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Is Artificial Intelligence Really the Next Big Thing in Learning and Teaching in Higher Education? A Conceptual Paper

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Is Artificial Intelligence Really the Next Big Thing in Learning and Teaching in Higher Education? A Conceptual Paper

Abstract

Artificial Intelligence in higher education (AIED) is becoming a more important research area with increasing developments and application of AI within the wider society. However, as yet AI based tools have not been widely adopted in higher education. As a result there is a lack of sound evidence available on the pedagogical impact of AI for learning and teaching. This conceptual paper thus seeks to bridge the gap and addresses the following question: is artificial intelligence really the new big thing that will revolutionise learning and teaching in higher education? Adopting the technological pedagogical content knowledge (TPACK) framework and the Unified Theory of Acceptance and Use of Technology (UTAUT) as the theoretical foundations, we argue that Artificial Intelligence (AI) technologies, at least in their current state of development, do not afford any real new advances for pedagogy in higher education. This is mainly because there does not seem to be valid evidence as to how the use of AI technologies and applications has helped students improve learning, and/or helped tutors make effective pedagogical changes. In addition, the pedagogical affordances of AI have not yet been clearly defined. The challenges that the higher education sector is currently experiencing relating to AI adoption are discussed at three hierarchical levels, namely national, institutional and personal levels. The paper ends with recommendations with regard to accelerating AI use in universities. This includes developing dedicated AI adoption strategies at the institutional level, updating the existing technology infrastructure and up-skilling academic tutors for AI.

Practitioner Notes

1. AI technologies have been adopted more widely in industry, Higher education sector globally is lagging behind this trend.
2. Even though the perceived benefits of AI in education have been reported repeatedly, the actual usage is low.
3. The current adoption of AI in higher education is mainly seen in the following areas: automated learning and information support; automated essay scoring; student dropout prediction and personalised learning.
4. AI has the potential to enhance learning and teaching in higher education, however, the barriers and challenges at the national, institutional and personal levels need to be dealt with promptly and appropriately.

Keywords

artificial intelligence, big data, data analytics, pedagogical approaches, pedagogical affordances

Introduction

Artificial Intelligence or AI is used as an umbrella term for several related technologies including but not confined to, classical machine learning, deep learning, robotics and natural language processing (NLP). With the advent of ChatGPT, it has become popular in everyday media and educational settings (Eager & Brunton, 2023). AI techniques enable computers to learn and perform human-like cognitive tasks, such as predictions, and decision making through processing and analysing very large amounts of data (Holzinger et al., 2019; Awacki-Richter et al., 2019). AI techniques are closely integrated with big data and data analytics. In an education context, big data refers to students' learning data and Data analytics is referred to as learning analytics, and is concerned with collecting, measuring and analysing students' learning behaviours within different learning contexts (Clow, 2013).

AI is now widely used in major industries, such as manufacturing, supply chain management, banking, and financial services. Not surprisingly, higher education sectors worldwide are attempting to follow the trend and aim to use AI technologies and tool to enhance learning and teaching. In fact, the two latest Horizon Reports (2022, 2023) have identified AI as one of the key technologies for postsecondary education and suggested potential applications of AI tools in learning and teaching in higher education. As discussed in the section below (affordances of AI), published studies, within the field of AIED have reported the implementation of different types of AI techniques (e.g., machine learning, natural language processing (NLP), automation and robotics) in higher education regarding providing automated information support to students, enabling tutors to auto-mark students' assessments; and predicting student dropout. In recent months, large language models (LLMs) based AI text generators or generative chatbots, notably ChatGPT, have attracted a great deal of attention. These chatbots are considered to potentially disrupt higher education practice, as they are very user friendly and have ability to generate "human-like" responses to various questions, including relatively complex natural language queries (Crawford et al., 2023a; O'Dea & O'Dea, 2023). As a result, there have been ongoing debates in the higher education sector at the local, national and international level regularly about the potential impact of such tool on ethics and academic integrity regarding academic assessments.

It appears that even though its perceived impact is high, the actual adoption of AI in higher education is relatively low (Celik et al., 2022). There is a lack of clear and convincing evidence on the pedagogical impact of AI for learning and teaching, in particular, in the areas of students' learning performance and learning experience (Chen et al., 2022; Ilkka, 2018). This is partially because so far much of the emphasis of the application of AI into education has not been placed on direct and immediate learning and teaching activities, but rather on digital administrative management (Chandra & Suyanto, 2019; Klos et al., 2021) or administrative workload of academic

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and support staff (Kumar & Boulanger, 2021; Uto et al., 2020). Moreover, most published studies in AI in education have been conducted by computer and/or data science specialists and tend to focus on whether or how a particular AI application or technique works, such as the algorithms and the types of mathematical processes used to operate these algorithms (Bates et al., 2020; Zawacki-Richter et al., 2019).

Hence, this paper investigates the current development of AIED. Adopting the TPACK (Koehler & Mishra, 2006) framework and UTAUT (Venkatesh et al., 2003) as the theoretical foundations, it aims to explore the causes of slow adoption of AI in higher education, and to identify possible approaches to accelerating AI adoption. The following research question guides this study: *is artificial intelligence really the new big thing that will revolutionize learning and teaching in higher education?* It is hoped that the findings will help expand the body of knowledge relating to AIED and have an input into universities' digital transformation policy and digital strategies through providing practical and valuable recommendations.

Literature

Technological Pedagogical Content Knowledge Framework (TPACK)

TPACK, or technological pedagogical content knowledge framework was developed by Mishra and Koehler (2006) and defines the intersections between the three core components: technology, pedagogy, and content (fig.1). PCK (Pedagogical Content Knowledge) refers to the teaching methods and approaches teachers adopt for teaching subject specific knowledge. TCK (Technological Content Knowledge) addresses the question "*what* technologies can most effectively be used in teaching a particular subject"? It describes the knowledge and understanding teachers should develop on how to apply technologies and tools within their specific subject area. Particular attention should be given to the new and innovative teaching approaches enabled by technology. TPK (Technological Pedagogical Knowledge) answers the question "*how* can the technologies be used in subject matter teaching"? It is concerned with teachers' technology awareness, competency, and skills in using technology to support subject teaching and learning. An important aspect of TPK is teachers' understanding of pedagogical affordances and constraints of different types of technology (Benson & Ward, 2013). Among the core components, TCK and TPK appear to be more challenging and crucial to tutors regarding AIED. This is because compared with other learning technologies, AI is much harder to learn and understand without a computer science or math background (Yang et al., 2020).

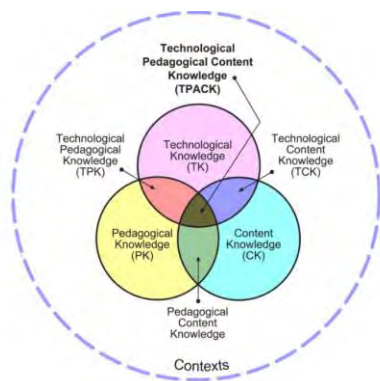


Figure 1:
TPACK framework (Mishra & Koehler, 2006)

Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT) is adopted as the analytical framework to explore and answer the research question. The UTAUT was proposed by Venkatesh et al. (2003) and indicates that the intended technology adoption is determined by four factors: performance expectancy; effort expectancy; social influence and facilitating conditions (Venkatesh et al., 2003; Williams et al., 2015).

Performance expectancy is concerned with extrinsic motivation, that is, the perceived benefits of the proposed technology. In the context of AIED, performance expectancy explores how AI technologies can be used to support and/or enhance learning and teaching. Effort expectancy is concerned with the perceived ease of use of the proposed technology. In other words, it describes the potential barriers and challenges at different hierarchical levels, such as macro, meso, and micro. Social influence refers to the acceptance of the proposed technology in a society, and also the level of individuals' ethical awareness. Facilitating conditions refer to the training and help provided by the organisation in supporting staff to adopt the proposed technology.

Apart from TPACK and UTAUT, there are other technology adoption models, such as technology acceptance model (TAM), diffusion of innovations theory (DOI), and social cognitive theory (SCT) (Taherdoost, 2018). TAM (Davis, 1989) is one of the most well known and widely used technology adoption models. It explores the intention of individuals in adopting new technology with two primary factors: perceived ease of use and perceived usefulness. DOI (Rogers, 1960) focuses on examining the spread of a new technology over time within a specific community and aims to find the reasons behind. The model proposes four factors for the examination, namely innovation, communication channels, time, and social system (Bandura, 1977; 1989). SCT however stresses the importance of learning from the social environment and interactions, and emphasizes three factors: behaviour, personal and environment (Taherdoost, 2018).

The TPACK framework and UTAUT are felt most appropriate for this paper because of the following reasons. First, the TPACK framework focuses on measuring the knowledge, skill, and abilities of educational practitioners in embedding technology to facilitate teaching and enhance

student learning (Fabian et al., 2019), and academic tutors are at the front line of teaching and student learning support. Second, the TPACK framework pays particular attention to the pedagogical affordances and effectiveness of the technology. And finally, UTAUT was developed upon existing technology adoption theories and combines multiple perspective views on user acceptance of new technology. While the theories and models mentioned above tend to focus on very different variables, stakeholders and use different types of units of analysis (Williams et al 2015). In addition, existing literature shows that these dominant theories have not yet been empirically compared, and hence their predictive power may be questioned (Marikyan & Papagiannidis, 2021).

Artificial Intelligence Affordances in Higher Education

AI's affordances in education refer to the possibility AI technologies and/or applications provide to enable enhancement in learning, teaching, and associated activities (Fu et al., 2020). Research (Major & Francis, 2020) shows that AI has strong potential to have a very significant impact on education. Even though these benefits have been reported repeatedly, there have been few studies that have presented any working examples of such systems in a higher education context, and/or studies that have examined the effectiveness of AI in supporting learning and teaching activities.

AI has long been considered as the key technology to unlocking personalised learning and enable the provision of tailored learning content, activities and support to students, based on their individual learning capacities, habits, interests and backgrounds (Major & Francis, 2020). Personalised learning essentially is "data based education", since learning and teaching activities are informed by student learning data (Kucirkova, 2018, p.3). AI recommender systems (Tavakoli et al., 2022) which utilise machine learning algorithms, to analyse and predict individual preferences and offer relevant suggestions through analysing and learning previous behaviours (Zhang et al., 2021) can enable this. Very similar AI recommender systems have been widely implemented in businesses, with examples including Amazon's product recommendations, Netflix's viewing recommendations and Spotify's playlist.

In learning and teaching contexts, it is possible to integrate a recommender system within the virtual learning environment (VLE) of the institution to predict and recommend customised module content and learning resources to students by means of analysing the available big data (or learning data), such as students' learning needs and characteristics (Shahbazi & Byun, 2022). This can potentially help universities reshape and design a more student-focused curriculum.

Alongside recommender systems, AI text generators, such as ChatGPT, BARD, Jasper and Copilot, are also considered to have the potential to offer personalized learning opportunities to students. These generative AI applications are powered by Large Language Models (LLMs). They can recognize relatively complex queries on a huge range of subjects and generate answers that are easy to understand. Whilst the impact of ChatGPT on education, particularly assessment, has been discussed in much detail, in the long run, once universities and educators have adapted to the technology it has the potential to be utilised to enhance learning performance (Crawford et

al., 2023a; Perkins, 2023). This type of tool is very user friendly and can analyse students' questions (input) and tailor its answers to accommodate individual needs. For example, Kasneci and colleagues (2023) have suggested that AI text generators can be used to support students in developing their critical thinking skills as the tool can quickly produce a summary of the main points of an article. The key affordance of the technology is that it frees up students from basic lower order skills tasks and focus on organising their thoughts for critical analysis and can enable educators to refocus assessments on higher order thinking skills.

Current Use of Artificial Intelligence in Higher Education

As shown in the examples below, the current research on AI adoption in higher education focuses mainly on two areas: digital administrative management, such as for grade or dropout prediction and virtual assistance, such as chatbots.

Automated information support – chatbots

Providing timely support to students, including answering their questions promptly is critical for motivating students to learn (Ahea et al., 2016). However, this can be difficult to achieve for tutors teaching large sized cohorts or lecturers with high workloads. Rule based chatbots have been used to support tutors in providing automated responses to some student inquiries and questions, such as timetables, assessment dates, exam results, and class location, on a 24/7 schedule. These chatbots tend to use a decision tree style flow (e.g., follow-up questions) to guide users to get to the correct solutions, and the structure and questions are all pre-defined.

Some universities are also using chatbots to answer admissions enquires of prospective students (Chandra & Suyanto, 2019; Santoso et al., 2018), and/or provide careers information and guidance to existing students (Lee et al., 2019). A study conducted by Gbenga and colleagues (2020) shows that among the students (221) who used such service, the accuracy of the chatbot in answering students' admin enquiries is fairly high (95.9%). Meanwhile, Chatbots are used to provide well-being support to students, aiming to help ease their anxiety and depression (Gabrielli et al., 2021; Klos et al., 2021).

In addition, chatbots are used to provide basic knowledge acquisition in some subject areas, for instance, for testing and reinforcing memorization of key definitions (Lee et al., 2020). Increasingly, language learning chatbots have become popular with language learning and teaching in the higher education sector. Research shows that this type of chatbot is beneficial to language learners. For instance, a study conducted by Kim (2021) regarding the use of a chatbot to teach English to Korean university students shows that the students (sample size: 35) who used the chatbot (AI voice chatting function) achieved much better speaking performance (4.55 vs 5.36, pre- and post-test) compared to those ($n = 37$) who did not (4.47 vs 5.16, pre and post-test). Similar results have also been reported in other studies (Lin & Chang, 2020).

In recent years, social robots have been introduced to higher education with an intention to address issues relating to the lack of social interactions and intrinsic motivation while students

carrying out self-directed learning (Donnermann et al., 2022; Rosenberg-Kima et al., 2020; Weber & Zeaiter, 2018). Unlike chatbots and other similar virtual agents, a social robot has a physical body and is designed to have conversations and other social interactions (e.g., pointing, hugging, and eye gazing) with learners (van den Berghe et al., 2019). In higher education contexts, social robots so far have been trialled to support teaching basic subject knowledge (e.g., HTML basics) (Phobun & Vicheanpanya, 2018), a second language (van den Berghe et al., 2019), and help facilitate small group discussions (Rosenberg-Kima et al., 2020).

The benefits of chatbots and social robots in providing more user-friendly, just-in-time information and administrative support, as well as addressing some basic psychological needs of students have been recognized (Donnermann et al., 2022; Klos et al., 2021). Nevertheless, due to current limitations of AI, both chatbots and social robots are not yet fully able to understand human contexts and engage in more intellectual interactions with students (Rosenberg-Kima et al., 2019). The majority of chatbots, are merely AI interfaces to structured information repositories (Caldarini et al., 2022).

Automated essay scoring

Automated essay scoring (AES) systems employ natural language processing and machine learning techniques to automatically grade text based essays, and have a potential to offer more timely and constructive feedback to students (Darwish & Mohamed, 2020). The grading is commonly based on different types of categories, such as statistical (e.g., average word and sentence length), style (e.g., sentence structure, and vocabulary) and content (e.g., consistency and relevance of information) (Ramesh & Sanampudi, 2021). The accuracy of AESs varies. The AES designed by Contreras and her colleagues (2018) using ontology based on text mining achieved an accuracy score of 0.5. Whilst the AES developed by Darwish and Mohamed (2020) using the fusion of fuzzy ontology and latent semantic analysis (LSA) achieved an accuracy score of 0.77. However, it seems that AESs have not been widely implemented in the higher education sector, and there has not yet been any convincing evidence on the reliability of such system. This maybe because research in this area, due to ethics and data privacy concern, does not tend to use real-time student learning data (Kumar & Boulanger, 2021; Uto et al., 2020).

Student dropout prediction

Machine learning has also been used to help predict student dropout from university. Kemper et al. (2020) used two machine learning approaches: logical regression and decision trees to predict student drop out at a German university. These techniques have achieved very high predictive accuracy (95%). Similarly, Alban and Mauricio (2019) used a neural networks approach through the application of multilayer perceptron algorithms and radial basis function, to predict undergraduate student drop out at the Public University of Ecuador. Their results indicate good predictive accuracy as well (96.3% and 96.8%). Similarly, Alamri et al. (2019) used machine learning to predict MOOC dropout rates and saw 82 percent to 94 percent accuracy in drop out prediction. Research conducted by Tsai et al. (2020) focused on predicting both drop out and academic performance. The research findings in this area have enabled some of these authors

to suggest several interventions, such as providing a dedicated personal tutoring system, and monitoring their learning conditions. Such measures could be adopted to improve students' academic performance, and prevent dropping out and it is here, where the application of AI to educational problems has had probably the most significant impact so far.

Method

This paper seeks to answer the following question: is artificial intelligence really the new big thing that will revolutionise learning and teaching in higher education? It is recognized that there is a much lower acceptance rate of AI in higher education compared with other industries, although the perceived benefits of AI in education have been repeatedly reported. Consequently, it is critical and necessary to explore the reasons behind this.

The method applied in this paper includes searching and evaluating existing literature on the topic of AIED. Peer reviewed journal papers, conference proceedings and book chapters written in English, and published through academic databases such as Web of Science, Scopus, ACM digital library and IEEE from 2015 to 2023 were included in this paper, as the publications in this area have become more popular since 2015 (Pinkwart, 2015). Particular attention was paid to practical papers and case studies, with the intention to find the best practices for using AI applications in higher education.

The selected publications were then analysed using the thematic method. Adopting the TPACK framework and UTAUT as theoretical foundations, the key areas explored including AI affordances and examples; the main challenges and barriers relating to AI adoption in higher education; extrinsic motivations of academic tutors and their universities in trying out these new technology and tools; the ethical issues and implications relating to AIED; and the support provided to staff. Similar content was then grouped into the following themes, namely performance expectancy; effort expectancy; social influence and facilitating conditions. The main components of the TPACK sit within the individual themes, such as effort expectancy and facilitating conditions and provide a more nuanced understanding for academic staff. Since the performance expectancy has been discussed in detail within the literature review section above, the focus of the sections below will be on the other three factors.

Discussion

The findings are grouped and presented following two factors of the UTAUT, namely effort expectancy and social influence. In addition, facilitating conditions will be presented in the conclusion and recommendation section.

Effort Expectancy

Effort expectancy mainly describes the barriers and challenges for user acceptance of new technology. In the context of AI in higher education, it is very important to examine the challenges academic tutors face in adopting AI applications in learning and teaching, as their main responsibilities include delivering teaching, providing learning support to students and assess

student learning performance. Nevertheless, research suggests that the adoption of AI in higher education is also affected significantly by contextual issues situated at national and institutional levels, which are also worth exploring.

National Level

At the national level, many countries such as the UK, the US and Australia have published a national AI strategy. This has consequently stimulated AI implementation in many business sectors. However, the higher education sector appears to be falling behind (Celik et al., 2022). Much of the AI that has been applied to education are plug-and-play type applications, borrowed or transplanted from industrial applications of AI, such as chatbots or machine learning used for grade and drop out prediction. One of the main reasons is that AI is more complex than other widely applied technologies in education, such as online conference platforms, augmented reality (AR) and virtual reality (VR), and it requires users to have a high degree of technical knowledge to get a grasp of the inner workings of the technology (Celik et al., 2022; Bates et al., 2020). Consequently, developing a comprehensive understanding of the full affordances of AIED can be extremely difficult for non-computer or data science educational practitioners and researchers. Further discussion of academic tutor AI capacity is provided in the section below (personal level).

In addition, research shows that the higher education sector is traditionally conservative towards technology adoption (Celik et al., 2022; Ogwu et al., 2022). For instance, it has taken nearly four decades for virtual learning environments (VLEs) to be effectively and fully integrated into university learning and teaching (Hamber & Smith, 2021; Browne et al., 2006). It took the Covid-19 shock to finally push the technology into the forefront of all teaching and learning in universities and for VLEs to finally become much more than just centralised file repositories for teaching material (O’Dea & Stern, 2022; Yeon, 2021).

Institutional Level

Barriers and challenges at this level are concerned mainly with technology and data readiness at the institutional level. Many universities do not seem to have clear and focused AI adoption strategies and plans in place, even though they have shown their keenness in this area (Pells 2019). This means that these universities may not have the appropriate infrastructure, such as computing power, storage capacity, networking infrastructure and security, and financial budget to enable and implement AI.

In a business context, any new technology adoption and implementation is affected directly by the senior management team of the organisation (Ghobakhloo et al., 2012; Bernstein et al., 2007). Some influencing factors include the managers’ “perception of and attitude on IT, support and commitment, IT knowledge and experiences, innovativeness” (Ghobakhloo et al., 2012, p.40). Therefore, to adopt AI appropriately and effectively in learning and teaching environments, university senior management teams need to develop and/or enhance the existing technology and data capabilities (Davenport, 2018). This may include developing their understanding of some of the resource requirements of AI, since AI applications are often very highly resource intensive.

University management teams also need to consider putting dedicated strategic plans in place, with the appropriate financial budget and support, to update their existing technology infrastructure, and to provide access to high performance computing environments such as those available on the cloud, namely Amazon Web Services, Microsoft Azure, or Google Cloud Platform (Jarrahi et al., 2020).

To use AI to enable more innovative pedagogical approaches and provide more customised learning support to students, it is also essential and critical for universities to develop a comprehensive understanding of the factors that affect students' engagement in learning and their academic performance (Yağcı, 2022). This can be achieved through collecting and analysing large volumes of relevant and valid student learning data sets such as their Internet browsing history, library searches, the access (length, repetition) of certain learning materials, percentage of online participation of learning activities, and study approaches, in a continuous manner (Avella et al., 2016; Ifenthaler, 2015). This may then enable AI algorithms to help in for example, categorising students based on their learning patterns and preferences, or predicting their academic achievements. Universities indeed are used to collecting student data, such as personal details (including module choices and special learning needs), attendance information, exam results, and module evaluation responses at a large scale (Jones 2019). However, not all of these data are considered effective or relevant to make personalised learning recommendations to students. For example, research conducted by Yağcı (2022), Bernacki and colleagues (2020) suggest that demographic data do not provide a valid explanation for academic failure. In addition, the current information systems universities adopt, such as student records management systems (SITs), and VLEs are not yet geared up to provide a wide variety of statistics relating to student learning activities (Ifenthaler & Yau, 2020).

Individual Level

The TPACK framework considers that successful and effective technology integration into education requires a combination of three types of knowledge: Technology, Pedagogy and Content (Fabian et al., 2019). This means that academic tutors need to have some basic knowledge and understanding of the technology that they are adopting in teaching.

AI, as discussed, is not easy to communicate to the social system (educators). It is described in a very technical language, and requires at least some basic competencies in probability, logic and statistics to truly understand it, and to use AI specialist tools and software properly (Bates et al., 2020; Zawacki-Richter et al., 2019). So, while non-technology specialists may have good pedagogical and subject content knowledge, few of them possesses AI specific technology knowledge, and more importantly, the knowledge where pedagogy, technology and content intersect.

It is also worth noting that many academic staff are not keen to try out new technologies, because, in part, the process often takes a large amount of time. Besides, technology adoption, in many universities, is not a requirement, but a recommendation (Mercader & Gairín, 2020).

Consequently, the associated achievements relating to technology enhanced learning and teaching are not formally recognised and rewarded at the departmental or institutional level.

The barriers and challenges mentioned above have covered areas such as finance, infrastructure, familiarity/awareness of AI technologies, and knowledge and confidence of some key stakeholders, such as university senior managers, and academic tutors. To accelerate the adoption of AI in higher education, all these barriers and challenges need to be addressed properly and promptly. However, it should be noted that upskilling academic tutors and training them to work with AI technologies should be considered as one of the top priorities, because they are at the front line to deliver teaching and learning support. They are likely to be the group of users that use these technologies and tools at a regular basis, and can then drive the adoption and integration into learning and teaching. In addition, educational practitioners (apart from those teaching Computer Science, Data Science and Math) are not likely to have the knowledge base and experience in AI technology, and may require a much longer time to get familiar with such technology.

Social Influence

AI is considered a young discipline. However, it has developed rapidly in the last several decades. To date, AI technologies and applications are not only adopted widely in various industries but are also used more commonly in people's everyday life. Some of the well-known examples include voice assistants, facial recognition, personalized search engine results, and recommender systems (e.g., Spotify, Netflix). Consequently, society awareness of AI is on the rise.

Alongside the rapid advancement of AI, there are growing concerns towards the ethics of AI. Ethics of AI refers to the moral principles of individuals in guiding and governing their behaviours regarding the use of AI applications. In the context of higher education, ethics of AI is often revolving around academic integrity and plagiarism. For instance, one of the recent debates in this area is about AI text generators, such as ChatGPT, Bing Chat, Bard (Alphabet) and Ernie (Baidu).

Many concerns have already been raised by educational practitioners and researchers due to this type of tool being able to mimic human writing style, and easily and quickly generate texts based upon request. It is believed that already many university students might have used this type of tool to generate parts of or an entire assessment. These AI generated texts are often not able to be detected accurately by AI detectors or plagiarism detection software (Crawford et al., 2023b).

Conclusion

AIED is a popular and emerging field in digital education and educational technology. However, research in this area often neglects the pedagogical benefits of AI tools on learning and teaching in higher education. This paper helps overcome the research gap and has the following

contributions to the literature. Nevertheless, it is worth noting that the findings cannot be generalized, since this is a conceptual paper, and no empirical data were collected.

First, it offers a detailed overview and a better understanding of current development in AIED. The findings indicate that AI technologies, at least in their current state of development, are used mainly to provide automated admin support (e.g., information seeking and assessment marking) and do not afford any real new advances for pedagogy in higher education. Second, this paper provides directions for the future research. For example, further research is needed to explore specifically the pedagogical benefits of AI tools in supporting learning and teaching in both social science and science disciplines, such as business management, psychology, biology, and math. In addition, it is important to examine the views and perceptions of academic tutors and students towards AI adoption in higher education. Furthermore, practical and case study papers are needed to showcase and share the best practices with wider communities.

And finally, this paper offers practical recommendations for breaking down barriers to AI adoption in higher education, since the potential for AI to make an impact in learning and teaching in the university sector is significant. These recommendations are mainly concerned with facilitating conditions, that is, the infrastructure, the training and support provided to help the main stakeholders particularly academic staff in gaining knowledge and developing skills need to adopt AI technology. In responding to the barriers and challenges mentioned above, the facilitating conditions are explained also in the three hierarchical levels, that is, national, institutional and personal level.

At the national level, the government should consider including AI in education in national initiatives, adopting the 2019 Beijing consensus may be an appropriate initial step (UNESCO, 2019). In this way education will be seen as a legitimate area for the application of AI technology and for the development of specialist AI software. Dedicated funding may encourage specialists from industry to consider education as a sector where techniques developed in other sectors can be fruitfully applied.

At the institutional level, university senior management teams should provide an environment to enable AI to operate both in terms of support and funding for appropriate technical environments and in terms of providing the opportunities to increase the skill base of academic tutors, so that AI affordances can be identified from and within the higher education sector. To begin this process, the foundations may be created through CPD events at departmental or university level on the basics of AI and big data or through orientating staff training by including AI as part of academic practice qualification, for example, HEA fellowships. In other words, the Professional Standards Framework (PSF) should be updated to include criteria relating to AI knowledge adoption. To achieve better results, these training events should be face-to-face, and participants should be given opportunities to have hands on practice. Regular showcase sessions within the university will also help share good practices among teaching and support staff. In addition, staff achievements in this area need to be formally recognised, for example, as part of academic promotion policy for teaching only contracts, and also as part of university wide learning and teaching awards. Furthermore, student learning data could be made more readily available to researchers and educational practitioners within their own university (EUA, 2020).

At the personal level, academic tutors need to take initiative to participate actively in the CPD and other training sessions provided by their university. As mentioned, the intention is to develop a good understanding of AI basics, including what is AI, the main AI techniques, and how AI is used to better understand and make predictions (Ransbotham et al., 2017), and the limits from an authorship perspective (Crawford et al., 2023b). So that instead of borrowing solutions from other sectors, educational practitioners can develop them for the unique characteristics of education. With the regard to the TPACK framework, learning and training should be focused on the pedagogical affordances, the potential applications of AI in different subject areas, and the type of learning data needed.

Conflict of Interest

The author(s) disclose that they have no actual or perceived conflicts of interest. The authors disclose that they have not received any funding for this manuscript beyond resourcing for academic time at their respective university.

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