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An investigation of barriers to Hong Kong K-12 schools incorporating Artificial Intelligence in education

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ABSTRACT

Artificial Intelligence in Education (AIED) has been the focus of significant attention in recent years because of its growing social importance and pedagogical value. In Hong Kong, an increasing number of K-12 schools are planning or piloting their grassroots AIED incorporation practices. However, progress is reportedly slow due to a number of barriers. Unfortunately, because of their limited scope, disputed interpretations and contextual irrelevance, current research literature seems to be of limited referencing value in aiding schools to address the issues and overcome the barriers. This paper highlights the necessity of embracing AIED as wide-ranging given the current understanding of it as a collective notion. Three major directions of AIED are identified: *Learning from AI*, *Learning about AI*, and *Learning with AI*. A collective case study, which examined the perceived barriers to AIED incorporation in Hong Kong K-12 schools with different AIED directions, was conducted. Qualitative data were gathered via ten semi-structured interviews with key stakeholders from two schools. Ertmer's (1999) typology was applied to segregate the barriers. The findings showed that both first-order and second-order barriers existed, although they varied between the cases. It was also found that the barriers did not hinder in isolation but appeared to be interconnected. The findings suggest that schools use differentiated strategies to tackle barriers according to their approach to incorporating AIED. Moreover, there is a need to trace the links between barriers and prioritise school efforts to remove or reduce them with high linkage. Several recommendations for practice are given.

1. Introduction

With the heightening of computing power, increased sophistication of algorithms, and the explosion of data, Artificial Intelligence (AI) is achieving a notable momentum and is expanding into many areas of daily life. AI, the technology genre that allows tasks to be done in a similar way to which humans do them, has progressively transformed the labour market (Bessen, 2019) and overall economic structure (Goolsbee, Hubbard, & Ganz, 2019). The establishment of the *Beijing Consensus* (UNESCO, 2019), the first-ever document of AI and education adopted by the UNESCO Member States, has compelled education leaders and policymakers worldwide to recognise the urgency of charting the future of education. As a result, AI in Education (AIED)—the intersection of AI and education domains—has become a strategic priority in many countries and regions, especially in their K-12 education sector (Knox, 2020; Zimmerman, 2018). Hong Kong, with its ambition to become a world-class "Smart City"(Innovation and Technology Bureau, 2020), is no exception when it comes to promoting AIED (Yeung, 2019). A recent report (One Country Two Systems Research Institute, 2020) by a semi-official think tank emphasised that Hong Kong must seize the opportunities offered by AI, particularly in the finance, healthcare, and education sectors, so as to maintain the city's international standing. Many K-12 schools in Hong Kong seem to be in agreement that promoting AIED is essential for ensuring the city's continued competitiveness and prosperity, and an increasing number have introduced grassroots practices to implement AIED despite the absence of a government blueprint for AIED development. Examples include the injection of AI-related elements in school-based ICT/STEM activities, exploration of applying AI in assessment, and the identification of AI-powered Apps to support student subject knowledge learning.

Regrettably, anecdotal reports have revealed that the progress of those AIED incorporation plans in Hong Kong K-12 schools are slow because there are barriers and schools have found it challenging to navigate this new paradigm. Some preliminary exploration has also

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noted that schools lack clear pathways to move AIED forward (Chai et al., 2020; Chiu & Chai, 2020; Wong, Ma, Dillenbourg, & Huan, 2020). Current literature seems to have decidedly limited guiding values, for three reasons in particular. First, existing research related to AIED has, for the greater part, been confined to higher education contexts (Popenici & Kerr, 2017; Zawacki-Richter, Marín, Bond, & Gouverneur, 2019) while K-12 AIED research is reportedly still in its nascent stages (Knox, 2020). Second, the absence of a unified understanding of the AI concept itself (Wang, 2019) has also led to ambiguity in AIED research. AI can refer to a variety of frontier technologies, which could have disparate educational implications for K-12. Each interpretation of AI could thus have its related barriers that hinder AIED incorporation. Because much of the existing literature fails to recognise the incompatibility between the interpretations (Wang, 2019) and their different objectives of AIED, the directions needed for the correct efforts are not clear. Third, contextual relevance is believed to be critical for the effectiveness of any strategy that addresses the challenges (Wang, 2017). Undoubtedly, there is a need for further research regarding Hong Kong K-12 AIED with a focus on incorporation challenges.

To help Hong Kong K-12 schools advance their AIED incorporations, it is necessary to understand the barriers that are involved in the way AIED is interpreted. Thus, the research question of this study is "*What are the perceived barriers to AIED incorporation in Hong Kong K-12 schools?*" The findings will help us gain an up-to-date understanding of the reality Hong Kong K-12 schools are facing, strengthen our knowledge of current obstructions, and generate strategies that could help Hong Kong K-12 schools incorporate AIED more effectively.

2. Literature review

2.1. Towards a collective notion of AI

There is no universally accepted scholarly definition of AI (Monett & Lewis, 2018), with its *status quo* being described as the parable of "the blind men and an elephant" (Nilsson, 2009) – the moral of which is that humans have a tendency to claim absolute truth based on their limited, subjective experience as they ignore other people's limited, subjective experiences which may be equally true. While it is clear that AI involves human-made technologies, only a fair degree of consensus has been achieved as to what extent, or whether it is possible, AI may display those properties that we equate with human intelligence (Tegmark, 2018). Based on the capacities, some scholars have distinguished weak/strong AIs (e.g., Russel & Norvig, 2010) and narrow/general/super AIs (e.g., Fjelland, 2020). Perhaps the most significant challenge to establish a well-accepted definition is that AI relates to different branches of the knowledge domain due to its historical development (Wang, 2019). Because of the varied perspectives of each field, answers to the questions of what constitutes AI and what is appropriate AI terminology have been inconsistent (Monett & Lewis, 2018). The relentless pace of technological advancement further complicates the definition of AI (Hoeschl, Bueno, & Hoeschl, 2017). Many technologies under the AI banner would not be labelled as such anymore and would become "just algorithms" when they are general enough and adopted by mainstream developers (Nilsson, 2009). The relatively recent recognition of AI as a particular genre of pervasive technology extracted from ICT (Schmidt, 2016) also has blurred boundaries between associated concepts. Therefore, before the boundaries and the "correct use" are formed, it might be useful for AI to be tentatively conceived as a collective notion that covers all the current and future working definitions, while maintaining its status as being "*nothing but what the AI researchers have been doing*" (Wang, 2019, p.3). Keeping the definition open accurately reflects the constantly evolving and wide-ranging capacity of AI.

2.2. Varied directions of AIED

Corresponding to AI as a collective notion, one way to approach AIED is by embracing its tentative status of being wide-ranging (Hwang, Xie, Wah, & Gašević, 2020). In current literature, the researchers identified three major directions of AIED: *Learning from AI*, *Learning about AI*, and *Learning with AI*.

2.2.1. Learning from AI

In the first category of AIED research, AI serves as the principal means by which students learn, i.e., *Learning from AI*. Powered by rule-based or machine learning algorithms, these instructional platforms, notably Intelligent Tutoring Systems (ITS), have the adaptive capacity to deliver customised content and progressing paths according to student's interests, aptitude, and behaviour profiling (Kose & Arslan, 2016). A review of ITS research (Ma, Adesope, Nesbit, & Liu, 2014) found that these systems were effective sources of instruction and support for student learning. However, the results could be challenged because the studies primarily focus on system development and only include pilot study results. Further, the applicability of ITS have been found limited as the target subject area, knowledge to be taught and skills to be developed must be amenable to a rule-based or machine learning AI architecture (Craig, 2018). The ramification of this shortcoming is that ITS need to be constrained to specific disciplines and less able to support the learning of complex, difficult-to-assess, higher-order skills. Perhaps the greatest criticism of ITS, is the underlying design principle of AI replacing teachers (Selwyn, 2019). Such a rationale is not aligned with the contemporary understanding of the teacher's role, which is colloquially referred to as the "guide on the side" as opposed to the old-fashioned notion of the "sage on the stage." ITS usage is, therefore, often supplemental, being relegated to independent learning time.

2.2.2. Learning about AI

The second category of AIED encompasses efforts towards equipping learners to thrive in an AI-saturated future, i.e., *Learning about AI* (interchangeably, AI education). While many educators and education authorities have reportedly been considering the inclusion of AI topics in K-12, practical application has been minimal and the education models are still being explored (Chiu & Chai, 2020; Wong, Ma, Dillenbourg, & Huan, 2020). Some noticeable initiatives on *Learning about AI* include *AI4K12*[1] in the US, *AI Basics for Schools*[2] in Europe, *AI for Kids*[3] in Singapore, and *Go AI Scheme*[4] in Hong Kong.

The technical complexity was a common reason that AI had seldom been part of K-12 teaching but only in higher education subjects previously (Steinbauer, Kandlhofer, Chklovski, Heintz, & Koenig, 2021). However, the emergence of drag-and-drop, block-based platforms such as *Cognimates*[5] and *Machine Learning for Kids*[6] in recent years have made it possible for users to programme applications that involve AI elements without mastering the complex syntax of coding languages. This opens up many educational possibilities as the platforms allow K-12 teachers to facilitate programming activities at technical levels that young learners can manage. As a result, block-based coding has become a predominant approach for many grassroots *Learning about AI* pilots (Steinbauer, Kandlhofer, Chklovski, Heintz, & Koenig, 2021).

Wong, Ma, & Huen (2019) reported an initiative of schools collaborating with the private sector to promote the extra-curricular learning of AI fundamentals through coding activities. They found students were generally intrigued about AI technologies shown to them, and interested in using them, but struggled to realise the importance of understanding

[1] https://ai4k12.org.
[2] https://www.europeanschoolnetacademy.eu/courses/course-v1:CodeWeek+AI+2021/about.
[3] https://learn.aisingapore.org/students/#ai4s.
[4] https://www.hkedcity.net/goelearning/resource/6092065e0da87e7d42738dcd.
[5] http://cognimates.me/.
[6] https://machinelearningforkids.co.uk.

AI on a deeper level due to the general disconnect between the AI learning activities and the regular school curriculum. It was also noted that the individual level of foundation in mathematics could inhibit students' progress. Given these disconnection and misalignment issues, it was concluded that identifying how AI would fit within the existing curriculum is essential.

Marques, Gresse von Wangenheim, & Hauck (2020) suggested K-12 AI education can expand from the existing ICT curriculum, and central to that would be the mastering of machine learning concepts by students. The authors reviewed 30 existing instructional units aimed at teaching machine learning concepts in schools. The general strength they found lay in the focus on demonstrating machine learning applications through activities such as data classification tasks. However, because of the complexity behind machine learning, the related concepts, even when taught at high school level, still needed to be presented by the most accessible processes or at a highly abstract level, which could be considered superficial by certain AI professionals. They also noted the absence of a systematic instructional design framework and evaluation framework among the instructional units, which means the learning goals achieved are questionable.

Many scholars advocate a broader focus of AI education beyond learning coding skills that applies to machine learning. For example, Wong (2020) suggested a more balanced and inclusive approach to AI education; while maintaining the focus on enhancing students' computational thinking, students can make sense of abstract concepts and engage in deductive and logical reasoning practices. In addition, it has been argued that the computing education curriculum is not necessarily the only option that can make room for AI education, despite AI's computer science roots. Non-programming activities can also be designed to raise students' awareness about AI and practice skills relevant to AI; by considering AI as a problem-solving tool, AI learning experience can aim to teach students to apply it to solve problems under different disciplines (Zhou, Van Brummelen, & Lin, 2020). For example, Sakulkueakulsuk et al. (2018) considered AI education as part of STEM education, and they encouraged the students to connect the emerging technological solutions with the pressing real-world problems in a playful environment.

A broader focus of AI education also calls for more comprehensive knowledge coverage. Long & Magerko (2020) suggested a need to develop student knowledge for more general, non-technical *AI Literacy*. Touretzky, Gardner-McCune, Martin, & Seehorn (2019) envisioned what they see as the "big ideas" in AI that K-12 students should know: *perception*, *representation and reasoning*, *learning*, *natural interaction*, and *societal impact*. These recent proposals might be valid but are so far under-investigated by researchers and educators.

2.2.3. Learning with AI

The third category encompasses research into using AI tools to improve learning and teaching practices, i.e., *Learning with AI*. This category is an emerging direction inspired by some teaching and learning enhancement practices in higher education. Some steps in this direction are being explored by K-12 schools, albeit slowly.

A prominent example of *Learning with AI* is teachers using AI-powered analytical systems to improve learning processes. Research in this direction in recent years has, to a large extent, focused on Learning Analytics (LA). This type of emerging AI application uses algorisms to analyse data about learners and their environments to help users improve learning experiences and outcomes. For example, some education institutions piloted LA dashboards that displayed learning behaviour patterns so that teachers could provide more just-in-time support to students (Chen, Wang, & Hsu, 2021). Others have developed predictive LA to help identify students who may be considered "at-risk" of failing and who may need additional support (Bahadır, 2016; Herodotou et al., 2020; Viberg, Hatakka, Bälter, & Mavroudi, 2018). There are uses of LA that learn and validate students' language use patterns from their daily work so that academic integrity is ensured (Amigud, Arnedo-Moreno, Daradoumis, & Guerrero-Roldan, 2017). Some pilots provide LA data directly to students to support their self-regulation (Winne, 2017; Rienties, Tempelaar, Nguyen, & Littlejohn, 2019). These LA attempts, serving as assessments for learning, have empowered teachers to make informed decisions, deliver responsive pedagogies, offer differentiated instruction, and provide timely feedback.

While these LA may be highly effective in some contexts, several potential risks and issues are associated with using machine-learning approaches. For example, the risk of students' misclassification may have serious negative consequences (Okoye, Nganji, & Hosseini, 2020). Issues such as access to the appropriate data to train the models, biases in the models introduced through training data sets, and a lack of transparency into how the models work have also been documented (Kitto & Knight, 2019; Kitto, Shum, & Gibson, 2018).

2.3. Barrier to change

Barriers are circumstances or obstacles that prevent progress, and teachers naturally face various kinds of barriers when coping with change (Fullan, 2015). Although "*there is not a single accepted classification of barriers*" (Nikolopoulou & Gialamas, 2015, p. 287), Ertmer's (1999) typology has been broadly supported and widely used in research literature with regards to barriers that affect innovation incorporations in schools over the last two decades (e.g., Basarmak & Hamutoglu, 2020; Mercader, 2020; Wang, 2017). While other typologies such as Stage of Concerns (Hall & Hord, 2011) and Technology Acceptance Model (Venkatesh & Davis, 2000) look at barriers to innovation adoption from an individual's perspective, Ertmer's (1999), typology considers the hindering factors using a holistic approach; it accounts for both teachers and their institutional environments. Using a typology of holistic view can help the researchers have a more comprehensive understanding of the barriers involved, and the findings can inform and enable different stakeholders to address them in concerted efforts rather than leaving teachers to contend with the barriers all by themselves (McCorkle, 2021).

Ertmer (1999) distinguished two types of barriers. First-order barriers include issues that are extrinsic to teachers, and second-order barriers represent teacher's internal obstacles. Several barriers have been identified in the literature. For example, first-order barriers may involve a lack of access to resources, insufficient time, inadequate support, and unresponsive policies, while second-order barriers could be posed by teacher's attitudes, confidence and beliefs (Wang, Jong, & Towey, 2015). As different kinds of barriers are likely to appear at various points in the innovation incorporation process, effective strategies for dealing with them will be needed. For example, Wang (2017) suggested that teacher's capacity building, with a particular focus on pedagogical justifications, may be an effective strategy for addressing barriers related to teacher belief.

Ertmer and her colleagues' more recent developments suggest that second-order barriers probably are "the true gatekeepers" as many first-order barriers have been eliminated with the growing ubiquity of ICT in schools (e.g., Ertmer, 2005; Ertmer, Ottenbreit-Leftwich, Sadik, Sendurur, & Sendurur, 2012; Ertmer & Ottenbreit-Leftwich, 2010, Ertmer & Ottenbreit-Leftwich, 2013; Ottenbreit-Leftwich, Liao, Sadik, & Ertmer, 2018). Many researchers have accepted this claim in recent years (e.g., Hamutoglu, 2021; Makki, O'Neal, Cotten, & Rikard, 2018; Wang, 2017). As a consequence, significant attention has been given to strategies that address second-order barriers including altering teacher dispositions and helping them appreciate why they need to adopt the new paradigm (e.g., Ottenbreit-Leftwich, Liao, Sadik, & Ertmer, 2018; Wang, 2017).

Because of the emphasis placed on incorporating technology in education and the holistic view of hindering factors, Ertmer's (1999) typology could provide us with useful pair of lenses to look into AIED incorporation barriers in Hong Kong K-12 education. Therefore, drawing on Ertmer's barriers to change the categorisation and classification of AIED directions (*Learning from AI*, *Learning about AI*, and *Learning with AI*), a conceptual framework was made to facilitate this exploratory research, as Fig. 1 shows.

3. Method

3.1. Research design

This study employed an exploratory research design (Creswell, 2014). Specifically, qualitative case studies were conducted with Hong Kong K-12 schools of different AIED incorporation directions. Qualitative case studies (Yin, 2009) were implemented based on the nature of our research question. This method enabled the researchers to understand the real-life, intricate situation via the actor's perspective by closely examining the data within a specific context. It helped the researchers to gain insights that might not be achieved with other approaches. The unique circumstances – that only a few schools in Hong Kong had or were about to incorporate AIED – also suggested case studies would be an appropriate method.

3.2. Case selection and research settings

Case selection is a primordial task of case studies (Seawright & Gerring, 2008); researchers have to purposively select cases from which they can learn most (Creswell, 2014). Literature suggests selecting cases that allow easy access and are hospitable to the enquiry (Stake, 1995). In this collective case study, two criteria were established to select the appropriate cases. The first criterion ensured relevancy by identifying Hong Kong K-12 schools that had or were about to incorporate AIED. A peer-recommendation strategy was employed. Initial engagement was made through school visits and informal talks with personnel. These visits were to confirm whether schools met the first criterion. The second criterion was the classification of potential participating schools according to the three directions of AIED identified in our literature review. In this screening process, none of the schools fit in the *Learning from AI* category, which confirmed the limited applicability of this direction that has been reported (e.g., Craig, 2018; Selwyn, 2019). As a result, two Hong Kong public K-12 schools, namely School A and School B, were selected as the cases, the units of analysis.

Established in 1964, School A is an aided, co-educational secondary school. School A has been exploring AI education and has been drafting its AI education curriculum. School B is a secondary school with a century-long history. In 2020, there were discussions at School B leadership level to introduce an AI-based LA system, with the collaboration between the school and a university. Both School A and School B are pioneering and award-winning schools in Hong Kong K-12 sector's technology-enhanced teaching and learning, ICT, and STEM education. The researchers were confident the schools' track records proved they were unique and ideal cases for examining barriers to incorporating AIED.

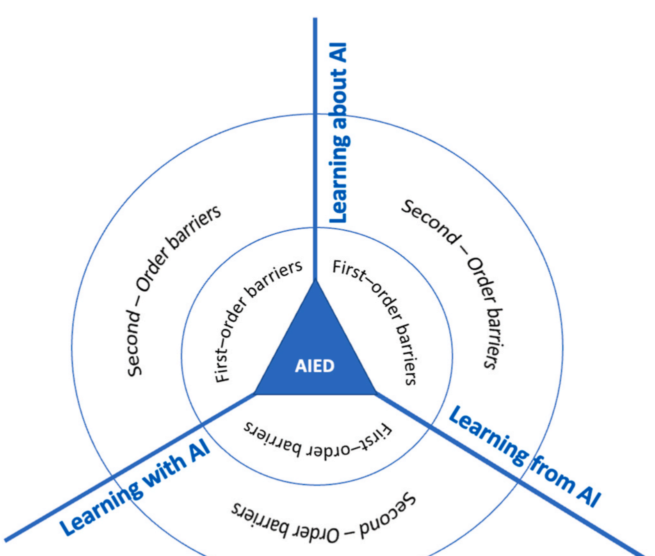

Fig. 1. Conceptual framework.

3.3. Data collection

The researchers served as the key instruments for data collection. The semi-structured individual/focus-group interview method allowed the researcher to control the line of questioning and enabled new ideas to be aired during the interview as a result of what the interviewee said (Creswell, 2014).

A total of ten individual/focus-group interviews were carried out in Spring 2021. Six semi-structured interviews were conducted with the principal, curriculum leaders, and teachers involved in AIED at Schools A and B (See Table 1). In line with the research question, the guiding questions of the interviews covered: (a) perspectives on AIED and approaches to AIED in their school, and (b) perceived barriers involved in their school's AIED. Subsequently, another four follow-up interviews were conducted with related persons to clarify uncertainties, triangulate the data/emerging findings, and learn issues that were not apparent to the researchers previously (See Table 2). An example of the follow-up question would be: "Can you further explain why you said … in the previous interview?". With these ten interviews, the researchers created a detailed picture of AIED at School A and B and their respective incorporation barriers.

All interviews were conducted virtually using the video conferencing tool *Zoom* due to restricted physical access during the Covid-19 Pandemic. The languages used in the interviews were primarily in English and aided with Chinese. Given the status of Hong Kong as China's bilingual territory and "Asia's World City", this strategy ensured participants could express themselves clearly and effectively and any nuances would be understood by researchers. Each interview lasted approximately 30 min. With participants' approval, the interviews were videotaped using *Zoom* and stored using an encrypted drive. Verbatim transcriptions were made using word processing software for further coding. The researchers who conducted the interviews transcribed the verbatim records, which allowed them to add context, non-verbal information and bracketed notations. If clarification or additional information was needed, participants were contacted via instant messaging.

Table 1
Initial interviews conducted.

Interview	School	Interviewee	Age	Gender	Years Of Teaching/ Working	Teaching Discipline
1	A	Principal A	59	Male	34	N/A
		Vice-principal A	41	Male	20	Math
2	A	ICT Panel Head A	41	Male	15	ICT/ STEM
3	A	Teacher/ Panel Member A-1	34	Male	7	ICT/ STEM
		Teacher/ Panel Member A-2	36	Male	10	ICT/ STEM
4	B	Principal B	56	Male	30	N/A
5	B	ICT Panel Head B	40	Male	15	ICT
6	B	Teacher B-1	37	Male	10	Math
		Teacher B-2	34	Male	6	Science

Table 2
Follow-up interviews conducted.

Interview	School	Interviewee	Age	Gender	Years Of Teaching/ Working	Teaching Discipline
7	N/A	Affiliated Member of Education Bureau	43	Male	25	ICT/ STEM
8	A	ICT Panel Head A	41	Male	15	ICT/ STEM
9	A	Teacher/ Panel Member A-1	34	Male	7	ICT/ STEM
		Teacher/ Panel Member A-2	36	Male	10	ICT/ STEM
10	B	Teacher B-1	37	Male	10	Math
		Teacher B-2	34	Male	6	Science

3.4. Data analysis

The researchers used a hybrid inductive and deductive thematic analysis to identify themes related to our conceptual framework. Maxwell's (2013) qualitative analysis approach was generally followed, which, in this study, broadly comprised three key steps: *data familiarisation*, *coding*, and *explanation building*. In addition, research trustworthy measures were taken as needed. The data analysis process was aided by using spreadsheet software as an efficient means to store, organise, and code data. Detailed procedures are listed as follows:

Step 1. *Data Familiarisation*. The researchers read the transcripts line by line to ensure they had a close familiarity with the participant, the school context, and all the information presented in the transcripts. The researchers then annotated the text with descriptive and conceptual comments which extracted key meaning from the data, to create generic, low-inference descriptions and preliminary interpretative notes for coding.

Step 2. *Coding*. Using the open coding technique, the leading researcher first analysed each comment, reviewed the original text as needed, and developed a code representing each comment. Some exemplary codes included "AI definition", "resource investment", and "curriculum guideline", to name a few. Upon completing open coding, the leading researcher applied axial coding (Corbin & Strauss, 2015) by grouping the codes generated in the previous open coding stage into existing meaningful categories – in particular, first-order barriers and second-order barriers in Ertmer's (1999) categorisation (See Table 3). Combining inductive and deductive thinking through axial coding helped create a deeper understanding of the data. Because the codes from the previous open coding were not mutually exclusive, special attention was given to the hidden connections between the codes after categorisation and the possibility the codes could not be fitted.

After the leading researcher completed the coding, the other researcher reviewed and examined the codes thoroughly to identify any differences in interpretations. The two researchers then discussed differences in coding to reach a consensus. This process was repeated until both researchers were satisfied.

Step 3. *Explanation building*. Once all of the codes had been carefully analysed and categorised, the next step was to search for themes as the foundation for building explanations. The researchers may cluster some themes together as superordinate or split some into subthemes in this process. Each superordinate theme and subtheme was checked with the original data to ensure it could be accounted for. This theme-building process was critically reviewed until both researchers were satisfied.

Table 3
Coding scheme for axial coding.

Code	Definition
First-order Barrier	Obstacles that are extrinsic to the teacher
Second-order Barrier	Obstacles that are intrinsic to the teacher

By taking these steps, 14 themes emerged. Based on these themes, the analytic findings of the case studies are described in the following section.

4. Findings and discussions

4.1. Case I: School A, Learning about AI

4.1.1. First-order barriers

4.1.1.1. Lack of explicit curriculum guideline. A significant challenge was the need for explicit curriculum guidance from the Education Bureau, especially in terms of key intended learning outcomes of AI education. As the principal pointed out, "*We know AI education is the 'next big thing,' and we want to be well-prepared for that. Until this point, there is no official curriculum guideline that we can reference. Curriculum guideline is crucial because it functions as a blueprint; learning outcomes, lessons, and evaluations have to be aligned with it*" (I–C1–P-1).

In a follow-up interview with an affiliated member of Hong Kong Education Bureau, it was stated that achieving official guidelines for AI curriculum development in Hong Kong is highly difficult at present; he explained, "*AI education is still at its early stage; the wide-ranging interpretations and continual development make it challenging to make curriculum guidelines at this point. Despite so, we have been looking around at what is happening with AI education, not just within Hong Kong but across the world. Unfortunately, we haven't seen many practices that are matured enough or that can convince us to promote them as models or exemplars*" (I–C1-E−1).

This has brought about a paradoxical situation where government departments are intent on identifying promising practices from schools, while schools are waiting for government guidelines to move forward to implement an AI curriculum. Under these circumstances, schools need to figure out where AI education fits in their already crowded curriculum. Teachers need to work out the details of a potential curriculum, which is difficult due to the lack of proven successes in Hong Kong K-12 education contexts. The challenge for teachers to create such precedents while also fulfilling their other commitments represents a theoretically sensible but onerous objective in practice.

4.1.1.2. Uncertainty of hardware and Learning Kits Purchases. An associated issue with an unspecified AI curriculum is the school's investment hesitation due to the fragmentation of hardware and learning kits to be purchased. Schools in "Smart City" Hong Kong have adequate infrastructure and sufficient funds for purchasing tools to teach AI-related content. However, they could still suffer from resource accessibility issues, as what is needed is heavily dependent on the AI curriculum. It can be difficult for schools to make cost-effective purchasing decisions if they do not have a clear agenda for what they want to achieve with the equipment. This is seen as a dilemma voiced by the vice-principal, "*It is not about the money … our school has already reserved budgets for AI education. Hong Kong government also has* funding *schemes that would allow schools to upgrade the computer rooms into AI labs or STEM spaces. The real problem is what we shall buy. There are too many options out there that are self-proclaimed as AI learning kits. They often bundle with vendor-specific learning materials, so the overall costs can be quite expensive. It could be a big waste of money if they turn out to be not aligned with the curriculum*" (I-C1-VP-1). Such a dilemma highlights that the *Uncertainty of Hardware and Learning Kits Purchases* barrier hinges on the *Lack of Curriculum Guideline* barrier.

4.1.2. Second-order barriers

4.1.2.1. Disputed Views of Learning about AI. In the interview, the principal said the reason his school took a cautious approach to pushing forward with AI education was largely due to the discrepancy between his perception of the trend and the practices he had learned from other schools. He was particularly concerned that AI education be age-appropriate, and outlined his primary goal to promote student interest and build their awareness of AI's ubiquity and social issues. He said, "*Students could be easily swallowed by the technological exercises that are probably beyond their appreciation and comprehension levels. For me, this is not aligned with our education spirit. Young learners need to spark their interests first and manufacture their interpretations of related topics, as they are ushered in the AI era*" (I–C1–P-1). He also voiced his reservations about many of the available textbooks and learning materials, such as the ready-to-use learning packages, in particular, for their emphasis on technology. He further argued that these resources were designed for high school students who wanted to pursue further study or work in AI disciplines rather than for providing general AI literacy — "*This is a question of what we what to achieve via AI education: nurturing AI-literate individuals or training AI-competent technicians. Apparently, these textbooks get them mixed-up*" (I–C1–P-1).

The principal also expressed concern with the relevance of some content in the fast-evolving pace of the AI domain. He pointed out, "*What students are learning today could quickly become irrelevant before they enter society. If the introduction of AI is a forward-thinking move with which students are equipped for the future, we must think forward what we can offer them so that they can be future-proof*" (I–C1–P-1). This concern prompted him to determine what might be the core competencies and generic skills necessary for more meaningful K-12 AI education in Hong Kong. He said such traits were required for lifelong learning and noted they have not reached a desirable level in Hong Kong—a situation he attributed to the city's intensely competitive culture and examination-focused education traditions.

The principal's perspectives on AI education were not entirely shared by all teachers, several of whom indicated they would opt to keep AI teaching within the scope of those current practices. Said one, "*We probably shouldn't veer too far from the course that others have tracked*" (I–C1-TS2-2). In a follow-up interview with the school's computer education and STEM panel members, the concepts and inner mechanisms of AI systems were perceived as key content to be taught. As one of the members explained, "*Machine learning, deep learning, and neural network are the cornerstone of AI today; students' mastery of how they work would be a prerequisite if their future is built on AI*" (I–C1-TS1-1). Given the "groping for stones to cross the river" status noted in the literature, and taking into account the different attempts made by Wong, Ma, & Huen (2019), Marques, Gresse von Wangenheim, & Hauck (2020) and Wong (2020), the views voiced by the principal and teachers are equally valid. What was clearly demonstrated was the depth of the challenge involved in establishing their school-based AI education curriculum.

4.1.2.2. Immature Pedagogical Understanding of AIED. In a well-intended gesture, the panel members said they were open to different ideas as they acknowledged the confusing reality of AI education. As one of the members admitted, "*Just by looking at what we learned from other schools' practices, I'm not very sure how AI education, besides the inclusion of AI-related elements, is distinctive from the STEM that we had already been doing here; I don't know if it is just coding education wearing different hats*" (I–C1-TS1-1). In several assertions the teachers made, the researchers further noticed that the nascence could be attributed to the lack of clear agenda and pedagogical goals of STEM and coding education (where AI elements can be squeezed in). Teachers in the interview spoke in favour of the notions of design thinking and computational thinking, but they struggled to illustrate the true meaning of these terms beyond literal levels. None of the teachers in the interviews could explicitly convey that coding education and STEM are bridges rather than a destination. The researchers' observation was triangulated and supported by the self-reported teaching episodes from a STEM teacher. This teacher regretted his occasional deviation from the lesson designs, which, he claimed, resulted in a waste of class time for completing learning activities and meeting the lesson schedule. This unfortunate reality was acknowledged by the principal. It was concluded that his teachers, including ICT and STEM teachers, did not have enough exposure to promising AI education practices. It further highlighted the necessity of advancing pedagogical understanding of AIED.

4.1.2.3. Lukewarm Attitude of teachers. Another barrier identified was an absence of enthusiasm among teachers. In his interview the principal confided, "*Our teachers lack a sense of urgency when it comes to AI*" (I–C1–P-1). He further attributed this to teachers' pragmatism *as* AI has not been established as a part of the formal curriculum. This perception was corroborated in a follow-up interview with teachers who said they were unaware that AI education could involve topics beyond computer education or STEM and, although they did recognise AI would be an essential topic for the future, they presumed it to be "important but probably not concerning me". Their insufficient understanding of AI and mistaken assumptions about AIED, could prove challenging to implementing a broader coverage of AI education, as Long & Magerko (2020), Touretzky, Gardner-McCune, Martin, & Seehorn (2019) and Zhou, Van Brummelen, & Lin (2020) advocated, especially when it comes to topics that need coordination between subjects and go beyond science and technology-based domains, a situation that Wong, Ma, & Huen (2019) have researched.

4.1.3. Summary

Both first-order and second-order barriers are the obstacles that have been hindering School A's AIED incorporation, as listed in Table 4.

As the researchers further dug into barriers with the apprehensions and circumstances the participants reported, it was revealed that the barriers affecting School A's AIED incorporation in ways that were not mutually exclusive. More particularly, the researchers uncovered that the barriers were interrelated with five noticeable links, as illustrated in Fig. 2 and summarised below.

Lack of Curriculum Guideline appeared to be a plausible root of School A's *Uncertainty of Hardware and Learning Kits Purchases* and *Disputed Views of Learning about AI* between the principal and teachers. For School A, making budgetary/purchasing decisions required clear agenda of their AIED incorporation. The absence of explicit curriculum guidelines from the government made such decisions difficult; the leadership level worried their school-based agenda might deviate from the government's when the official guideline becomes available. Similarly, the absence of explicit curriculum guidelines also meant concerned school members making their own interpretations as the school pursued AIED. Such interpretations were understandably not fully shared given the differences in personal background and professional roles between different stakeholders.

Similarly, School A *Teachers' Lukewarm Attitude* might also be attributed to their *Insufficient Teacher Knowledge of AI* and subsequent *Immature Pedagogical Understanding of AIED*. While teachers recognised the changing education landscape and agreed that teaching and learning

Table 4
School A's barriers to AIED.

First-Order Barriers	Second-Order Barriers
Lack of Curriculum Guideline Uncertainty of Hardware and Learning Kits Purchases	Disputed Views of Learning about AI Lukewarm Attitude of Teachers
	Insufficient Teacher Knowledge of AI Immature Pedagogical Understanding of AIED

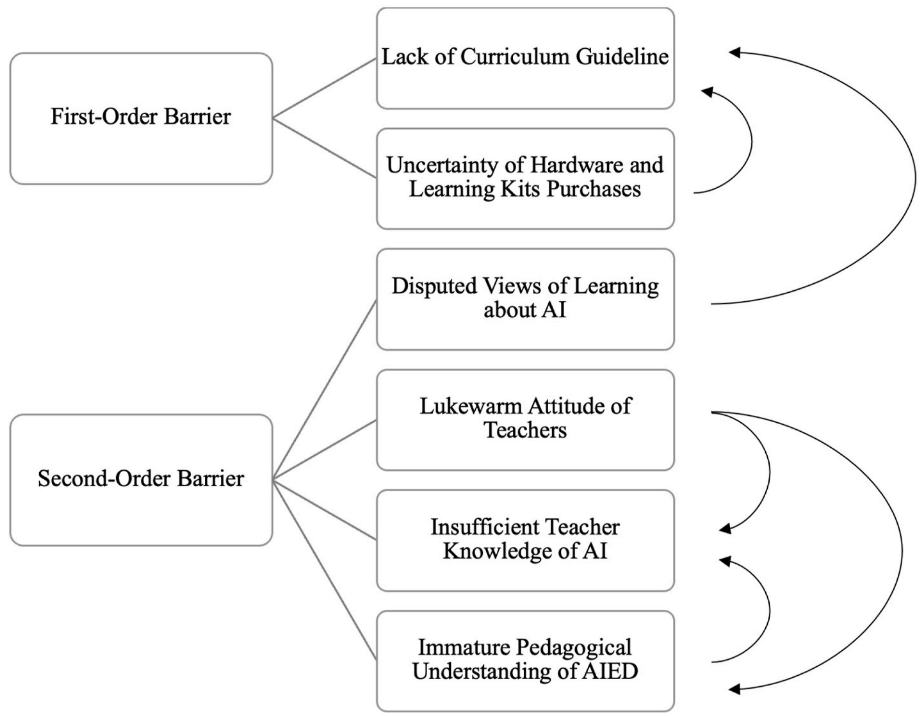

Fig. 2. School A's barriers to AIED, *Learning about AI*.

need to keep pace, they were not made aware that the scope of AIED could arguably go beyond computer education or STEM as Long & Magerko (2020), Touretzky, Gardner-McCune, Martin, & Seehorn (2019) and Zhou, Van Brummelen, & Lin (2020) advocated. In other words, teachers' current knowledge of AI and understanding of AIED limited the extent to which they saw the urgency to take further actions. As a result, they were not as enthusiastic as they might have been.

4.2. Case II: School B, *Learning with AI*

4.2.1. First-order barriers

4.2.1.1. Cautious system and human resource investment. For School B, a highly significant first-order barrier is the struggle to identify or develop appropriate AI systems for teacher use. Although the school had sufficient financial resources, there was a degree of investment risk, and the school could not take an all-in approach to invest in these technologies, especially given the fact that AI incorporation is new and there are no established practices that his school can reference. As the principal indicated, *"I am obligated to make good use of our school resources and set the tone for coming years, which could be introducing AI. As a synergetic effort made together with a university, what we are doing is very experiential; without knowing if it is the right path that can address our teachers' needs, we cannot put all the eggs into the same basket*" (I–C2–P-1). Apart from purchasing hardware and setting up the platform, substantial investment would also be needed in terms of human resources and training. This means that the investment must be made strategically. In addition, to ensure a high level of teacher use and sustainability, schools need to gather sufficient feedback and input from them. In order to gain good quality feedback, it is necessary for teachers to have an awareness of the affordances (Norman, 1999) of AI, which many of them currently do not. Promoting such awareness is a delicate process, and this is an important reason why the schools are being cautious about rolling out their AI systems.

4.2.1.2. Practical complications in privacy, ethical data collection and data protections. The struggle with deploying AI systems is not confined to investment strategy. AI systems – particularly the one School B intended to deploy – comprise LA with generative mechanisms for extracting data, which could present practical complications with privacy, ethical data collection, and data protection issues that are similar to the ones reported by Okoye, Nganji, & Hosseini (2020) and Kitto, Shum, & Gibson (2018). Several of the teachers interviewed raised questions about the debate over informed consent in data-intensive environments. They pointed out that consent in the age of Big Data is not straightforward when data use boundaries are not clear. As the IT panel head argued, "*Getting consent could be tricky. There is too much data, and this is not like listing 'terms and conditions.' I don't know if we can even confine when, where, what, to what extent and how the data is going to be used*" (I–C2-IT-1). Given the students' age range is that of minors, the concern was that parental permission might not be granted. As he further doubted, "*We cannot ensure all the parents will tick 'yes'. If some won't, what shall we do?*" (I–C2-IT-1). Further, as the data could contain personal information or other digital footprints, any mishandling or leak could be disastrous for the school. In light of these concerns, the teachers question how these complications can be resolved as they could undermine the school's ability to move forward toward *Learning with AI*. A teacher concluded, "*we need to have clear policies in place*" (I–C2-IT-1).

4.2.1.3. Time constraints. Another first-order barrier was teachers' perceived time constraints, which has been frequently mentioned in the literature (e.g., Wang, 2017). More specifically, a teacher voiced that his various roles in the school meant that he had many tasks, and he had limited time for studying new technology tools such as the LA. The teacher further expressed his desire to spend more time working with students and believed that teaching performance was key to his job evaluation, and outstanding results from his students carried a more immediate allure. He was emphatic that, with compelling needs for daily teaching and administrative duties, exploring LA or educational data mining methods could probably not be a top priority, saying, "*Time is a luxury that I don't always have. The temptation to learn new tools could not eclipse my duty to teach*" (I–C2-TM-1). It was a common refrain from teachers in this top-tier school. Practical considerations also intensified the perceived time constraints. Unlike universities, the school does not have a well-established learning management system (LMS) so any learning activities such as exercises and quizzes still follow conventional paper-based practices. This would indicate a possible data processing task whereby teachers would need substantial support for inputting data, digitalising records, and tidying up the formats, which all are necessary for the AI system to generate an analytic report.

4.2.1.4. Under-user-friendliness of AI systems. Further investigation revealed that the validity of perceived time constraints could be relative and dependent on the user-friendliness of the AI system. Teachers' overall impression of some of the LA systems they had seen was poor, mainly because they were difficult to use, and the analytical reports generated were hard to understand, which the teachers admitted was partly because they were not very knowledgeable about statistics. As a result, they concluded that using AI systems would be time-consuming, even when assured the systems could serve as a powerful means to improve teaching practices.

4.2.2. Second-order barriers

4.2.2.1. Biased teacher attitude and teachers' incomplete understanding of AIED. Teachers' attitudes toward AI could be another stumbling block for the effective incorporation of it in Hong Kong K-12 schools. Comments made in the interviews suggested many teachers who were not directly involved in the school's LA development, feared AIED AI would replace them. Some expressed that AIED was an elusive objective, and some seemed to think that AIED was equal to education using sophisticated teaching machines. This reflected what was conceived in our literature review, particularly in terms of the possibilities of *Learning with AI* and despite the fact their school is already pursuing such a direction. Based on their single-sided perception of AIED, teachers found that essential human touch was missing from this paradigm. This situation reinforced the researchers' view that the teachers lacked a comprehensive understanding of AIED. Although there were notable points of comprehension when researchers gave examples that indicated the compatibility of human touch and demonstrated additional teacher attention—such as differentiated instruction and individualised support through *Learning with AI*—some teachers worried that it was probably still not within their capacity.

4.2.2.2. Lack of confidence and misconception of AI. Teachers indicated concern that their limited capacity signalled a lack of confidence, which also falls under the category of a second-order barrier. To some extent, their concern was valid; School B's introduction of AI could be perceived as unsolicited. Without any formula for success, the technical levels needed are unknown to the teachers, which could have fuelled their anxiety of failure. As one teacher who would be involved in School B' LA piloting project expressed, "I'm *neither an old-school teacher nor a tech-savvy one. But my experience suggests new technologies could bring many unknowns or difficulties. As I haven't learned enough about AI, I won't claim to have full confidence in the AI initiative. I won't know if the requirement would exceed my capacity, but my overall feeling is that using AI to teach is too early for massive adoption*" (I–C2-TS-1). Teachers reported that this apprehension made them lean toward a reactionary rather than proactive approach to AI, as one of them added, "*While I'm happy that our school would like to pilot AIED, many of us are still scratching our heads about how much we can move forward*" (I–C2-TS2-1).

However, the teachers have, in fact, been using technology tools in their pedagogy, possibly without realising AI as a genre of ICT (as stated by Schmidt, 2016) and many of those technology tools are powered by AI. Teachers appeared to have formed a generally positive attitude towards ICT usage, contrasting with their critical view of the AI notion. As one teacher stated, "*Teaching with ICTs has been promoted among Hong Kong education circles for many years. I'm sure all the teachers nowadays use ICTs, more or less. We have reached the point of no return*" (I–C2-TM-2). In line with this assertion, he commended the use of several ICT tools in class that made their students highly engaged with gamified experience and potentially increased their knowledge retention as well as those tools that brought convenience. This contradiction was another example of how teachers' lack of confidence in AI could be attributed to their misconceptions.

4.2.3. Summary

Both first-order and second-order barriers have been hindering School B's AIED incorporation, as listed in Table 5.

Like Case I, the researchers found that the barriers affected School B's AIED incorporation in ways that were not mutually exclusive. More specifically, the barriers were interrelated with three noticeable links, as illustrated in Fig. 3 and summarised below.

The *time constraints* are tangentially associated with the *user-friendliness of AI systems*. Perceived user-friendliness often serves as a straightforward reference for the amount of time investment needed (Naidu & Laxman, 2019). In School B, teachers' overall impression of LA systems being complicated, and analytical reports being difficult to interpret, led to them reaching the conclusion that adopting AI systems could be time-consuming.

Biased teacher attitude appears to be an unfortunate repercussion of the *incomplete understanding of AIED*. Teachers misconceived that AIED is equal to AI replacing teachers. This fuelled their biased attitude that AIED is incompatible with the human touch—an element they believed essential for engage with students and their learning.

Teachers' *lack of confidence* seems also to stem from their *misconception of AI*. On the one hand, the technical requirements were unknown to the teachers, which could indeed trigger their concerns and affect their confidence levels. On the other hand, teachers' positive attitude towards ICT usage, despite not knowing many of those tools are powered by AI, suggests their confidence is likely to be boosted by having a comprehensive and accurate perception of AI—a collective notion as Wang (2019) put forward.

4.3. Cross-case analysis

The previous literature (Ertmer & Ottenbreit-Leftwich, 2010, Ertmer & Ottenbreit-Leftwich, 2013; Ertmer, Ottenbreit-Leftwich, Sadik, Sendurur, & Sendurur, 2012; and Ottenbreit-Leftwich, Liao, Sadik, & Ertmer, 2018) claims that growing technological access effectively reduces, and in many cases even eliminates, first-order barriers. However, our study revealed a contrary situation as we found both schools experienced first-order barriers. In other words, first-order barriers still exist and represent challenges when it comes to AIED incorporation in Hong Kong K-12 schools. This is understandable given the fact that AIED is still at the nascent stage in Hong Kong K-12 education, as described by Chiu & Chai (2020) and Wong, Ma, Dillenbourg, & Huan (2020). Meanwhile, our study showed that second-order barriers in both cases were also of high intensity. This result aligns with Ertmer & Ottenbreit-Leftwich (2010), Ertmer & Ottenbreit-Leftwich (2013), Ertmer, Ottenbreit-Leftwich, Sadik, Sendurur, & Sendurur (2012), and Ottenbreit-Leftwich, Liao, Sadik, & Ertmer (2018) conclusions that second-order barriers are "gatekeepers" to innovation incorporation.

Moreover, both cases show barriers did not hinder in isolation; they were interconnected and presented as a "chain of reactions." In other

Table 5
School B's barriers to AIED.

First-Order Barriers	Second-Order Barriers
Cautious System and Human Resource Investment	Biased Teacher Attitude
Practical Complications in Privacy, Ethical Data Collection and Data Protections	Incomplete Understanding of AIED
Time Constraints	Misconception of AI
Under-User-Friendliness of AI Systems	Lack of Confidence

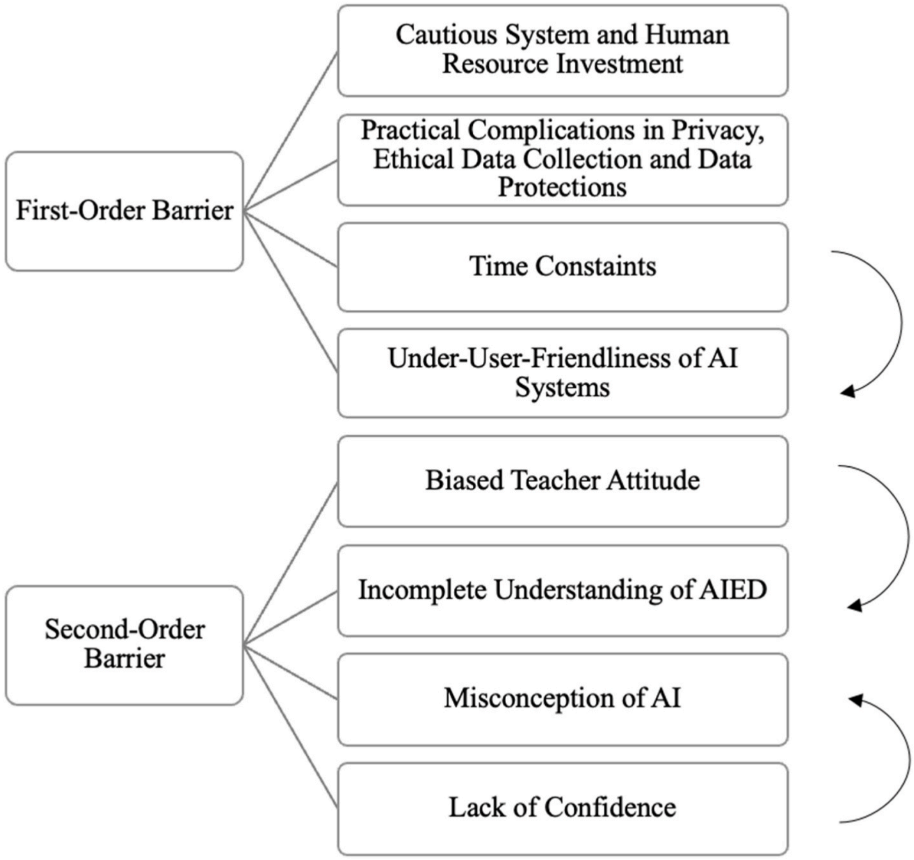

Fig. 3. School B's barriers to AIED, *Learning with AI.*

words, while the reportedly slow incorporation of AIED in Hong Kong K-12 schools could indeed be attributed to certain barriers, this study further added that the barriers might affect the incorporation status in a dynamic way. Admittedly, considering the data were only collected from two case schools, these interconnections, may not be substantiated proof of direct causal relationships or strong correlations. But the *prima facie* evidence of links does provide some insights into the dynamics of barriers faced in Hong Kong K-12 AIED incorporation. In addition to their practical implications, such insights would help elevate the current understanding of barriers and provide interesting pointers to future research.

5. Implications and recommendations for practice

Based on the findings of this study, there are two practical implications that schools need to pay attention to as they incorporate AIED.

First, a bespoke approach to overcoming barriers would be required. In particular, measures must take into account schools' AIED approach (i.e., *Learning from AI*, *Learning about AI*, and *Learning with AI*) so that targeted strategies can be created. We saw how, despite both first-order and second-order barriers experienced by both cases, the barrier items varied.

Second, the interconnection between barriers that emerged in this study implied the need for the schools to look into those barrier links to optimise efforts. Perhaps they should prioritise measures that can address barriers with high linkage, which would probably help ease several associated barriers. Further, as schools can face barriers not of equal intensity, it would make sense that strategies for addressing barriers should probably take intensity levels into account.

Several additional recommendations are given that might help Hong Kong K-12 schools overcome the barriers to AIED. These recommendations are drawn from proven strategies provided by previous studies (e.g., Wang, 2017), promising practices learned within the Greater China region (e.g., Ministry of Science and Technology, 2019), and lessons learned from international organisation reports (e.g., UNESCO, 2019). They are as follows:

5.1. For Learning about AI schools

First, before the establishment of a curriculum guideline at the government level, the school would be well advised to keep a more balanced and inclusive approach as Long & Magerko (2020), Touretzky, Gardner-McCune, Martin, & Seehorn (2019) and Wong (2020) suggested. Schools could thoroughly review the AI and AIED landscape to achieve a comprehensive understanding. While many perspectives of AI education are valid, clear learning objectives must be set. One way of organising these learning objectives could be by building rapport with different readings of AI education. A learning objectives taxonomy could also be made based on students' age-appropriateness and comprehension levels. The development of which could reference similar AI curriculums in other countries and regions. The taxonomy will inform how AI will fit within the existing school curriculum and its subsequent impact on teacher's pedagogy and assessment.

Second, it is crucial to keep the curriculum frequently updated while identifying the core competencies, as UNESCO (2019) suggested. Until the establishment of official curriculum guidelines, this would have to be done by the school. As the competencies required for thriving in the forthcoming AI-pervasive *Industrial 4.0* could differ from what students are equipped with today (OECD, 2019), schools need to consider how the curriculum could be aligned for responding to a shift.

Third, as Wang (2017) recommended, extensive professional development needs to be provided for those who will teach AI content. Teachers would need to work closely with education specialists in the AI-related field—especially since curriculum and materials for AI education are not readily available across all age groups. A recent example of this is the training available from Hong Kong Education City (EdCity, 2021), a government-owned professional development portal.

Fourth, successful AIED necessitates collective will as opposed to the principal or individual teacher's personal efforts. School leader's vision and teachers' understanding of an education innovation like AIED don't always fully align (Fullan, 2015). While it is important to "speak a common language" of AIED within a school, professional dialogue between all stakeholders can help introduce possibilities some may not have considered and, ultimately, assist the school to re-envisage AIED.

5.2. For Learning with AI schools

First, investment in the development or purchasing of AI systems has to take into account teachers' needs, which will ensure cost-effectiveness and sustainable use. This may require additional design considerations, such as a more intuitive user interface and straightforward analytical reports.

Second, reward and incentive schemes for teachers can ease the tension of time constraints (Wang, 2017). For example, initiative piloting of AIED and professional development programmes undertaken by teachers could be factored into their staff appraisals. Merits and awards for AIED may also be effective means by which teachers' efforts get recognised.

Third, *learning with AI* will likely require complementary investment in data, skills and digitalised workflow, as well as changes to teacher roles. Such investments would probably trigger an acceleration of the school's digital transformation. However, in this process, societal concerns such as misuse, algorithmic bias, and data privacy highlighted by Kitto & Knight (2019), Kitto, Shum, & Gibson (2018) and Okoye, Nganji, & Hosseini (2020) have to be seriously considered.

Fourth, given that several barriers were associated with teacher's understandings of AI and AIED in this study, it is clear there is a pressing need to confront the issues. Teacher's AI and AIED understanding will be enhanced through professional learning opportunities such as Communities of Practice (Wenger, 2011) – group activities with teachers who share a concern and passion for AIED can generate new or deeper levels of knowledge, and such collective knowledge can subsequently be transferred into individual practices.

6. Limitation, future research and significance

One limitation of this study was the absence of an existing *Learning from AI* case during the selection process. Future studies would benefit from one because it could help researchers determine whether the barriers involved in such a case are consistent with, or different from, those identified and whether there are also interconnections.

Nonetheless, the contribution of this study is fourfold. First, it contributes to an expanded understanding of AIED incorporation in Hong Kong K-12 education, specifically with regard to the various barriers faced by schools incorporating their own AIED. Second, identifying links between barriers contributes to establishing a more dynamic view of Ertmer's (1999) barrier typology framework. Third, the barriers highlighted by this study support K-12 schools when revisiting their efforts, creating enabling conditions and fostering conducive environments for effective AIED incorporation. Fourth, the tripartite AIED directions identified by the researchers and their integration with Ertmer's (1999) typology offer the AIED research community a possible new approach to investigating related topics.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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