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REVIEW ARTICLE

History, Status, and Development of AI-Based Learning Science

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Abstract
The development and innovation of data mining, learning analysis, and artificial intelligence have brought new opportunities to promote the study of learning mechanism in the fields of neuroscience, learning engineering, and precision education. Although learning science has been studied for nearly 40 years, it has not been deeply integrated with artificial intelligence technology at present. The purpose of this paper is to present an overview of the application research of artificial intelligence (AI)-based learning science. Taking the literature of empirical research of learning science from 2017 to 2022 as a sample, the descriptive results show that foreign researchers focus on using artificial intelligence technology to explore and analyze brain, psychology and biological data, and support the construction of learning environment and the development of personalized learning path. Finally, according to the research results, the article shows the future development trend of AI-based learning science, to provide reference for the construction and development of the research field of AI-based learning science.

Keywords Learning science · Artificial intelligence · Learning technology · Literature review

Introduction

Since its introduction, learning science has received extensive attention and exploration by researchers worldwide. The Cambridge Handbook of Learning Sciences mentions that the purpose of learning science research is, first, to better understand cognitive and socialization processes to achieve better quality learning, and, second, to use learning science knowledge to reprogram the existing teaching and learning environments to facilitate learner learning. The rapid development of artificial intelligence technology has brought greater opportunities and challenges for research on the nature of learning. Expert systems, machine learning, evolutionary computation, fuzzy logic, natural language processing, and other technologies have great potential for exploring brain learning mechanisms, social culture, and learning environments, and a large number of artificial intelligence (AI)-based educational and teaching tools are applied in different scenarios and gradually accepted by educators and learners.

Learning science has been studied by academics for about 4 decades, but at present, learning science research has not been deeply integrated with artificial intelligence technology. Since the twenty-first century, AI has become a separate system and evolved into a separate branch, and AI-based learning science was born. Therefore, this study hopes to answer the following research questions through the review.

(1) What are the trends in publishing in AI-based learning sciences? What are the characteristics of the authors' geographical distribution and disciplinary backgrounds?
(2) What are the research areas in which AI-based learning science research is concentrated?
(3) What are the future research directions of AI-based learning science?

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Learning science has its roots in cognitive science, while artificial intelligence has its roots in computer science and engineering; therefore, AI-based learning science is heavily influenced by other disciplines, such as philosophy, neurology, and economics. Due to the interdisciplinary nature of AI-based learning science, researchers have not yet reached a consensus on its understanding [1]. Kelkar [2] points out that many scholars are unaware of the historical lineage of its development and are particularly unclear about its scope of study. Given the purpose of this study, it is proposed to sort out the lineage of the development of the term in the next section to clarify the meaning and scope of the research on the term.

The Evolution of AI-Based Learning Science

AI-based learning science is derived from cognitive science and has been developed for more than a hundred years. By contrast, AI-based learning science has gone through three stages of development since the 1950s, building on the results of cognitive science, described as follows.

AI-based learning science has its roots in the first generation of cognitive science. In the early nineteenth century, Herbart, a German philosopher, psychologist, and educationalist, suggested the study of education on the basis of psychology, with an emphasis on the use of psychological knowledge to explain the laws of education and instruction. Educational research has therefore been influenced to varying degrees by psychological research [3]. In the 1960s, the rise of computer science triggered a wave of psychological reform and a "cognitive psychology revolution" in the field of psychology. At the same time, the rise of computing unleashed a wave of psychological reform and a "cognitive psychology revolution" in the area of psychology. Gagné drew on psychological ideas to build a theory of information processing that illustrated the differences and connections between human learning and the processing of external stimuli by the human brain, and the processing of information by computers. The flourishing of computer science provided a directly comparable cognitive model for cognitive psychology: it seemed that all processes could be seen as having a “twin” in computers, that natural or human intelligence was achieved by the biological nervous system—the human brain—and that artificial or machine intelligence was achieved by the human brain. The natural or human intelligence system is realized by the biological nervous system, the human brain, while the artificial or machine intelligence is realized by the electronic components of the computer [4], which enables the merging of human and artificial intelligence.

Learning science was born in the late 1980s, when researchers integrated cognitive science further into the educational environment [5]. In 1991, the Journal of the Science of Learning was launched, marking the birth of the science of learning. Rejecting the “computational metaphors” advocated by the first generation of cognitive science, the second generation of cognitive science argued that “to understand the mind, we must go back to the brain.” According to philosophers, embodied cognition has been a major factor in cognitive science research in four domains: recognition of body models in artificial intelligence, research on neural bodies, the body nature of skill learning, sociality, and body nature [6]. At the same time, expert systems and machine learning are making new progress and are being used on a large scale in the field of learning science. Experts systematically analyze a large amount of data stored by computers and their derived patterns, so as to realize the effective management of learning content. Since 1991, iterative improvements in machine learning algorithms have enabled expert systems to emulate the knowledge and experience of human experts to tackle more complex challenges, achieving a dramatic breakthrough from the examination of general reasoning strategies to the application of expertise.

Since the beginning of the twenty-first century, some cognitive scientists have considered the close connection between brain science and research in computer science and psychology as a turning point in the development of the third generation of cognitive science [7]. In terms of theoretical foundations and practical applications, AI became a separate system in its own right and gradually evolved into a separate branch with the birth of AI-based learning science. Using AI technology to analyze and process a wide range of data, combining the disciplinary expertise of educational data scientists, learning engineers, and precision education specialists in psychology, biology, and neuroscience, a new field of AI-based learning science is being established [8]. Neuroscience has opened up new paths in learning science, and the development of new experimental techniques, particularly brain imaging, has provided new perspectives on the scientific analysis and tools for integrating physical and mental knowledge to fit real-life scenarios [9]. AI-based learning science, with the help of neuroimaging tools, has reached the brain level by analyzing learners' thinking and learning processes. Sufficient research shows that the demand for sleep, arithmetic, bilingualism, music, reading skills, and sports will affect learning, and more attention should be paid to the brain, mind, consciousness, and self.

Literature Sources and Search Methods

Study Sample Search

The Web of Science platform was selected as the main source of literature sample for this study. According to Williamson's definition of the research scope of AI-based learning science [10], searches were conducted with the themes of learning science, learning engineering, precision education, and artificial intelligence; the search terms are listed in Table 1. The search time frame was set to 2017–2022, and 3,824 articles were initially retrieved.

Study Sample Screening

This study strictly followed the process related to systematic reviews with literature screening criteria (PRISMA) [11], as shown in Fig. 1. The retrieved literature was screened according to the following criteria: (1) the study was an empirical study with complete and clear data information, excluding theoretical or review articles; (2) the study population was a normal population, and other special groups (e.g., subject groups with various types of mental disorders) needed to be excluded; (3) duplicate published articles were excluded, and the same batch of data used repeatedly should be counted only once, and the inclusion criteria are shown in Table 2. According to after the initial screening of sample keywords and abstracts by exclusion criteria, a sample

Table 1 Search terms

Topic	Keyword
Learning science	"Learning science" OR "learning sciences" OR "science of learning" OR "design research" OR "learning community" OR "cognitive apprenticeship"
OR	
Learning engineering	"Learning engineering" OR "engineering sciences" OR "Engineering design" OR "double-loop learning" OR "educational engineer*"
OR	
Precision education	"Precision education" OR "personalized education" OR "genome"
AND	
Artificial intelligence	"Artificial intelligence" OR "AI"

Fig. 1 Flowchart of literature screening

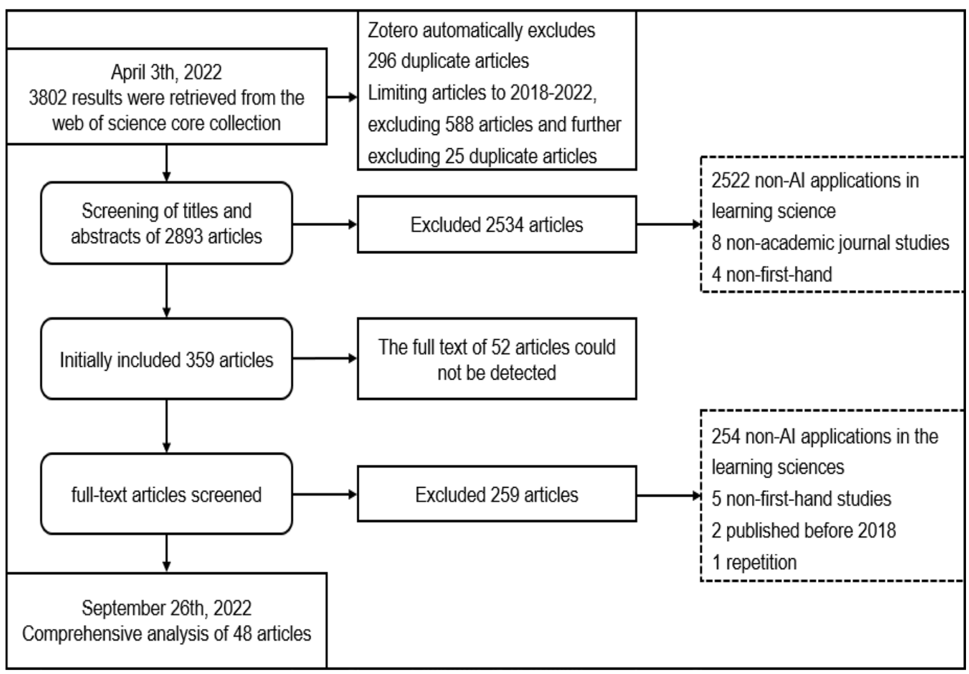


Table 2 Final inclusion and exclusion criteria

Inclusion criteria	Exclusion criteria
Published: January 2017–December 2022	Published before 2017
English	Non-English
Empirical, first-hand research	Non-first-hand (e.g., narrative reviews)
Indexed in the web of science	Non-academic journal papers
AI in Learning Science	Without AI

of 359 articles was obtained (as in Fig. 1). However, 52 of these articles could not be retrieved in full text, and the full text was not available through the library subscription system and by contacting the authors. Therefore, the remaining 307 articles were re-screened, and 252 documents with low relevance were excluded, resulting in a final research sample of 55 articles.

Study Sample Coding

All literature was uploaded to the specialized software EPPI Reviewer to extract the data and to draw up a coding system. The coding includes information about the articles (journal name, year of publication, author, and subject background), research directions, and application scenarios. The literature coding for this study was extracted independently and simultaneously by two coders [12]. The two coders, both master's students in educational technology with strong literature reading and statistical analysis skills, regularly discussed whether the first 100 papers met the inclusion criteria to reach a consensus. In this study, 30 papers were randomly selected and the Cohen kappa (k) coefficient was used to test the reliability between the two coders (A and B) [13] to determine the extent to which the different coders agreed on the degree of coding [14]. Kappa values of 0.40–0.60 were considered moderate, 0.60–0.75 were considered good, and 0.75 or more were considered excellent [15]. The degree of coding agreement between coders A and B was $k = 0.85$, indicating that the study was coded more accurately and effectively in the literature. In addition, studies with inconsistent coding were agreed upon through further discussion, resulting in a final sample of 55 studies.

General Situation of AI-Based Learning Science

Overall Trend

In terms of the overall trend, the 55 selected papers showed a fluctuating growth (see Fig. 2), with a yearly increase in the number of publications between 2017 and 2022, and a high and substantial increase in the number of publications from 2021 to the present, indicating that the international academic community has continued to pay high attention to the scientific research on AI-based learning in the past 2 years, producing fruitful research results.

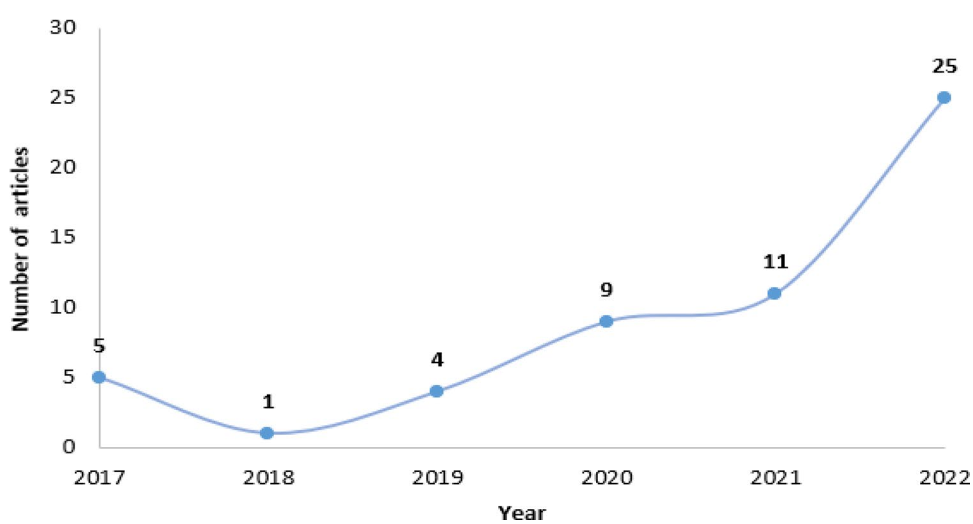
Country Distribution

Table 3 shows the distribution of the first author's nationality. The United States, China, and the United Kingdom are in the leading position in terms of the number of publications, which is inextricably linked to the strong research strength of the developed countries themselves; Singapore, as a country with greater influence on independent research, has a lower output; most Asian countries have a large gap in the number of publications compared with the developed countries in Europe and the United States, and Asian countries should further improve their comprehensive research strength.

Author Affiliation

Table 4 shows that authors from the facility of education had the highest number of publications, followed by the faculties of Mechanical Engineering, Computer Science, and Art and Design. Only four of the first authors were from the Department of Psychology.

Fig. 2 AI-based Learning Science annual publication volume (2017–2022)



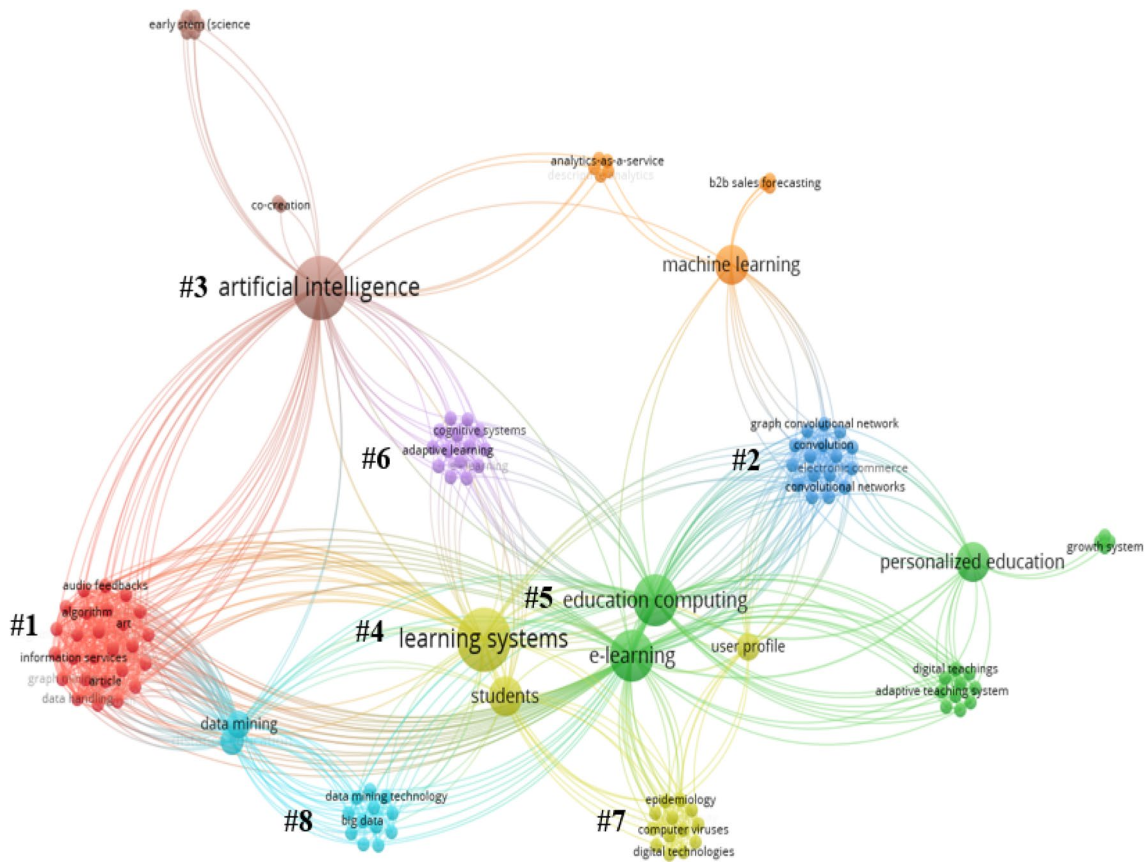


Fig. 3 Keyword co-occurrence mapping of AI-based learning science research

Table 3 Number and percentage of national issuances ($N=55$)

Rank	Country	*N*	%	Rank	Country	*N*	%
1	United States	18	0.40	11	Germany	1	0.02
2	China	16	0.31	12	India	1	0.02
3	England	3	0.07	13	Iran	1	0.02
4	Kuwait	2	0.04	14	Italy	1	0.02
5	Brazil	1	0.02	15	Netherlands	1	0.02
6	Bulgaria	1	0.02	16	Russian	1	0.02
7	Canada	1	0.02	17	Scotland	1	0.02
8	Cario	1	0.02	18	Singapore	1	0.02
9	Denmark	1	0.02	19	Slovenia	1	0.02
10	Finland	1	0.02	20	Switzerland	1	0.02

Hotspots in AI-Based Learning Science Research

Keywords reflect the most core content in an article, and the research hotspots in the field at a certain time can be summarized by statistically analyzing the keywords in the related field literature. The sample literature was imported into SATI software and the data were analyzed for word frequency, and the top 14 keywords in the high-frequency keywords were derived, as shown in Table 5. The focus of academic scientific research on AI-based learning is more concentrated, and artificial intelligence, machine learning, learning analytics, precision education, cooperative learning, and mobile learning are still the focus of research.

Based on the keyword word frequency analysis, the keywords of the 55 sample documents were further analyzed using VOSviewer software, and the co-occurrence mapping

Table 4 Affiliation to which the first author belongs ($N = 55$ articles)

Affiliation	*N*	%
Education	15	0.27
Mechanical engineering	14	0.25
Computer science	10	0.18
Art and design	7	0.13
Psychology	4	0.07
Civil engineering	3	0.05
Not mentioned	2	0.04
Total	55	100.00

was constructed after eliminating keywords that were not related to the research topic (as in Fig. 3). The network included a total of 8 clusters, of which the 4 largest clusters contained a total of 65 nodes, accounting for 54% of the whole network. This study focuses on these 4 clusters to synthesize the progress of AI-based learning science during 2017–2022.

Research on the Mechanisms Underlying Learning

Personalized learning has become a key concept in today's data-driven education, as highlighted by clusters #1 "Algorithm", #5 "Personalized Education", and # "Data Mining Technology", which have remained active in recent years. Based on the collection of multiple data sources, such as mental states, genetic genes and digital data, educational psychology, genomics, neuroscience researchers, and others, have gained insights into the dynamic processes and complex mechanisms of learning and are further advocating the use of big data, AI algorithms, educational data mining, and learning analytics to respect learners' wishes and choices and provide personalized learning experiences [16, 17]. The following sections reveal how the mechanisms underlying learning can be studied through data and emerging technological approaches.

Brain Data: Mapping Numbers and Understanding Learning Patterns

Brain data provide a rich source of data for the study of brain and cognitive mechanisms. It allows us to look at the structure, function, and plasticity of the brain from a scientific perspective. In recent years, researchers have focused on the complex processes of influence between different variables, with more in-depth discussions around attention and spatial ability.

Attention has been the focus of research on human cognitive activity. In the last 5 years, research has focused on aspects of working memory revealed mechanisms of attentional control during primary education, finding that students in grades 1–5 were sensitive to visually distracting information, and from grade 3 onwards, students gradually became more responsive to audiovisual sensory information [18]. Scrimin et al. explored the effects of classroom climate and self-regulatory abilities on the control of attention by recording cardiac sympathetic nerve activity in the role of attentional control in primary school children. To support real-time monitoring of learner attentional status, the FocusEDU neural headset developed at Harvard University captures brainwave signals and translates them into an attention index to quantify real-time learner engagement and provide teachers with timely adjustments to teaching strategies [19].

Researchers in AI-based learning sciences have also been focusing on the development of spatial abilities. In the last 5 years, researchers have combined spatial ability, creativity, and mathematical ability with an increased focus on designing or developing adaptable methods or teaching aids for training spatial ability. Bates elucidated the role of the mental intention framework in explaining children's mathematical computational skills [20]. Harris et al. experimentally demonstrated that improved spatial ability can facilitate students' mathematical learning [21]. Mix et al. found that the control group receiving mental rotation and spatial visualization skills in Year 1 and Year 6 students led to significant improvements in mathematics performance [22].

Table 5 High-frequency keywords of AI-based learning science research

Rank	Keyword	*F*	%	Rank	Keyword	*F*	%
1	Artificial intelligence	17	9.24	8	Constructive	2	1.00
2	Machine learning	5	2.72	9	Deep learning	2	1.08
3	Learning analytics	4	2.17	10	E-learning	2	1.07
4	Precision education	4	2.17	11	Mobile learning	2	1.05
5	Education	3	1.63	12	Neural network	2	1.03
6	Collaborative learning	2	1.10	13	Personalized education	2	1.01
7	Bigdata	2	1.10	14	Adaptive instruction	1	0.54

*F = frequency

Psychological Data: Insights into the Inner World and Provision of Emotional Needs

Non-cognitive factors in learning, such as motivation, self-regulation, perseverance, attitude, engagement styles, and expectation levels, are equally important to learning. Various techniques for measuring learners' emotional state include the collection of recent indicators related to learning through camera-detected facial expression techniques as well as video, eye tracking, skin temperature, and conductivity. In recent years, learners' psychological characteristics have increasingly been included as objective data, and educational psychologists have conducted in-depth research around emotions, self-regulation, and learning interaction processes. Williamson et al. explored the relationship between changes in facial emotion and students' engagement and attention in learning tasks, and found that feedback systems facilitate teachers' dynamic understanding of student dynamics to make timely adjustments to teaching styles [10]. The feedback system was found to be useful for teachers to dynamically understand student dynamics to adjust teaching methods or progress in a timely manner, thus achieving better teaching outcomes. Verkijika used a game that integrated brain–computer interaction technology to measure learners' neural activity during the game, visualized the neurofeedback results to suggest learning emotional states, and found that monitoring emotions could reduce learning anxiety [23]. Donolato et al. explored the impact of mathematics anxiety on mathematics performance and suggested effective measures to alleviate anxiety [24]. Whiting et al. found that the more stressed children were, the more likely they were to be distracted and to have difficulty participating in learning programs [25].

Biological Data: Decoding the Genetic Code and Foretelling the Future of Learning

In biomedicine research, genome-wide association studies (GWAS) in recent years have focused on intelligence and cognitive ability, with a focus on in-depth analysis of individual genetic data through machine learning and predictive analytics. Plomin developed a system that can score individuals based on DNA information to predict their educational attainment, achievement, and intelligence, offering the possibility of identifying potential problems in students early and taking effective action [26].

The American Social Science Genetics Association published a sample of genetic analysis of the educational attention of 1 million people and found that GWAS predicted up to 12% of a person's educational attainment and 9% of their cognitive ability, demonstrating the strong influence of genes on educational attainment [27]. Rabinowitz documented long-term changes in mathematics and reading achievement among African Americans in the Mid-Atlantic region of the United States and found that genes were significantly associated with mathematics but not with reading achievement [28]. Hill et al. found that cognitive ability and academic performance were positively correlated in an independent sample of subjects [29]. In addition, game-based teaching and student physical health are also of interest to biomedical researchers. The Zamzee platform is based on sensing technology that measures learners' steps, speed, and activity trajectories, allowing educators to analyze learners' physical condition based on data collected by the platform.

Study on the Design of Learning Environments

With the rapid development of artificial intelligence and big data, researchers have also begun to turn their attention to creating intelligent learning environments to provide personalized learning services, as reflected in clusters #4 "Learning Systems" and #6 "Adaptive Learning ". "Adaptive Learning" has been a focal term for the past few years, providing a new research horizon for AI-based learning science research, and allowing researchers to work deeply on developing learning activities and learning systems.

Songer et al. proposed a "navigated learning" framework to investigate whether Year 5 students could achieve desired learning outcomes in mathematics [30]. Besides, they designed a generic model for teaching transmembrane transport, and explored the usefulness and value of this model for learning plant and animal physiology. Scott et al. found that university students rarely considered flux changes in complex physiological contexts when learning biology [31]. Sabatini et al. created a model for assessing reading, and conducted a validation of the model for learner knowledge review [32]. Lindgren et al. built on previous research in brain cognition and developed a simulation learning system called ELASTIC3S. Experimental studies showed that this system can help solve the problem of inefficient learning transfer [33]. Hidayah developed an adaptive metacognitive scaffold for algorithmic learning, and experimental results demonstrated that the scaffold significantly facilitated algorithmic learning [34]. Sedrakyan et al. followed the principles of design science in information systems research and designed a dashboard that visualizes learners' cognitive and behavioral processes [35]. Khosravi et al. designed and developed RiPPLE, an adaptive learning system that provides personalized learning services for students to enhance learners' interest in learning and fill in gaps in their knowledge [36]. Thomas et al. introduced cybersecurity into a card game and designed a game-based learning platform, which was found to help to address people's low awareness of cyber security [37]. O'Mahony followed a "research by design" approach to build a platform for validating scientists' visual designs for discussion and communication, helping to improve their scientific communication [38]. Winne et al. developed and validated a tool to track cognitive and metacognitive processes and to monitor motivation. A software system that tracks cognitive and metacognitive processes and monitors motivation is an effective platform to promote learner self-regulation and enhance learners' reflective activities [39]. Nazari explored technology acceptance and designed an AI-based tool to assess learners' writing performance and investigated its impact on learners' self-efficacy [40].

Future Trends in AI-Based Learning Science

In recent years, the study of learning science has been divided into two main branches: one is to explore the nature of human learning to better understand the cognitive and social processes of student learning; the other is to redesign student learning environments based on an understanding of learning, that is, to explore how to help students learn in authentic classroom learning environments through the reconfiguration and design of mechanisms, environments, and teaching and learning tools [41]. This study argues that future trends in AI-based learning science include three directions of development.

Focus on Research Studies in the Context of Sociological Theory

Learning is a complex systemic phenomenon in which learning and learning mechanisms operate at different levels as semi-independent self-management systems. As the individual is one of the key elements in social ideology, learning scientists have begun to pay sustained attention to the organizational and socio-cultural dynamics of learning in different cultural contexts and the impact of cultural diversity on students' abilities and cognitive emotions. In recent years, many research projects have looked at the mechanisms of learning in informal contexts such as natural learning and everyday learning, in addition to focusing on school learning and the construction of school environments, exploring the cultural dynamics and organizational roles behind the learning that takes place. Under the influence of the Vygotsky School of Cultural History, learning scientists have increasingly focused on the complex socio-human environment in which intelligent behavior occurs.

Focus on the Use of Adaptive Technologies to Enhance Learning

The rapid development of AI technologies, especially in the field of adaptive technologies, has laid a solid foundation for personalized teaching and learning. Automatic analysis of behavioral operations, and cognitive and emotional processes are becoming more sophisticated in both learning and problem solving. The use of intelligent technologies not only provides more adaptive feedback to individual learners, but also supports teachers in monitoring and intervening in learners' learning processes. Data-driven AI technologies can go a long way in mining learners' learning data and recommending accurate learning resources for learners, enabling targeted and tailored teaching and learning, personalized learning, and reduced load and efficiency. In addition to thinking about how technology can be applied to learning, learning scientists are currently more concerned with how adaptive technology can be used to enhance learning and improve learning efficiency.

Emphasis on Well-Designed Human–Machine Interfaces

As a research paradigm in the learning sciences, design-based research requires a research design process that will integrate participant observation of design and refinement of design methods, and improve on them as they are practiced, to achieve an iterative cycle. In addition to this, the design of teaching systems or learning software interfaces that are highly interactive with learners should be enhanced to optimize the design for the learner's learning experience, such as efficiency of use, discoverability, and simplicity. Interaction interfaces are a medium and conversational interface for human-to-human information transfer and communication, and following learner-centered design principles facilitate a deeper understanding of the learner's learning needs, which includes more than just initially involving the design implementer in the design process; the best path is to involve the learner in the development process, thus achieving a win–win situation for both the learner experience and the success of the system.

Discussion and Conclusions

This paper analyzes the authors and publishing journals in artificial intelligence-based learning science. It is found that the publishing trend has been rapid in the last 2 years and has entered an explosive phase, with the main researchers in this field coming from the United States, China, and the United Kingdom, most of whom are employed in education and mechanical engineering faculties. More importantly, this review shows that AI technologies play a pivotal role in learning science, engineering, and precision education, both in terms of exploring human learning mechanisms and designing learning environments and learning tools to support learners, pedagogues, and education departments online and offline.

Although the review is more rigorous in its approach, any review is limited by its search methodology. The two large international educational research databases selected for this study specify that the articles entered must be published in English and peer-reviewed, so this review does not include articles in other languages. In addition, although conference papers and proceedings papers were indexed in both of these databases, they were all excluded, because they were not within the scope of scholarly journal articles. Future studies may consider increasing the number of databases, publication types, and languages to expand the scope of the review.

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Declarations

Conflict of Interest The authors declare that they have no conflict of interest.

Ethical Approval This article does not contain any studies with human participants or animals performed by any of the authors.

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