potentials for educational organizations made possible by AI include expanding access to education, increasing student success, improving student retention, lowering costs and reducing the duration of studies. The application of AI systems in the context of education can be categorized on various levels (Bates et al., 2020).

The first level is aimed at institutional processes. These include scalable applications for managing application and admission procedures (Adekitan & Noma-Osaghae, 2019) and AI-based support for student counselling and services (Jones, 2019). Another field of application is aimed at identifying at-risk students and preventing students from dropping out (Azcona et al., 2019; Hinkelmann & Jordine, 2019; Russell et al., 2020). For example, Hinkelmann and Jordine (2019) report an implementation of a machine learning algorithm to identify students-at-risk, based on their study behaviour. This information triggered a student counselling process, offering support for students toward meeting their study goals or understanding personal needs for continuing the study programme.

The second level aims to support learning and teaching processes. This includes the recommendation of relevant next learning steps and learning materials (Schumacher & Ifenthaler, 2021; Shimada et al., 2018), the automation of assessments and feedback (Ifenthaler, Grieff, et al., 2018), the promotion of reflection and awareness of the learning process (Schumacher & Ifenthaler, 2018), supporting social learning (Gašević et al., 2019), detecting undesirable learning behaviour and difficulties (Nespereira et al., 2015), identifying the current emotional state of learners (Taub et al., 2020), and predicting learning success (Glick et al., 2019). For instance, Schumacher and Ifenthaler (2021) successfully utilised different types of prompts related to their current learning process to support student self-regulation.

Furthermore, a third level, which encompasses learning about AI and related technologies, has also been identified (U.S. Department of Education, 2023). AI systems are also used for the quality assurance of curricula and the associated didactic arrangements (Ifenthaler, Gibson, et al., 2018) and to support teachers (Arthars et al., 2019). For example, Ifenthale, Gibson, et al. (2018) applied graph-network analysis to identify study patterns that supported re-designing learning tasks, materials, and assessments.

2.3 Ethics Related to Artificial Intelligence in Education

The tension between AI's potential and ethical principles in education was recognized early on (Slade & Prinsloo, 2013). Ifenthaler and Tracey (2016) continued the discourse on ethical issues, data protection, and privacy of data in the context of AI applications. The present conceptual and empirical contributions on ethics and AI in the context of education show that data protection and privacy rights are a central problem area in the implementation of AI (Li et al., 2023).

AI systems in the context of education are characterised by their autonomy, interactivity and adaptability. These properties enable effective management of the dynamic and often incompletely understood learning and teaching processes. However, AI systems with these characteristics are difficult to assess, and their predictions or recommendations can lead to unexpected behaviour or unwanted activities (i.e., black box). Richards and Dignum (2019) propose a value-centred design approach that considers ethical principles at every stage of developing and using AI systems for education. Following this approach, AI systems in the context of education must (a) identify relevant stakeholders; (b) identify stakeholders' values and requirements; (c) provide opportunities to aggregate the values and value interpretation of all stakeholders; (d) ensure linkage of values and system functionalities to support implementation decisions and sustainable use; (e) provide support in the selection of system components (from within or outside the organisation) against the background of ethical principles. Dignum (2017) integrates a multitude of ethical criteria into the so-called ART principles (Accountability, Responsibility, Transparency).

Education organisations must embrace the ART principles while implementing AI systems to ensure responsible, transparent and explainable use of AI systems. Initial study results indicate (Howell et al., 2018; Viberg et al., 2022; West, Heath, et al., 2016; West, Huijser, et al., 2016a, 2016b) that students are not willing to disclose all data for AI applications despite anticipated benefits. Although a willingness to share learning-related data is signalled, personal information or social user paths are not. This remains a critical aspect, especially when implementing the many adaptive AI systems that rely on a large amount of data.

Future AI systems may take over decision-making responsibilities if they are integrated into education organisations' decision-making processes. For instance, this could happen if AI systems are used in automated examination or admissions processes (Prinsloo & Slade, 2014; Willis & Strunk, 2015; Willis et al., 2016). Education organisations and their stakeholders will, therefore, decide against the background of ethical principles whether this responsibility can be delegated to AI. At the same time, those involved in the respective education organisations must assess the extent to which AI systems can take responsibility (if any) for the decisions made.

2.4 Context and Research Questions

EDUsummIT is a UNESCO (United Nations Educational, Scientific and Cultural Organization; https://www.unesco.org) endorsed global community of researchers, policy-makers, and practitioners committed to supporting the effective integration of Information Technology (IT) in education by promoting active dissemination and use of research. Approximately 90 leading researchers, policymakers, and practitioners from all continents and over 30 countries gathered in Kyoto, Japan, from 29 May to 01 June 2023, to discuss emerging themes and to define corresponding action items. Previous to the meeting, thematic working groups (TWGs) conducted research related to current challenges in educational technologies with a global impact. This paper is based on the work of the TWG, which focuses on 'Artificial Intelligence for Learning and Teaching'. The authors of this article constituted the TWG.

The research questions addressed by the researchers of TWG 'Artificial Intelligence for Learning and Teaching' are as follows:

1. What recent research and innovations in artificial intelligence in education are linked to supporting learning, teaching, and educational decision-making?
2. What recommendations for artificial intelligence in education can be proposed for policy, practice, and research?

3 Delphi Study

This study aimed to uncover global trends and educational practices pertaining to AI in education. A panel of multinational specialists from industry and research institutions reached a consensus on a set of current trends using the Delphi method.

3.1 Methodology

The Delphi method is a robust approach for determining forecasts or policy positions considered to be the most essential (Scheibe et al., 1975). A Delphi study can be conducted using paper-and-pencil instruments, computer- or web-based approaches, as well as face-to-face communication processes. For this study, the researchers applied a mixed Delphi design, including (a) computer-based and (b) face-to-face discussion methods. In order to assure the reliability and validity of the current study, we closely followed the guidelines proposed by Beiderbeck et al. (2021), including the general phases of preparing, conducting, and analysing the Delphi study.

In the first phase, using the *computer-based method,* a panel of international researchers in artificial intelligence in education were invited to submit trends and institutional practices related to AI in the educational arena. The initial list consisted of $N = 70$ trends. This initial list was then aggregated through agreement, eliminating duplicates and trends with similar meanings. Agreement on aggregated constructs was met through in-depth research debriefing and discussion among the involved researchers. The final consolidated list included $N = 20$ topics of AI in education. In an additional step of the computer-based method, the list was disseminated to global specialists in AI in education. Each participant was asked to rate the 20 topics on the list concerning (1) importance, (2) impact, and (3) key challenges on a scale of 1–10 (with 10 being the highest). The instructions for the ratings were as follows:

- Please rate the IMPORTANCE of each of the trends (on a scale of 10, where 10 is the highest IMPORTANCE) for learning and teaching related to AI in organizations within the next 3 years.
- Please rate the IMPACT of each of the trends (on a scale of 10, where 10 is the highest IMPACT) on learning and teaching related to AI and how organizations will utilize them.
- Please rate the KEY CHALLENGES of each of the trends in AI in education (on a scale of 10, where 10 is the highest CHALLENGE) that organizations will face within the next 3 years.

In preparation for the second phase, *face-to-face discussion*, the panel of international researchers were asked to provide three relevant scientific literature resources related to the identified key areas in the first phase and explain their contribution to the respective development area. Next, the panel of international researchers met face-to-face for a 3-day workshop. During the face-to-face meeting, the panel of international researchers and policymakers followed a discussion protocol made available before the meeting (Beiderbeck et al., 2021). Discussion questions included but were not limited to: (1) What new educational realities have you identified in AI in education so far? (2) What are recommendations for future educational realities in AI in education for practice, policy, and research? The panel of international researchers discussed and agreed on several trends, challenges, and recommendations concerning research gaps and important implications for educational stakeholders, including policymakers and practitioners.

3.2 Participants

The research team sent open invitations to recruit participants through relevant professional networks, conferences, and personal invitations. As a result, a convenience sample of $N = 33$ participants (14 = female; 17 = male; 2 = undecided) with an average age of $M = 46.64$ years ($SD = 9.83$) took part in the study. The global specialists were from research institutions ($n_{ri} = 26$), industry ($n_{in} = 5$), and government organizations ($n_{in} = 2$). They had an average of $M = 17.8$ years ($SD = 9.4$) of experience in research and development in educational

Table 1 IMPORTANCE of each of the trends for learning and teaching related to AI in organizations within the next 3 years ($N=33$)

	M	*SD*	*Min*	*Max*
[Privacy and ethical use of AI and big data in education]	8.7	1.286	4	10
[Trustworthy algorithms for supporting education]	8.3	1.608	3	10
[Fairness & equity of AI in education]	8.2	1.674	1	10
[Informed policy regarding AI in education]	8.0	1.804	2	10
[Teaching and Learning about AI]	8.0	1.548	3	10
education]	7.9	2.095	1	10
[Explainable AI in education]	7.9	2.12	1	10
[Diversity & inclusion through AI in education]	7.8	2.097	1	10
[Customizable, adaptable and adaptive AI for education]	7.3	1.952	1	10
[Dashboards as interface of AI in education]	7.3	1.804	1	10
[Adoption & accessibility of AI in education]	7.3	2.134	1	10
[Human-AI collaboration in education]	7.3	2.203	1	10
[Multimodal learning analytics in education]	7.1	1.763	1	10
[Ready to use AI technology for education]	7.0	1.886	1	10
[AI for assessments]	6.9	1.946	1	10
[AI for predicting students outcomes and engagement]	6.7	2.004	1	10
[Pedagogy with AI]	6.7	2.494	1	10
[Generalization of AI models in education]	6.2	2.018	1	10
[Intelligent and social robotics for education]	5.8	2.335	1	10
[Blockchain technology in education]	4.9	2.482	1	9

Scale 1–10, where 10 is the highest IMPORTANCE. Colours in the mean values indicate the strength of importance (green = high; red = low)

technology and are currently focused on artificial intelligence. Participants were based in Argentina ($n=1$), Australia ($n=3$), Canada ($n=2$), China ($n=1$), Croatia ($n=1$), Finland ($n=1$), France ($n=1$), Germany ($n=1$), India ($n=1$), Ireland ($n=3$), Japan ($n=2$), Philippines ($n=1$), Spain ($n=2$), Sweden ($n=1$), The Netherlands ($n=6$), UK ($n=4$), and USA ($n=2$).

3.3 Data Analysis

All data were saved and analysed using an anonymized process as per conventional research data protection procedures. Data were cleaned and combined for descriptive and inferential statistics using r Statistics (https://www.r-project.org). All effects were tested at the 0.05 significance level, and effect size measures were computed where relevant. Further, discussion protocols of the *face-to-face discussion* were transcribed and analysed using QCAmap, a software for qualitative content analysis (Mayring & Fenzl, 2022). Both inductive and deductive coding techniques were used (Mayring, 2015). Regular researcher debriefing was conducted during data analysis to enhance the reliability and validity of the quantitative and qualitative analysis. The deductive coding followed pre-established categories derived from theory and existing research findings as well as the initial list of trends (e.g., ethics and AI, diversity and inclusion). The inductive process included critical reflections on new realities that emerged since the project's initial phase (e.g., generative AI, LLMs).

Table 2 IMPACT of each of the trends for learning and teaching related to AI in organizations within the next 3 years ($N = 33$)

	M	*SD*	*Min*	*Max*
[Privacy and ethical use of AI and big data in education]	8.2	1.608	4	10
[Trustworthy algorithms for supporting education]	7.7	2.268	1	10
[Fairness & equity of AI in education]	7.7	1.736	3	10
[Teaching and Learning about AI]	7.6	1.781	4	10
[Informed policy regarding AI in education]	7.6	1.821	3	10
[Ready to use AI technology for education]	7.5	2.215	1	10
[Teacher professional development regarding AI in education]	7.5	1.849	3	10
[Diversity & inclusion through AI in education]	7.5	2.006	2	10
[Dashboards as interface of AI in education]	7.4	2.037	1	10
[Explainable AI in education]	7.3	2.174	1	10
[Adoption & accessibility of AI in education]	7.2	1.837	3	10
[AI for predicting students outcomes and engagement]	7.1	1.682	4	10
[AI for assessments]	7.0	1.94	3	10
[Customizable, adaptable and adaptive AI for education]	6.9	2.256	1	10
[Human-AI collaboration in education]	6.8	2.195	1	10
[Multimodal learning analytics in education]	6.6	1.958	1	10
[Pedagogy with AI]	6.5	2.338	1	10
[Generalization of AI models in education]	6.4	2.115	1	10
[Intelligent and social robotics for education]	5.5	2.298	1	9
[Blockchain technology in education]	5.0	2.65	1	9

Scale 1–10, where 10 is the highest IMPACT. Colours in the mean values indicate the strength of impact (green = high; red = low)

Table 3 CHALLENGES of each of the trends for learning and teaching related to AI in organizations within the next 3 years ($N = 33$)

	M	*SD*	*Min*	*Max*
[Privacy and ethical use of AI and big data in education]	8.5	1.455	5	10
[Trustworthy algorithms for supporting education]	8.3	1.804	1	10
[Fairness & equity of AI in education]	8.3	1.855	3	10
[Informed policy regarding AI in education]	8.2	1.833	3	10
[Pedagogy with AI]	8.1	1.611	4	10
[Adoption & accessibility of AI in education]	8.1	1.939	3	10
[Customizable, adaptable and adaptive AI for education]	8.1	1.69	4	10
[Human-AI collaboration in education]	8.0	1.698	5	10
[Diversity & inclusion through AI in education]	8.0	2.178	1	10
[Generalization of AI models in education]	7.8	2.123	1	10
[Explainable AI in education]	7.8	2.03	1	10
education]	7.7	1.744	4	10
[Ready to use AI technology for education]	7.4	1.932	3	10
[AI for assessments]	7.3	1.976	3	10
[AI for predicting students outcomes and engagement]	7.2	2.105	1	10
[Dashboards as interface of AI in education]	7.1	2.117	1	10
[Teaching and Learning about AI]	7.1	2.15	1	10
[Intelligent and social robotics for education]	7.0	1.941	3	10
[Multimodal learning analytics in education]	6.9	2.187	1	10
[Blockchain technology in education]	6.6	2.599	1	10

Scale 1–10, where 10 is the highest CHALLENGE. Colours in the mean values indicate the strength of challenge (green = high; red = low)

4 Results

4.1 Phase 1: Global Trends in Artificial Intelligence in Education

The first phase (i.e., computer-based method) resulted in a preliminary list of trends in AI in education. These trends were rated concerning importance (see Table 1), impact (see Table 2), and challenges (see Table 3).

As shown in Table 1, the most important trends included (1) Privacy and ethical use of AI and big data in education ($M = 8.7$; $SD = 1.286$), (2) Trustworthy algorithms for supporting education ($M = 8.3$; $SD = 1.608$), and Fairness & equity of AI in education ($M = 8.2$; $SD = 1.674$). Less important trends included (18) Generalization of AI models in education ($M = 6.2$; $SD = 2.018$), (19) Intelligent and social robotics for education ($M = 5.8$; $SD = 2.335$), and (20) Blockchain technology in education ($M = 4.9$; $SD = 2.482$) (see Table 1).

Table 2 shows the most impactful trends, including (1) Privacy and ethical use of AI and big data in education ($M = 8.2$; $SD = 1.608$), (2) Trustworthy algorithms for supporting education ($M = 7.7$; $SD = 2.268$), and (3) Fairness & equity of AI in education ($M = 7.7$; $SD = 1.736$). Less impactful trends included (18) Generalization of AI models in education ($M = 6.4$; $SD = 2.115$), (19) Intelligent and social robotics for education ($M = 5.5$; $SD = 2.298$), and (20) Blockchain technology in education ($M = 5.0$; $SD = 2.650$) (see Table 2).

Challenges related to the trends in AI in education are presented in Table 3. Key challenges included (1) Privacy and ethical use of AI and big data in education ($M = 8.8$; $SD = 1.455$), (2) Trustworthy algorithms for supporting education ($M = 8.3$; $SD = 1.804$), and (3) Fairness & equity of AI in education ($M = 8.3$; $SD = 1.855$). Even the weakest challenges received ratings above the mean (18) Intelligent and social robotics for education ($M = 7.0$; $SD = 1.941$), (19) Multimodal learning analytics in education ($M = 6.9$; $SD = 2.187$), and (20) Blockchain technology in education ($M = 6.6$; $SD = 2.599$) (see Table 3).

Overall, the challenges ($M = 7.68$, $SD = 0.315$) of AI in education have been rated significantly higher than impact ($M = 7.05$, $SD = 0.593$) and importance ($M = 7.28$, $SD = 0.829$), $F(2, 57) = 3.512$, $p < 0.05$, $Eta2 = 0.110$ (medium effect).

Table 4 Top 3 trends for learning and teaching related to AI in organizations within the next 3 years ($N = 33$)

	Importance		Impact		Challenges	
	M	*SD*	*M*	*SD*	*M*	*SD*
Privacy and ethical use of AI and big data in education	8.4	1.35	7.8	2.201	8.5	1.354
Trustworthy algorithms for supporting education	8.7	0.823	8.8	1.135	8.2	1.476
Fairness & equity of AI in education	8.3	0.949	7.7	1.829	8.2	1.476

Scale 1–10, where 10 is the highest IMPORTANCE, IMPACT, CHALLENGE

4.2 Phase 2: Consensus Related to Identified Areas of Artificial Intelligence in Education

For the second phase, the top three trends for importance, impact, and challenges of AI in education were critically reflected and linked with an in-depth and research-informed group discussion. However, all other trends have been recognized during the consensus phase and for developing recommendations toward strategies and actions. As shown in Table 4, the panel of international researchers and policymakers agreed that (a) privacy and ethical use of AI and big data in education, (b) trustworthy algorithms for supporting education, and (c) fairness and equity of AI in education remain the key drivers of AI in education. Further, the panel of international researchers and policymakers identified emerging educational realities with AI, including (d) new roles of stakeholders in education, (e) human-AI-alliance in education, and (f) precautionary pre-emptive policies preceding practice for AI in education.

5 Discussion

This Delphi study included global specialists from research institutions, industry, and policymaking. The primary goal of the Delphi method is to structure a group discussion systematically. However, reaching a consensus in the discussion may also lead to a biased perspective on the research topic (Beiderbeck et al., 2021). Another limitation of the current study is the limited sample size. Hence, our convenience sample could have included more participants and further differentiated the various experience levels in AI in education. Hence, future studies may increase the empirical basis as well as the experience of participants related to AI in education. Further, a limitation may be seen in possible overlaps between the identified constructs during the Delphi study. However, through the in-depth face-to-face discussion of the panel of international researchers, the constructs were constantly monitored concerning their content validity and refined accordingly.

In summary, the highest-rated trends in AI in education regarding importance, impact, and challenges included privacy and ethical use of AI and big data in education, trustworthy algorithms for supporting education, and fairness and equity of AI in education. In addition, new roles of stakeholders in education, human-AI-alliance in education, and precautionary pre-emptive policies precede practice for AI in education have been identified as emerging realities of AI in education.

5.1 Trends Identified for AI in Education

Privacy and ethical use of AI and big data in education emphasise the importance of data privacy (data ownership, data access, and data protection) concerning the development, implementation, and use of AI systems in education. Inevitably, the handling of these data privacy issues has significant ethical implications for the stakeholders involved. For instance, Adejo and Connolly (2017) discuss ethical issues related to using learning analytics tools and technologies, focusing on privacy, accuracy, property, and accessibility concerns. Further, a survey study by Ifenthaler and Schumacher (2016) examined student perceptions of privacy principles in learning analytics systems. The findings show that students remained conservative in sharing personal data, and it was recommended that all stakeholders be involved in implementing learning analytics systems. Thus, the sustainable involvement of stakeholders increases trust and establishes transparency regarding the need for and use of data.

More recently, Celik (2023) focused on teachers' professional knowledge and ethical integration of AI-based tools in education and suggested that teachers with higher knowledge of interacting with AI tools have a better understanding of their pedagogical contributions. Accordingly, AI literacy among all stakeholders appears to be inevitable, including understanding AI capabilities, utilizing AI, and applying AI (Papamitsiou et al., 2021; Wang & Lester, 2023).

Trustworthy algorithms for supporting education focus on trustworthiness, which is defined as the security, reliability, validity, transparency, and accuracy of AI algorithms and the interpretability of the AI outputs used in education. It particularly focuses on the impact of algorithmic bias (systematic and repeated errors resulting in unfair outcomes) on different stakeholders and stages of algorithm development. Research has demonstrated that algorithmic bias is a problem for algorithms used in education (OECD, 2023). Bias, which can occur at all stages of the machine learning life cycle, is a multilayered phenomenon encompassing historical bias, representation bias, measurement bias, aggregation bias, evaluation bias and deployment bias (Suresh & Guttag, 2021). For instance, Baker and Hawn (2021) review algorithmic bias in education, discussing its causes and empirical evidence of its manifestation, focusing on the impacts of algorithmic bias on different groups and stages of algorithm development and deployment in education. Alexandron et al. (2019) raise concerns about reliability issues, identify the presence of fake learners who manipulate data, and demonstrate how their activity can bias analytics results. Li et al. (2023) also mention the inhibition of predictive fairness due to data bias in their systematic review of existing research on prediction bias in education. Minn et al. (2022) argue that it is challenging to extract psychologically meaningful explanations that are relevant to cognitive theory from large-scale models such as Deep Knowledge Tracing (DKT) and Dynamic Key-Value Memory Network (DKVMN), which have useful performance in knowledge tracking, and mention the necessity for simpler models to improve interpretability. On the contrary, such simplifications may result in limited validity and accuracy of the underlying models.

Fairness and equity of AI in education emphasises the need for explainability and accountability in the design of AI in education. It requires lawful, ethical, and robust AI systems to address technical and social perspectives. Current research related to the three trends overlaps and emphasises the importance of considering stakeholder involvement, professional knowledge, ethical guidelines, as well as the impact on learners, teachers, and organizations. For instance, Webb et al. (2021) conducted a comprehensive review of machine learning in education, highlighting the need for explainability and accountability in machine learning system design. They emphasised the importance of integrating ethical considerations into school curricula and providing recommendations for various stakeholders. Further, Bogina et al. (2021) focused on educating stakeholders about algorithmic fairness, accountability, transparency, and ethics in AI systems. They highlight the need for educational resources to address fairness concerns and provide recommendations for educational initiatives.

New roles of stakeholders in education is related to the phenomena that AI will be omnipresent in education, which inevitably involves stakeholders interacting with AI systems in an educational context. New roles and profiles are emerging beyond traditional ones. For instance, Buckingham Shum (2023) emphasises the need for enterprise-wide deployment of AI in education, which is accompanied by extensive staff training and support. Further, new forms of imagining AI and of deciding its integration into socio-cultural systems will have to be discussed by all stakeholders, particularly minority or excluded collectives. Hence, AI deployment reflects different levels of influence, partnership and adaptation that are required to introduce and sustain novel technologies in the complex system that constitutes an educational organisation. Further, Andrews et al. (2022) recommend appointing a Digital Ethics Officer (DEO) in educational organisations who would be responsible for overseeing ethical guidelines, controlling AI activities, ethics training, as well as creating an ethical awareness culture and advising management.

Human-AI-alliance in education emphasises that AI in education shifted from being narrowly focused on automation-based tasks to augmenting human capabilities linked to learning and teaching. Seeber et al. (2020) propose a research agenda to develop interrelated programs to explore the philosophical and pragmatic implications of integrating humans and AI in augmenting human collaboration. Similarly, De Laat et al. (2020) and Joksimovic et al. (2023) highlight the challenge of bringing human and artificial intelligence together so that learning in situ and in real-time will be supported. Multiple opportunities and challenges arise from the human-AI-alliances in education for educators, learners, and researchers. For instance, Kasneci et al. (2023) suggest educational content creation, improving student engagement and interaction, as well as personalized learning and teaching experiences.

Precautionary pre-emptive policies precede practice for AI in education, underlining that, overwhelmed by the rapid change in the technology landscape, decision-makers tend to introduce restrictive policies in reaction to initial societal concerns with emerging AI developments. Jimerson and Childs (2017) highlight the issue of educational data use and how state and local policies fail to align with the broader evidence base of educational organisations. As a reaction toward uninformed actions in educational organisations, Tsai et al. (2018) introduced a policy and strategy framework that may support large-scale implementation involving multi-stakeholder engagement and approaches toward needs analysis. This framework suggests various dimensions, including mapping the political context, identifying the key stakeholders, identifying the desired behaviour changes, developing an engagement strategy, analysing the capacity to effect change, and establishing monitoring and learning opportunities.

5.2 Strategies and Actions

Based on the findings of the Delphi study as well as current work by other researchers, we recommend the following actions for policymakers (PM), researchers (RE), and practitioners (PR), each strategy linked to the corresponding challenges identified above. A detailed implementation plan for the strategies and related stakeholders can be found in a related paper published during EDUsummIT (https://www.let.media.kyoto-u.ac.jp/edusummit2022/):

- In order to support the new roles of stakeholders in education
- Identify the elements involved in the new roles (RE)
- Identify and implement pedagogical practices for AI in education (PR, RE)
- Develop policies to support AI and data literacies through curriculum development (PM)
- In order to support the Human-AI-Alliance in education
- Encourage and support collaborative interaction between stakeholders and AI systems in education (RE)
- Take control of available AI systems and optimize teaching and learning strategies (PR)

- Promote institutional strategies and actions in order to support teachers' agency and avoid teachers' de-professionalization (PM, PR)
- In order to support evidence-informed practices of AI in education
- Use both the results of fundamental research into AI and the results of live case studies to build a robust body of knowledge and evidence about AI in education (RE)
- Support open science and research on AI in education (PM)
- Implement evidence-informed development of AI applications (RE, PR)
- Implement evidence-informed pedagogical practices (PR, RE)
- In order to support ethical considerations of AI in education
- Forefront privacy and ethical considerations utilizing a multi-perspective and interdisciplinary approach as the core of AI in education (PM, RE, PR)
- Consider the context, situatedness, and complexity of AI in education's impacts at the time of exploring ethical implications (PR)
- Continuously study the effects of AI systems in the context of education (RE)

6 Conclusion

The evolution of Artificial Intelligence (AI) in education has witnessed a profound transformation over recent years, holding tremendous promise for the future of learning (Bozkurt et al., 2021). As we stand at the convergence of technology and education, the potential impact of AI is poised to reshape traditional educational paradigms in multifaceted ways. Through supporting personalised learning experiences, AI has showcased its ability to cater to individual student needs, offering tailored curricula and adaptive assessments (Brusilovsky, 1996; Hemmler & Ifenthaler, 2022; Jones & Winne, 1992; Martin et al., 2020). This customisability of education fosters a more inclusive and effective learning environment, accommodating diverse learning needs and regulations. Moreover, AI tools augment the role of educators by automating administrative tasks, enabling them to allocate more time to mentoring, fostering creativity, and critical thinking (Ames et al., 2021). However, the proliferation of AI in education also raises pertinent ethical concerns, including data privacy, algorithmic biases, and the digital divide (Baker & Hawn, 2021; Ifenthaler, 2023). Addressing these concerns requires a conscientious approach, emphasising transparency, equity, and responsible AI development and deployment. In addition, in recent years, the emergence of generative AI, such as ChatGPT, is expected to facilitate interactive learning and assist instructors, while concerns such as the generation of incorrect information and privacy issues are also being addressed (Baidoo-Anu & Owusu Ansah, 2023; Lo, 2023).

Looking forward, the future of AI in education holds tremendous potential for transformation of learning and teaching. Yet, realising the full potential of AI in education necessitates concerted efforts from stakeholders—educators, policymakers, technologists, and researchers—to collaborate, innovate, and navigate the evolving ethical and pedagogical considerations. Embracing AI's potential while safeguarding against its pitfalls will be crucial in harnessing its power to create a more equitable, accessible, and effective educational arena.

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Data availability The data that support the findings of this study are available from the authors upon reasonable request.

Declarations

Conflict of interests The authors have no relevant financial or non-financial interests to disclose.

Ethical Approval All procedures performed in studies involving human participants were under the ethical standards of the institutional and national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards. This article does not contain any studies with animals performed by any of the authors.

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