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Review Article

A Review of Artificial Intelligence (AI) in Education from 2010 to 2020

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This study provided a content analysis of studies aiming to disclose how artificial intelligence (AI) has been applied to the education sector and explore the potential research trends and challenges of AI in education. A total of 100 papers including 63 empirical papers (74 studies) and 37 analytic papers were selected from the education and educational research category of Social Sciences Citation Index database from 2010 to 2020. The content analysis showed that the research questions could be classified into development layer (classification, matching, recommendation, and deep learning), application layer (feedback, reasoning, and adaptive learning), and integration layer (affection computing, role-playing, immersive learning, and gamification). Moreover, four research trends, including Internet of Things, swarm intelligence, deep learning, and neuroscience, as well as an assessment of AI in education, were suggested for further investigation. However, we also proposed the challenges in education may be caused by AI with regard to inappropriate use of AI techniques, changing roles of teachers and students, as well as social and ethical issues. The results provide insights into an overview of the AI used for education domain, which helps to strengthen the theoretical foundation of AI in education and provides a promising channel for educators and AI engineers to carry out further collaborative research.

1. Introduction

The emergence of big data, cloud computing, artificial neural networks, and machine learning has enabled engineers to create a machine that can simulate human intelligence. Building on these technologies, this study refers to machines that are able to perceive, recognize, learn, react, and solve problems as artificial intelligence (AI) [1, 2]. Inevitably, such smart technologies will revolutionize the workplaces of the future [3]. Thus, while AI can interact and help humans perform at higher levels, it is emerging as the next disruptive innovation [4]. AI is currently viewed by many as a driver that is integral to the fourth industrial revolution, and it may trigger the fourth revolution in education. Learning about AI has also begun to be part of school curriculum [5, 6]. However, just as the emergence of television and computers was once touted to be game changers of education, they have been shown to in fact enhance access to information without substantially changing the core educational practices. Nonetheless, educators are obliged to review current AI capabilities and identify possible pathways to optimize learning. Given the increasing attention, it is timely to review recent AI research in education to provide educators with an updated understanding of the field as a preparation to possible changes.

AI has been increasingly propagated as having strategic value for education [7]. Loeckx [8] suggested that AI could be an effective learning tool that lessens the burdens of both teachers and students and offers effective learning experiences for students. Coupled with current education reforms such as the digitalization of educational resources, gamification, and personalized learning experiences, there are many opportunities for the development of AI applications in education. For example, the modelling potential of AI techniques has been exploited systematically to develop reactive and adaptive tutorials for the construction of individualized learning environments as compensation for the shortage of teachers through the use of intelligent tutoring system (ITS) [10]. ITSs provide personalized learning experience in four main ways: monitoring student's input, delivering appropriate tasks, providing effective feedback, and applying interfaces for human-computer communication [7]. When more ITSs are created for more subjects and topics, it is likely to change the role of teachers, and hence, schooling may need to be reconceptualized. There exist many concerns and worries among teachers on if AI challenges their jobs. At the same time, such questions as what is being learned and how AI is being used are being discussed currently by researchers as well as by educational practitioners. Some researchers wondered whether advancements in AI would challenge or even replace teachers since many other jobs are being replaced by automation [11]. There is an emerging recognition that teachers' professional roles need to be adjusted as AI advances and this will trigger new organizational forms [12]. Emerging challenges also included students' attitudes towards these changes [13]. To some extent, students as digital citizens are able to leverage AI to improve learning outcomes. Nonetheless, they may fail to use suitable AI techniques appropriately for a specific learning context, which would result in negative attitudes towards learning [14].

To summarize, this research involves a review of the studies of AI in education. Previous studies have included three essential perspectives of AI in knowledge processing: (a) knowledge representation, (b) knowledge obtaining, and (c) knowledge derivation [3]; this review will focus on AI techniques and tools that have been integrated into education recently after the proliferation of AI. The "first generation" of AI could support human intellectual work by applying rule-based expert knowledge, and the "second generation" may find the optimal solution by statistical/search model, while the "third generation" will dramatically improve recognition performance based on the brain model. This review focuses on articles published in the period from 2010 to 2020 from the Web of Science, as that represents the period when the second and third generation of AI began to make headways into education. The research questions that guided this review are as follows:

(1) What is the overall state of AI in education? Which research topics and research designs related to AI in education are evident from 2010 to 2020?

(2) What are the trends in published studies in terms of AI in education?

(3) What are the challenges generated from the current research of AI in education?

2. Method

This study is a systematic literature review. The objectives of the review were to analyze and interpret findings based on predefined research questions (see above) and criteria which serve to point out future directions [15]. The predefined research foci as shown in Table 1 are research purpose, learning subject, educational level, research approach, and effects. The review was conducted in three stages: planning, performing, and reporting the systematic review.

2.1. Planning the Review. As previous reviews about AI were conducted in the physical sciences [16, 17], the study aimed to conduct a review in the field of the social sciences.

The Web of Science database and the Social Science Citation Index (SSCI) journals were selected for the search for desired articles published from 2010 to 2020. Articles published in the SSCI database are generally considered as high-quality publication among education researchers. The keyword employed was "artificial intelligence," and the subject area was refined to "education and educational research". This process yielded 142 articles including 121 research articles, 10 review papers, one interview paper, and 5 book reviews. The selected articles include both analytic studies (primarily qualitative research) and empirical studies (primarily quantitative research).

2.2. Performing the Review. Following Wu et al. [18], this study was conducted in two steps: identification and coding. In the first step, an article was selected to the potential pool when it qualified for either of two criteria: (a) the research involved a specific AI technique as an intervention in assisting learning or teaching and (b) it provided empirical evidence or in-depth analysis. As already noted, only articles indexed in SSCI were considered. It should be noted that studies that focused on the development processes of AI without educational implications or only adopted AI as a learning subject without the employment of AI were excluded from this review. Second, as for the analytic studies, only studies that discussed the effect of AI techniques on education were included. Each full text of all the identified papers was read and screened individually by three-panel members with doctoral degrees or professorships in the field of learning technology. Studies that did not fit clearly with the criteria were brought up for panel discussion. The screening process yielded 100 articles out of the original set of 121.

In the second step, all the authors discussed thematic analysis principles and established a coding scheme in terms of how AI was used in education. Two main categories were investigated: research questions and technology adoption. Firstly, with regard to research questions, previous research has found three basic models of AI in knowledge processing: knowledge representation, knowledge obtaining, and knowledge derivation [3]. Building on that foundation, the

TABLE 1: The articles coded by research question, technology adoption, learning subject, educational level, research approach, and effects.

ID	Authors	Research question	Technology adoption	Learning Subject	Educational level	Approach	Effects
1	Chin et al. [38]	FEE	Teachable agent	Science education	58 6th grade students (study 1); teachers and 134 5th grade students (study 2)	EXP	OUT*
2	Ngai et al. [55]	AFF	Wearable biofeedback circuit	Circuitry	7 to 9 grade students	QE, SUR	OUT*
3	Wegerif et al. [42]	REA	Intelligent matching-pattern algorithms	Online dialogue	100 undergraduates and 12 postgraduate students	DA	OTH+
4	Thomas and Young [57]	GAM	Adaptive modelling	Educational game	16 college graduates	EXP, SUR	PER*
5	Yang et al. [27]	ADP	Higher-order item response algorithm	Elementary mathematics	158 six graders in Taiwan	EXP	PER+
6	Moon et al. [58]	GAM	Experience point data modelling	Digital game	40 plays	EXP	PER+
7	McLaren et al. [54]	AFF	Intelligent tutoring system	Chemistry	132 high school students	QE	OUT*
8	Jones [43]		Investigating decentralized theory of artificial intelligence				
9	Vattam et al. [24]	REA	Visualization	Exploring creative thinking Science education	157 middle school student	QE	OTH+
10	Jonassen [45]		Introducing an ask system: interactive learning system				
11	Magnisalis et al. [21]		Review of adaptive and intelligent systems for collaborative learning support: adaptive and intelligent systems				
12	Albin-Clark et al. [56]	ROL GAM	Graphic simulation	Construction	4 early childhood lectures and many students	EXP, SUR	PER+
13	Wong and Looi [59]		Exploring swarm intelligence				
14	Seni [60]		Investigating the relationship between neurosciences and organizational cognition				
15	Lin et al. [51]	AFF	Facial recognition	Digital art course	20 adults	EXP, SUR, INT	PER*
16	Heslep [61]		Introspection to the misunderstandings of AI in education motivated by AI enthusiasts				
17	Nguyen and Yang [28]	MAT	Extraction algorithm	Language learning	About 500 Vietnamese news on many kinds of mobile phone from 2009 to 2010	DA	0
18	Tierney [22]	REC	Natural language process	Language learning	Five interviews were conducted generating over seven hours of recordings	INT	0
19	Lawler and Rushby [4]		Interview with Rover Lawler to give comments on the effect of computer technique on AI in education				
20	Tüfekçi and Köse [34]	FEE	Constraint-based modelling	Programming	120 university students	EXP, SUR	OUT+
21	Zipitria et al. [19]	ADP	Automatic discourse measure	Language learning	17 summaries written in Basque language	EXP	PER+
22	Chin et al. [39]	REA	Teachable agent	Kit-based science curriculum	153 fourth grade students	QE	OTH*
23	Mukherjee et al. [30]	FEE	Text-to-diagram conversion	Reading	12 pupils; 4 teachers; 2 technical professionals; 2 nontechnical persons	QE	OTH+
24	Jain et al. [41]	FEE	Visualization	History	Two undergraduate classes in computer science	QE	PER+
25	Higgins and Heilman [62]	REC	Automated scoring system	Language learning	Game team (not mentioned the educational level)		0
26	Melo et al. [9]	REC AFF	Computational organization	Multidisciplines	148 students involved were either in high school or in early college years	EXP	PER*
27	Flogie and Aberšek [13]	AFF	Transdisciplinary pedagogy	Natural science	100 students in 7th, 8th, 9th grades	SUR	OTH+

Table 1: Continued.

ID	Authors	Research question	Technology adoption	Learning Subject	Educational level	Approach	Effects
28	Rapanta and Walton [40]	REA	Argument map	Emirati and Spanish classes	205 university students	EXP	OTH+
29	Nabiyev et al. [29]	CLA	Visualization Intelligent tutoring system	Mathematical	476 motion problems from 9th grade mathematics textbooks of Turkish Ministry of Education	DA	0
30	Loeckx [8]		Analytic essay of opportunities for AI used in educational data mining, adaptive learning, and creativity				
31	Horáková et al. [3]	CLA	Comparison of artificial networks, classification, regression trees, and decision trees	Artificial neural networks	120 text fragments	QE, DA	0
32	Ijaz et al. [14]	IMM	Virtual reality	History	60 undergraduate university students	QE	PER+
33	Liu et al. [31]	REC	Intelligent tutoring system	Language learning	30 sports articles including 100 sentences	DA	0
34	Malik and Ahmad [32]	DEE	E-assessment system	Engineering	243 student of 8th graders	EXP	0
35	Malik et al. [23]	DEE	Query trend assessment system	Language learning	16 questions from Microsoft Students' QA Corpus	DA	0
36	Peng [63]	CLA REC	K-means algorithm, PageRank algorithm	Online learning	More than 700 scholars	EXP	0
37	MacIntyre et al. [64]	MAT	Text minding software	Language learning	10 accomplished adult musicians and dancers	INT	0
38	Aoun [65]		Book review in terms of importance and limitation of AI in education				
39	Williamson et al. [33]		Discussing the importance of neuroscience in education				
40	Munawar et al. [35]	FEE	Intelligent virtual laboratory	E-laboratory environment	161 university students	SUR	OTH∗
41	Samarakou et al. [47]	ADP	Learning system on diagnosis, assistance, and evaluation	Telecommunication networks	28 students studying informatics	EXP	OTH+
42	Fenwick [12]		Pondering the transformation of teacher' professional roles				
43	Kessler [44]		Analytic essay of AI in the language teaching				
44	Petit et al. [36]	GAM	Online educational programming platform	Programming	400 students and 12 teachers	EXP	OUT+
45	Kelly et al. [37]	DEE	Question authenticity measuring system	English and language arts	8-9 grade A large archive database of text transcripts of 451 observations from 112 classrooms and 132 high-quality audio recording from 27 classroom	DA	0
46	Ge et al. [20]	CLA MAT	Autonomous learning system	Sports	Students of 2016 from a college are selected for PE testing. Samples of the 150 questions are collected	DA	0
47	Sun [66]	FEE	Learning system	Language learning	176 valid enterprise questionnaires and 178 student questionnaires are obtained	QE, SUR	OTH∗
48	Auerbach et al. [67]	IMM	Robotic hardware and software platform	Artificial Evolution	42 postgraduate students	EXP	OUT∗
49	Boulet and Durning [68]		Exploring online assessments system applied for the measurement in medical education				

TABLE 1: Continued.

ID	Authors	Research question	Technology adoption	Learning Subject	Educational level	Approach	Effects
50	Cukurova et al. [69]	REA	Artificial intelligence and multimodal data	Debating skills	127 questionnaires and 47 audio recordings from candidates who have applied to become a tutor	SUR, DA	OTH+
51	Du Boulay [70]	ADP	Intelligent tutoring systems (ITSs)	STEAM, conceptual understanding, and dialogue-based learning	(Not mentioned the educational level)	EXP	OTH*
52	Hughes [71]	Review on papers about early self- and coregulation from artificial intelligence perspective included					
53	Kay and Kummerfeld [72]	FEE	Learning system	Lifelong and life-wide personal user models	(Not mentioned the educational level)		0
54	Kitto and Knight [73]	Investigating three tensions in ethics when applying artificial intelligence and data analysis (AIDA) in education					
55	Luckin and Cukurova [74]	REA	Learning sciences-driven AI	Problem-solving, learning data, and debating	Data in one case from high school	EXP,INT	OUT*
56	Sellar and Gulson [75]	DEE	AI and data science	Education policy	4 semistructured interviews with five senior policymakers, technical staff, and data scientists	INT	0
57	Sharma et al. [76]	ADP	Online adaptive self-assessment procedure with multimodal data	Web technologies	Thirty-two undergraduate students	EXP	0
58	Wang and Wang [77]	Developing an artificial intelligence anxiety (AIA) scale Exploring the relationships between AIA and motivated learning behaviour					
59	Webb et al. [78]	Discussing how time and temporality are used and inflected with the introduction of AI in education policy contexts					
60	Williams [79]	Analyzing implications of artificial intelligence, data analytics, and blockchain technology for the academy					
61	Williamson [80]	FEE	Learning analytics, AI, and other software for data collection	Higher education	Higher education	SUR	OUT+
62	Winters et al. [81]	Investigating the existing digital structural violence and the approaches to tackling it					
63	Rowe [82]	Exploring the effect on education reform brought by intangible economy which is shaped by globalized datasets such as OECD PISA and artificial intelligence					
64	Ally [83]	Identifying the shaping forces for future education and competencies required by future digital teachers					
65	Song and Wang [84]	Analyzing analysis of worldwide educational artificial intelligence research development in recent twenty years					
66	Ulum [85]	FEE	Versant English test	English language learning	30 students from a state university in Turkey	DA,INT	PER+
67	Costa-Mendes et al. [86]	REA	Multilinear regression model	High school grades	Educational data collection from preschool, primary, and high school	EXP	OUT+
68	Zhai et al. [87]	Investigating the factors impacting machine-human score agreements in machine learning-based science assessments					
69	Loftus and Madden [88]	FEE	Bayesian networks	Internet of Things	First year students from Bachelor of Science in Computing program	EXP	OUT+
70	Breines and Gallagher [89]	Introducing the application cases of teacherbot in the University of Edinburgh					
71	Campo et al. [90]	REA	Middle, a Moodle plug-in using a Bayesian network model	Computer science	45 university students	EXP	OUT*
72	Papadopoulos et al. [91]	Critically reviewing the research on the use of socially assistive robots (SARs) in the pretertiary classroom and its benefits and disadvantages					
73	Berendt et al. [92]	Examining benefits and risks of artificial intelligence (AI) in education in relation to fundamental human rights					
74	Standen et al. [93]	ADP	The MaTHiSiS system	Teachers selected learning material from a library to create their own learning activities and learning graphs	67 participants aged between 6 and 18 years	EXP	OTH*

Table 1: Continued.

ID	Authors	Research question	Technology adoption	Learning Subject	Educational level	Approach	Effects
75	Liu et al. [94]	FEE	BP neural network	Undergraduate education	870 observations have been collected from 5 consecutive academic years in one university	EXP	OUT+
76	Knox [6]	Analyzing the political economy of artificial intelligence (AI) and education in China, with government policy and private sector enterprise introduced					
77	Cope et al. [95]	FEE	CGScholar (Common Ground Scholar)	Disciplinary knowledge	Students studying at the masters and doctoral levels	EXP	OUT*
78	Westera et al. [96]	Reviewing the artificial intelligence (AI) for serious games, presenting reusable game AI components and their relevance for learning and teaching, AI approach, and application cases					
79	Bonneton-Botté et al. [97]	FEE	The Kaligo, a digital notebook application	Handwriting	Kindergarten	EXP	OUT*
80	Smutny and Schreiberova [98]	ROL	Chatbots	Disciplinary knowledge	(Not mentioned the educational level)	DA	0
81	Lucy et al. [99]	DEE	Natural language processing	History	(Not mentioned the educational level)	EXP	OTH*
82	Yakubu et al. [100]	DEE	Artificial neural network (ANN)	Learning management systems (LMS)	1116 students in four Nigerian universities	SUR	PER*
83	Bonami et al. [101]	Analyzing the education through 21st-century skills and the impact of AI development in the age of platforms, taking research, application, and evaluation into consideration					
84	Koć-Januchta et al. [102]	DEE	Inquire Biology (artificial intelligence-enriched textbook)	Biology	24 students from Stockholm University	EXP,SUR	OUT*
85	Tran and Meacheam [118]	Introducing four innovative projects that aim to extend learning management systems and improve the level of automation					
86	Nye et al. [103]	DEE	MentorPal	STEM	31 high school students	SUR	PER*
87	Webb et al. [104]	Investigating the implications of recent developments in machine learning for human learners and learning					
88	Tsai et al. [105]	DEE	Deep neural networks	Disciplinary knowledge	3552 students from a university in Taiwan	SUR	0
89	Alyahyan and Dustegor [106]	Constructing guidelines to apply data mining techniques to predict student success					
90	Renz and Hilbig [107]	Analyzing the drivers and barriers that currently affect data-based teaching and learning paths from the perspective of EdTech companies					
91	Gulson and Witzenberger [108]	Investigating how automated education governance assemblage includes new forms of expertise and authority and constitutes EduTech as an important policy space					
92	Kerimbayev et al. [109]	Review the research aimed at studying robot-man interaction, taking Russia and Kazakhstan as an example of the international cooperation in the sphere of robotics					
93	Fu et al. [110]	FEE	AI-enabled learning tools	Language learning	15 language learners	INT,SUR	PER+
94	Salas-Pilco [111]	Examining the use of artificial intelligence (AI) and robotics in learning designs from the perspective of learning sciences					
95	Yıldız [112]	FEE	SCM-AI	Conceptualization performances	53 five-year-old and 49 seven-year-old Turkish monolingual children from a primary school	EXP	OUT*
96	Tolsgaard et al. [113]	Critically reviewing the published application and potential role of data science and machine learning in Health Professions Education					
97	Hsu [114]	DEE	AI Chatbot	English language learning	30 university students	EXP	OTH*
98	Wu et al. [115]	CLA	Machine learning classification model	A hybrid advanced statistics course	24 university students	EXP	0
99	Wang et al. [116]	ADP	Squirrel AI learning	Math	200 eighth grade students	EXP	OUT*
100	Rybinski and Kopciuszewska [117]	AFF	Natural language processing (NLP) models	Higher education	640,349 reviews of 132 universities	EXP	0

CLA: classification; MAT: matching; REC: recommendation; DEE: deep learning; FEE: feedback; REA: reasoning; ADP: adaptive learning; AFF: affection computing; ROL: role-playing; IMM: immersive learning; GAM: gamification; EXP: experiment; QE: quasiexperiment; DA: discourse analysis; INT: interview; SUR: survey; OUT: outcome; PER: perception; OTH: others including affection, critical thinking, and creativity. *: statistically significant change. +: recognizable change without conducting significance tests. 0: focus on algorithms test without examination of learning performance.

research questions of the sample papers were classified into three dimensions: (a) development, focusing on the knowledge presentation model; (b) extraction, centering on how to obtain knowledge from data mining; and (c) application, emphasizing the human-computer interaction through information derivation. Secondly, with regard to technology adoption, the focus was on the types of technology that the study adopted, which were further categorized into software (e.g., algorithms and programs) and hardware (e.g., sensors and devices such as virtual reality). It should be noted that a study with technology without an AI purpose in education was not included. A detailed description is shown in Table 1 and it includes learning subject, educational level, research approach, and effects. Moreover, the researchers conducted further frequency comparisons on the associations between the research purposes and some factors such as AI technology adoption as well as time periods to predict the trends and challenges of AI in education.

3. Findings and Discussion

According to the above coding criteria and content analysis, the three dimensions of research questions are shown in Table 2 and the 72 studies from 63 empirical studies (5 papers have two studies and 2 papers have three studies) are further subclassified into 11 categories. There are 23 studies in the dimension of development. The AI technique was utilized as a development tool for the construction of a smart learning environment, which can be subclassified as focusing on the development of algorithms including classification, matching, recommendation, and deep learning for teaching and learning purposes. Additionally, 35 reviewed studies were found in the dimension of extraction, which referred to the application of developed AI techniques, normally based on algorithms, to offer students feedback, reasoning, and adaptive learning. 14 empirical studies were found in the dimension of application which consisted of affection computing, role-playing, immersive learning, and gamification. In the integration dimension, AI techniques included those involving human factors as vital variables to identify and analyze learners' personalized features. In such studies, human-computer interaction was generated to improve such characteristics as creativity, responsibility, and critical thinking that can impact learners' performances and perceptions. The following sections describe what educational issues were dealt with in the age of AI and how AI technique was employed in each research question.

3.1. Dimension of Development. As shown in Table 2, 16 empirical studies were found focusing on the development of education systems such as intelligent tutoring system (ITS) and electronic assessment. The development procedure was usually conducted with an induction-deduction approach, in which prior experiments and data were analyzed to predict the variables followed by the algorithm testing to obtain the final modelling equation [19].

Generally, the development of an educational system is constituted of three components: the presentations, logical modelling, and data dimension [20]. All the 23 studies centered on logical modelling, while no study was found on the presentation methods or data mining. The possible explanation may due to that the modelling techniques were the foundation of AI technique and fundamentally penetrate throughout the procedure of system development. In this dimension, the research was generally conducted in the domain of computer science or information science, and the domain knowledge as the source material was imported into algorithm frame (shown in Figure 1(a)) with few pedagogical designs reported. For example, Horakova et al. [3] aimed to explore the classification ability of a text mining machine using three classification techniques. The results show that artificial neural networks (ANNs) were significantly more effective than regression trees and decision trees to separate educational texts or text fragments.
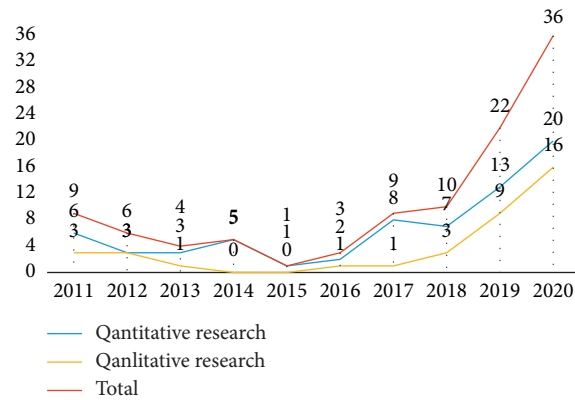
Additionally, in terms of the matching/group formation modelling, prior research employing stereotype theory has assessed that the Bayesian networks, association rules, clustering, fuzzy C-means, and the fuzzy and genetic algorithms were well-accepted algorithms for the modelling of individual properties of the student. These techniques provide potential indications for the investigation of forming homogeneous and heterogeneous groups in an educational context [21].

Moreover, the trends of the growing amount of data challenge educators to analyze qualitative data efficiently. Natural language processing (NLP) provided a means to diagnose the problem and make a recommendation by simplifying and accelerating the discovery of what lies within the data [22]. However, the assessment of a complex educational system requires more profound information retrieval. The integration of multiple approaches, such as benchmark in NLP/Semantic Web field, was suggested to model smarter computer-aided systems in which agents could be trained automatically [23].

To optimize the modelling in the learning context, the hierarchical structures were considered as potential solutions to model the educational system. This is because education is generally a complex system with the exhibition of subsystems and components, in which the invisible causal processes among subsystem/component behaviours would causally affect each other [24]. It was suggested that systematic modelling should analyze three dimensions in the education context: learner's variation, learning domains, and learning activities [25, 26]. For example, some researchers constructed the higher-order item response theory framework involving the overall ability at the first dimension and multiple domain abilities at the second dimension, which has been well adopted in the automatic problem-solving process [27].

Based on the above and Nguyen and Yang's suggestion [28], the aims of developing an AI-integrated system in education could be grouped into four types: classification (5 studies), matching (3 studies), recommendation (5 studies), and deep learning (10 studies). (1) Classification refers to the reconstruction of knowledge bases, in which the materials

TABLE 2: The number of studies concerning AI in education from 2010 to 2020.

[Line chart, x-axis years 2011–2020, y-axis 0–36. Legend: Qantitative research (blue), Qanlitative research (yellow), Total (red). Selected data labels: 2011: 9, 6, 3; 2012: 6, 3; 2013: 4, 3, 1; 2014: 5, 0; 2015: 1, 1, 0; 2016: 3, 2, 1; 2017: 9, 8, 3; 2018: 10, 7, 3; 2019: 22, 13, 9; 2020: 36, 20, 16]

Quantitative research topics		2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Total
Development (N = 23)	Classification							1	2	1		1	5
	Matching				1				1	1			3
	Recommendation				1		2		2				5
	Deep learning								2	1	1	6	10
Extraction (N = 24)	Feedback	1				1	2			2	3	7	16
	Reasoning	1	1		1			1			4	2	10
	Adaptive learning		1		1					1	4	2	9
Application (N = 12)	Affection computing	1	1	1			1	1				1	6
	Role-playing		1									1	2
	Immersive learning									1		1	2
	Gamification	1	2								1		4
Quantitative research		4	6	3	3	5	1	2	8	7	13	20	72
Qualitative research		0	3	3	1	0	0	1	1	3	9	16	37
Total		4	9	6	4	5	1	3	9	10	22	36	109

(a)

Algorithms — Domain → Classification matching, Recommendation deep learning → System development

(b)

AI technique, Pedagogical design, Domain knowledge → Reasoning, Adaptive learning, Feedback

(c)

AI technique, Pedagogical design, Domain knowledge, Human factor → Role-playing, Affection Computing, Gamification, Immersive learning
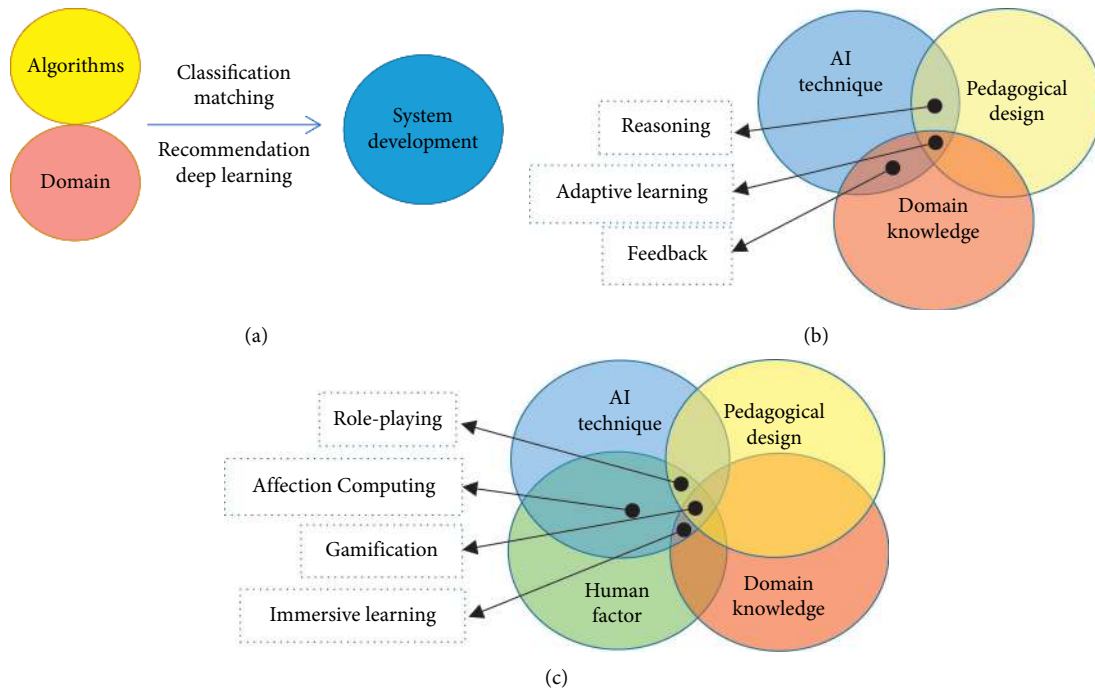
FIGURE 1: The hierarchy of artificial intelligence in educational implementation. (a) The dimension of system development, (b) the dimension of extraction, and (c) the dimension of application.

could be categorized according to varied characteristics. Classification demarcates knowledge content, which contributes to the accuracy of text analysis [3]. For example, some researchers developed an ITS with the characteristics of categorizing motion problems, by which learners could easily access different types of motion problems in Mathematics [29]. (2) Matching refers to a conversion mechanism, in which varied sets of classification are connected to specific learning purpose. For example, a text-to-diagram system was developed for blind students to link geometry words to an underlying diagram on the Braille printout, which has been certified as an effective teaching/learning tool at a Blind school [30]. (3) The recommendation is regarded as an intelligent authoring tool. With the support of the natural language process, it could automatically create new themes, theories, and pedagogical contents as a response to learners' feedback, to help teachers save time and effort [31]. It constructed a human-computer interaction and widely used to generate real-time and intelligent feedback according to learners' input, which has been regarded as a reliable feature in modern assessment system [32]. (4) Deep learning, or machine learning, is a comprehensive approach of big data processing and learning behaviour analysis. Based on the proliferation of big data in education, such as learning or teaching behaviour, the system could self-adjust to meet users' dynamic requirements by upgrading its algorithms [33].

To date, some studies have reported the lack of significant impact on improving teaching. The challenge was largely attributed to the weak pedagogical design and lack of appropriate assessment criteria [8]. Future research should therefore be grounded in learning theories so that more acceptable, accessible, and efficacious AI can be an integral part of learners' lives.

3.2. Dimension of Extraction.

3.2. Dimension of Extraction. Educators have begun to explore suitable applications of AI techniques in their teaching. There are currently some AI applications that have achieved the integration of technique, domain knowledge, and pedagogical design. The three types of pedagogical applications of AI identified in this review were feedback (16 studies), reasoning (10 studies), and adaptive learning (9 studies). While these applications could be interlinked, they were categorized as such based on the classification explicated by the authors of the reviewed articles.

3.2.1. Feedback. One of the challenges impairing personalized learning is the inappropriate sequencing of contents. The restructuring of presentation sequences is seeking a way to redefine the organization of knowledge according to the student's reaction. In this situation, feedback is an important approach to meet learners' proximal learning patterns [9]. Using an artificial neural network, the system provides immediate feedback according to students' input to help them gradually get access to the abstract concepts and perform practical exercises. Besides, researchers perceived a positive trend towards the system, which may attribute to two perspectives.

(1) Based on Ohlsson's theory, students can learn from the feedback generated as the result of an error [34]. In a physical teaching environment, the teacher could interact with students immediately as difficulties arise. It is, however, difficult for such just-in-time interaction in an online context. The situation requires intelligent algorithms to provide feedback automatically. For example, with the help of pedagogical agent-based cognitive architecture, the intelligent virtual laboratory was developed to give appropriate feedback to students who encounter difficulties in the laboratory [35]. Besides, a learning website, Jutge.org, was developed with the features of a rich and well-organized problem repository. The website provides instant feedback and helps students to progressively solve problems and learn from their mistakes [36]. (2) Immediate feedback promotes active training in interactive learning environments that would benefit learner's comprehension diagnosis [19]. The previous study combined speech recognition, natural language processing, and machine learning to measure the quality of classroom talk, in which new forms of interaction were created to provoke thoughts and further shape the effective interaction of the learning environment [37]. Another AI system used path traversal algorithms to establish causal chains, by which students were provided with elaborated feedback and hints rather than the correct answers. The learning-by-teaching context was constructed by learners' self-organization of interactions and their interpretation of feedback [38].

Although a large number of benefits were reported with respect to automated feedback of domain knowledge, no research in this review had established the connection to pedagogical theories. Most of the authors in the development dimensions were from the computer science domain, which leads to their focus on the presentation of source data (domain knowledge) technically without much pedagogical consideration.

3.2.2. AI-Supported Reasoning. The recursive feedback may have the potential to foster learners' abilities to reason in specific ways because the human-computer interaction is able to engender among the students a sense of responsibility toward improving the construction of knowledge repository [39]. The reconstruction of the knowledge repository was seen as a process of using modelling to realize pedagogical design as shown in Figure 1(b). However, some researchers found that novices such as students and preservice teachers showed minimal understanding of the invisible causal behaviours in the system compared to experts and experienced teachers [24]. Another research showed a similar conclusion: students were able to learn the relevant facts and pairwise relations, while they may still fail to reason with them very well [39]. One possible explanation could be that reasoning is largely invisible and it is difficult to induce the processes of reasoning through the observation of the behaviours. AI techniques such as the visualization technique could be applied to foster learners' reasoning.

To help learners improve their reasoning, the graph structure [29] and learners' engagement [24] techniques

have been studied. For the graph structure, intelligent systems could be developed to make thinking visible. In a sense, the simulation approach of the AI technique was employed to mimic thoughts tracking the reasoning visually in real time. For example, the argument-mapping tools were designed to assist learners with visualization of the premises and conclusions of arguments. The findings showed that a sequence of connected arguments was chained together for learners to make an ultimate conclusion [40]. Drawing from the sociocultural theories of learning in designing AI to support students' reasoning, Vattam et al. [24] reported that engaged learners could better understand the multiple levels of organization in complex systems. Therefore, students' engagement is an essential aspect to be considered for the design of a learning system that aims to support reasoning.

The hierarchical reasoning generated by the intelligent system had beneficial effects on students' learning. Firstly, it may help learners to optimize the elucidation of the relationships between the subcomponents of a particular topic. In return, the intelligent reasoning system can be used as a form of evaluation to assess if the student has captured enough concepts for the given topic [41]. Secondly, the system could provide an argumentative interaction which placed great significance in the construction of collaborative learning atmosphere. It is because, as a result of peers' reasoning, learners tend to externalize their arguments and improve their premises. Jain et al. [41] combined visualized mapping tool with collaboration scripts. The design successfully helped learners to analyze and evaluate opposing positions on contentious topics. Generally, researchers regarded the reasoning visualization tools as valuable scaffolds to develop learners' critical thinking and writing [40].

However, using AI techniques, including visualization and hierarchical reasoning modelling, may be inadequate to support reasoning. The four studies reviewed focused on the utilization of modelling to support general reasoning, while the reasoning model should be largely domain-specific [24, 39, 40, 42]. Moreover, there is an unresolved challenge in coding learners' behaviours as far as AI-supported reasoning is concerned. The reasoning process may be more effective when learners' personalized performance is considered. Although the visualized reasoning tools could perform well in a small-scale group setting, it is difficult to obtain adequate reasoning analysis of the data from a large population because the reasoning system fails to adjust itself automatically. Therefore, the requirements of dealing with increasingly large and diverse data demand self-adaptive alternatives [9].

3.2.3. Adaptive Learning.
Based on the new decentralized theories of AI and social cognition, the apparent complexity of learners' behaviour was largely a reflection of the complexity of the learning environments. This prompted educators to provide adaptive scaffolds for diversified learning environments with various types of learners. Different from the feedback system that offers stock responses, the adaptive educational system is a formative and corrective automated

system that can adjust itself (target of intervention) to suit individual learners' characteristics, needs, and preferences (pedagogical objective) [43]. Although only three empirical studies were identified in this review, some researchers were very positive to the future promotion of adaptive system in teaching and learning. Technologies such as intelligent speech recognition and automated writing evaluation [44] have been tested with promising findings. In addition, there was substantial evidence showing that adaptive intelligence enhances learning by automatically enabling learners to locate and access proximal educational resources with respect to navigation and presentation support [45].

Previous research has emphasized that the design dimension was a worth exploring alternative in the application of adaptive system [46]. To design successful adaptive systems in education, curriculum designers and system designers have to leverage on to include the modelling of the problem-solving process in the specific domain knowledge and the use of big data [21, 44]. Firstly, the mechanism of the adaptive system connects learners' prior domain knowledge and the evaluation of their current domain performance to scaffold their problem-solving [47]. In particular, the pedagogical design is essential in adaptive intelligent context. It involves the selection of adaptive algorithms and considerations about the compatibility of the learning style and the intelligence supportive methods. In this sense, the assumption that AI would threaten the teachers' position may be unfounded because of teachers' vital role as curriculum designers. Secondly, the adaptive system is empowered by big data. Since the main feature of the adaptive learning system is personalization, accumulation of big data such as the range of diverse individual characteristics and learning style and preferences is necessary for intelligent personalization to be realized. However, research on personalization in the context of the adaptive system is limited to the users' characteristics related to domain knowledge. The deeper internal characters, such as human mental status and creativity, were barely noticed and studied [21]. This however has vital research potential with the development of advanced AI techniques such as biofeedback techniques.

3.3. Dimension of Application

3.3.1. Technology Adoption in the Application Dimension.
The dimension of application highlights the importance of including human affection in the application of AI in education. The latest research has indicated that affection had increasingly been reported to exert a significant influence on decision-making, perception, and learning [48]. Previous studies on the measurement of learning performance only focused on two dimensions: learning outcomes (e.g., scoring and achievement) and perceptions (e.g., satisfaction and acceptance), whereas other aspects were less noticed. Based on the maturity of biofeedback technique, such as eye-tracking and EEG, affection computing was increasingly adopted to investigate students' internal motivations on learning, such as creativity and responsibility [49, 50].

According to the content analysis of the selected papers shown in Table 1, there are five typical AI techniques that supported affection computing and analysis in the education sector. They are complex algorithms, visualization, XR (virtual/augmented/mixed reality), wearable technique, and neuroscience. In many situations, they supported each other to construct a smart learning environment and system. (1) Complex algorithms were designed with consideration of human factors rather than the simple combination of functional blocks. From the perspective of human-computer interaction, the learners should be treated as a knowledge creator rather than the receiver, which helps to generate positive affection status. From the perspective of presentation modes, the traditional declarative statements in a computer system should be replaced by more diversified verbal presentations such as dialogue, coaching, and generality. (2) Visualization was seen as an optimal method chosen for the solution of complex conception. One of the benefits of visualization is making complex knowledge entertaining, such as game-based learning, in which learners' motivation will be greatly generated. (3) XR including virtual/augmented/mixed reality provides a highly simulated learning context, which may be challenging to realize in physical classrooms. For example, to help learners understand complex landforms in geography, XR indulges students into a lively and creative status. (4) The wearable technique, such as Google glasses, helps to integrate learning activity into somatosensory moves. Although it was still in an exploratory period, it has great potential to advance domain knowledge in a practical context in daily life. (5) Modern neuroscience exploits how the brain works and this expands the research of learning to include the learners' physiological state. Research in this area would enrich understanding about individual variations and could provide additional avenues to match instruction with the most optimal guidance.

3.3.2. The Categories of the Application Dimension.

With the supports of the above five AI techniques, four types of learning models were generated with the application of affection analysis, which was biofeedback (6 studies), role-playing (2 studies), immersive learning (2 studies), and gamification (4 studies).

Affection computing refers to the analysis of human emotions and feelings captured by physical sensors and affective algorithms, which has gained much attention in recent years. Affection computing enhanced human-computer interaction. Based on the facial identification, some researchers improved the intelligent tutoring system by which students' emotional status was detected to give them timely emotional feedback [51]. Two essential aspects are needed to optimize the affection computing technique: first, teachers have to make timely appropriate instructional adjustments according to learners' affective status; second, comprehensive operation of multimode affection sources as a single source is unlikely to provide accurate analysis of affection. For example, the eye-tracking technique could capture learners' eye fixation to track the attended area, but the reasons for the foci may be attributed to different affections such as interest, anxiety, or even distraction. An additional source of data such as EEG could help to make a more accurate assessment [52].

Role-play is a learning method that inspires students to ponder on problems with affections assuming varied roles. Some algorithms were designed with the integration of role-play into the pedagogical design, where students are taught by an intelligent agent rather than being taught by the learning system [39]. Enlisting role-play can enhance learners' investment in their interactions with computers. More than that, learners' sense of responsibility was exerted towards the intelligent agent, which was consistent with the research from Chase et al., demonstrating that students may work harder on behalf of their agents than they would for themselves [53]. Additionally, to motivate students to act as a companion to an intelligent agent, the politeness presentation mode was employed in the intelligent tutoring systems, which was observed to benefit the needy students [54]. The future research of role-play may focus on granting access to students so that they could customize their roles and target agents.

Immersive learning is an approach that enables students to customize scenes of characters engaging in full-view learning settings. The enhancement of XR, 3D graphics, and wearable devices could promote the learning performance and these are strongly related to immersive affection, which generated students' academic performance and positive perceptions, such as excitement, enthusiasm, and creativity. For example, learners could obtain a high degree of excitement in the immersive learning environment. Immersive environment can also be coupled with immersive collaboration with gestures, emotions, and nonverbal communication [14]. Using immersive learning may also reduce students' sense of being intimidated by complex topics and technical concepts when they expose to simulated technological and computing issues [55]. Most importantly, many immersive learning tools encourage learners' enthusiasm to create and change the environments, which could foster creativity [56]. However, few studies were found to consider domain knowledge as a variable. The possible reason may be that many immersive learning tools were in the explorative stage. Further investigations in specific domains are eagerly needed.

Gamification has emerged as an important theoretical notion in the education sector. The most successful educational games tightly integrate the pedagogical design, domain knowledge, and affection elements with gameplay. AI has assisted the integration of the game and knowledge domain, and the further potential is making the game adapt to the learners' behaviours and affections dynamically [57]. One of the examples appropriately integrating domain knowledge with affection is Minecraft Edu. This is a historical simulation game where students can learn about historical figures and events or get insight into the spread of epidemics. Learners could get access to historical events with authentic emotions in the real-time interaction, and the collateral emotion would help them better understand the specific content knowledge [8].

Another example employed a game reward system as motivational mechanisms to promote voluntary and proactive learning. The results showed that the reward system had a desirable fit with the pedagogical design, and the future educational algorithms might better get associated with the field of artificial intelligence to motivate emergent learning [58].

3.4. The Results from Qualitative Research. According to selected qualitative research (as shown in Table 3), the exploration of AI in education experienced a process from theoretical research to a specific practice field, and at last back to review. Simultaneously, qualitative research also provided support for the development of quantitative research throughout the whole process. Some theoretical studies were at the forefront. For example, in 2011 and 2012, qualitative research on decentralized theory [43] and swarm intelligence [59] appeared, and then the real artificial intelligence research began. AI algorithms were not very mature at the beginning while advanced intelligent algorithms are usually based on big data technology, and they could constantly learn and improve in the massive data. The big data must be decentralized and group-oriented. Therefore, we believe that the early theoretical research has played a significant supporting role. In 2019, researchers attached more emphasis on the summary of previous studies and prospects for future development, and more consideration will be given to the status quo, future, and possible problems of AI in various sectors of education.

4. The Research Trends of AI in Education

4.1. Technology Adoption of Internet of Things. The existing research mainly focused on the virtual online system, and the Internet of Things (IoT) is less noticed. Learners' biofeedback also needs to be explored in future educational research. According to the reviewed papers, a majority of AI technology in education focused on online information technology or system (107 out of 109), such as intelligent tutoring system, intelligent virtual laboratory, and assessment system. Only one study [55] employed a wearable circuit to examine learners' biofeedback. This may be attributed to the fact that the intelligent online system is well established, easier to build on, and cost-effective. However, to cater to diverse learning contents and varied learning skills, the IoT holds much promise. It may enhance students' spatial and mechanical understanding of physical construction processes in science education. The IoT technology can simulate brain functions in physical context to sense and understand human's cognitive behaviours, which apparently optimizes human cognition and performance in two qualitative studies [33, 60]. Although no empirical studies in the selected papers were found to test the effect of IoT technique on education, the IoT with affordable costs and wearable computing devices could be a potential area of future development of AI in education. This is consistent with the Horizon report in 2019.

TABLE 3: Qualitative research topics.

2020
(1) AI research development in recent twenty years
(2) Machine learning-based science assessments
(3) Application cases of teacherbot
(4) Socially assistive robots (SARs)
(5) AIED in relation to fundamental human rights
(6) Political economy of AI and education
(7) AI for serious games
(8) Impact of AI development in the age of platforms
(9) Innovative projects extending LMS
(10) Machine learning
(11) Data mining techniques
(12) Data-based teaching and learning paths
(13) Automated education governance assemblage
(14) Robot-human interaction
(15) AI and robotics in learning designs
(16) Data science and machine learning

2019
(1) Assessment system
(2) Early self- and coregulation from AI perspective
(3) Ethical tension about applying AIDA in education
(4) Artificial Intelligence Anxiety (AIA) Scale
(5) AI in education policy contexts
(6) AI, data analytics, and blockchain technology
(7) Digital structural violence
(8) Intangible economy
(9) Future education and digital teachers

2018
(1) Neuroscience in education
(2) Teacher' professional roles

2017
(1) Human literacy

2016
(1) Educational data mining, adaptive learning, and creativity

2013
(1) Effect of AI in education

2012
(1) Swarm intelligence
(2) Neurosciences in Edu
(3) Misunderstandings of AI in Edu

2011
(1) Decentralized theory
(2) Interactive learning

4.2. Swarm Intelligence in Education. Swarm intelligence has become a vital development direction of AI, where the roles of teachers and students will be disruptively changed. According to the selected papers, the decentralized theory was firstly investigated in education in 2011 [43], followed by the introduction of swarm intelligence in education in 2012 [59]. However, no empirical study has explored how teachers and students meet the challenges brought by swarm intelligence. It is predicted that the following two topics may become the research trends according to the features of swarm intelligence. Firstly, swarm intelligence does not rely on centralized control of individual behaviours. In this situation, learners change from knowledge absorbers to creators. They actively constructed knowledge by interfacing with the system in a variety of contexts. Teachers'

"authorities" may be challenged by a group of experienced practitioners such as engineers and farmers, and a collaborative curriculum design would be constructed by swarm intelligence system [45]. Moreover, swarm intelligence may change teachers' duties from knowledge transmission to knowledge organization. Previous research has suggested the exploration of crowdfunding or crowdsourcing by teachers on education, and how teachers perform their organizing ability in the future [5]. However, as Figure 2 presents, the investigation from teachers' perspective is still inadequate, which needs further study. Secondly, swarm intelligence facilitated adaptivity in dynamic or unstable environments. Swarm agents usually exchange information by leaving marks and observing the activities of their peers. For example, the best solution in the current moment may become unavailable in the next moment. Therefore, it is suggested to invest further how AI performs dynamic recommendation for students on different learning progress [59].

4.3. Deep Learning and Neurocomputation. Deep learning or machine learning will reshape the interactions between human beings and machines in the future. The trends of human-computer interaction will no longer be based on the perspective of machine operation by a human. Instead, the machine can improve predictions by learning from big data without being specifically programmed. Two studies on deep learning were first mentioned in the selected papers in 2017 [23, 32]. In 2018, one empirical study [37] was published and it focused the deep learning technology on the modelling of scoring-based data. However, the data based on human's physical features were less noticed. Based on the basis of neuroscientific understanding of the brain, Pearson and IBM have proposed to investigate neurocomputation brain-based educational technologies [33]. However, only two qualitative studies [33, 60] suggested the integration of neuroscience and AI in the education sector. Future research trends in integrating brain function with deep learning techniques to optimize human-computer interaction could be expected. It will influence the application and integration of AI in education, such as adaptive learning and role-play. This view has been reported in the Horizon report in 2018. Specifically, the report forecasts that adaptive learning techniques will be further generalized in two to three years.

4.4. Evaluation of AI in Education. All empirical studies reviewed presented the positive effects of AI techniques on education (see Table 1). However, the interview and the review paper have, respectively, surfaced the challenges or misunderstanding of AI in education [4, 21]. There is a need to articulate a holistic evaluation criterion to measure the effectiveness of AI in education. To ensure the validity and reliability of the evaluation, a multidimensional model should be adopted, which includes technique, pedagogical design, domain knowledge, and human factors. Woolf's [119] Roadmap for Education Technology predicted that in the era of AI Educational Data Mining, the lifelong assessment of students' knowledge, their progress, and the

environments where they learn, as well as the success and failure in teaching strategies, can be chronologically tracked.

Besides, current research is disproportionately focused on specific educational contexts and a handful of variables. As shown in Figure 2, most research sampled students as participants, while teachers and professor practitioners were less noticed; additionally, most researchers considered science, humanity, and social science as subjects, but less attention was paid to sports, arts, and special education. For example, only one study was found to develop text-to-diagram conversion as a novel teaching aid for blind learners [30].

5. The Challenges AI Confronted in Education

AI is a promising field that faces many technology bottlenecks. The challenges would be more complex and intricate, especially when they are connected to an application in education. The challenges this review identifies could be classified into three categories: technique, teachers and students, and social ethics.

Although AI techniques displayed and predicted smart computation in the education domain, they generally fail to bring "added-value" to large-scale students because of the concern of costs, and the mainstream is still occupied by "basic value" [38]. Specifically, some researchers found that many AI techniques were designed for a general situation that could not address the needs of a particular domain, specific learning activities, or teaching goals. This would prevent the actualization of personalized learning experiences [8, 120].

Another great challenge reported in the Horizon report in 2018 is the reconceptualization of the role of educators. Teachers' attitudes towards AI have a significant influence on the effectiveness of using AI in education. Teachers may swing from total resistance to overreliance. The former could arise from inadequate, inappropriate, irrelevant, or outdated professional development. The latter may be due to teachers' unrealistic expectations. These teachers may focus too much on the emerging AI technologies rather than learning itself [44]. Additionally, from the perspective of students, AI technique may provide smart and efficient tools that cause students to avoid doing the knowledge processing work that teachers expect them to do. For example, the AI translators may offer ready-made illustrations, pronunciation, fixed phrases, and even a serial of examples. Students are thus unwilling to engage in the inquiry processes that facilitate deep learning.

The ethical issues brought by AI are also challenging for both researchers and educational practitioners. It was clear that AI has made great strides over the past few years, mostly because of cheaper processing and the availability of data; however, individual student data may be exposed, shared, or used inappropriately. It is a constantly mindful challenge that educators and AI engineers will face when considering how we access, evaluate, and share the big data and the results of data analysis [44, 65]. Another ethical debate was conspicuously found in gamification that emphasis should be put on learning and tend to "suck the fun out" of games, or on gameplay "suck out the learning" [57].
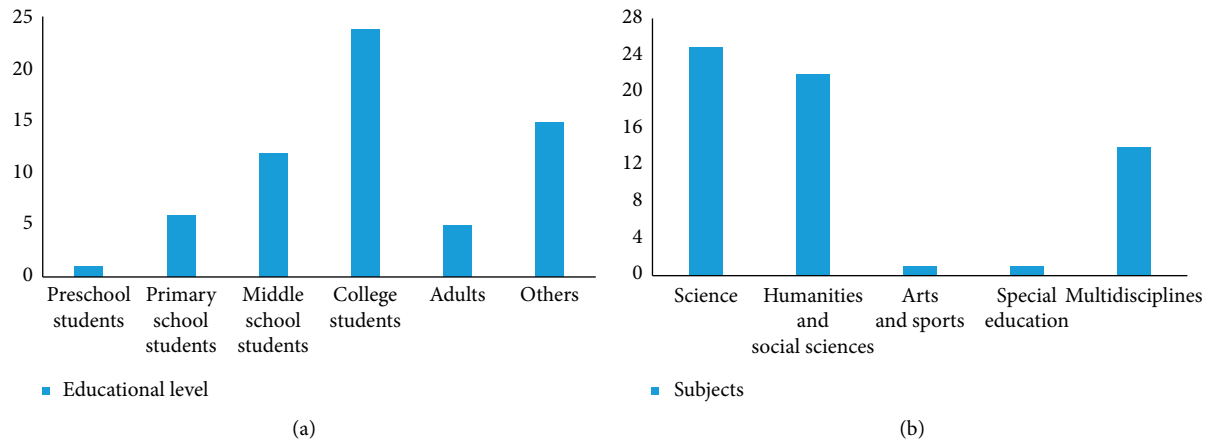
Figure 2: The number of reviewed studies by educational level and subjects.

6. Conclusions

Given the rapid growth of AI, there is an urgent need to understand how educators can best utilize AI techniques for the academic success of students. This paper reviewed AI in education research from 2010 to 2020. It is found that the research to date could be classified into three dimensions: the dimension of development including classification, matching, recommendation, and deep learning; the dimension of an extraction involving feedback, reasoning, and adaptive learning; and the dimension of application including affection computing, role-playing, immersive learning, and gamification. Moreover, based on the research questions and the related AI techniques, four research trends were identified. They are the Internet of Things, swarm intelligence, deep learning, and neuroscience, as well as an assessment of the effect of AI in education. The challenges of AI in education were also conspicuously seen in terms of technique perspective, teachers' and students' roles, and social ethical issues. These findings could be valuable references for educational researchers, students, and AI developers who plan to contribute to the relevant studies. Furthermore, it seems clear that educators need to work with AI engineers to address the gaps between technique and pedagogy.

7. Limitations and Future Study

Although this review does propose some valuable trends and potential research directions for AI in education, there exist several limitations. Firstly, the papers reviewed in this study were filtered from Social Science Citation Index, while other databases on natural science (e.g., SCOPUS and EI) and sources (e.g., reports, news, conference papers, and patents) could be involved to offer a more comprehensive overview in this field. For instance, articles from the *International Journal of Artificial Intelligence in Education* that has published 30 volumes were not considered. This review therefore is limited only to SSCI articles. Additionally, the initial search could be extended using more keywords such as adaptive learning and tutor system, which may lead to the latest technical reports of AI in education that were not included in this paper. Secondly, since the current review was not attempted to be inclusive but to provide a systematic overview of AI in education, the analysis in this review may provide a framework for future research integration. For example, a more formal meta-analysis could be conducted on selected empirical studies that reported effect sizes to see what impact on learning AI might be having. Besides, the future analysis could go back further in time to see if there were changes about the time that AI 2.0 started to make headways into education.

Data Availability

The content analysis data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest to report regarding the present study.

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