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Position Paper

Artificial intelligence in education: The three paradigms

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ABSTRACT

With the development of computing and information processing techniques, artificial intelligence (AI) has been extensively applied in education. Artificial intelligence in education (AIEd) opens new opportunities, potentials, and challenges in educational practices. In its short history, AIEd has been undergoing several paradigmatic shifts, which are characterized into three paradigms in this position paper: AI-directed, learner-as-recipient, AI-supported, learner-as-collaborator, and AI-empowered, learner-as-leader. In three paradigms, AI techniques are used to address educational and learning issues in varied ways. AI is used to represent knowledge models and direct cognitive learning while learners are recipients of AI service in Paradigm One; AI is used to support learning while learners work as collaborators with AI in Paradigm Two; AI is used to empower learning while learners take agency to learn in Paradigm Three. Overall, the development trend of AIEd has been developing to empower learner agency and personalization, enable learners to reflect on learning and inform AI systems to adapt accordingly, and lead to an iterative development of the learner-centered, data-driven, personalized learning.

1. Introduction

With the development of computing and information processing techniques, artificial intelligence (AI) has been widely applied in educational practices (Artificial Intelligence in Education; AIEd), such as intelligent tutoring systems, teaching robots, learning analytics dashboards, adaptive learning systems, human-computer interactions, etc. (Chen, Xie, & Hwang, 2020). Since the debut of AIEd nearly three decades ago, AI has been considering as a powerful tool to facilitate new paradigms for instructional design, technological development, and education research that are otherwise impossible to develop in the traditional education modes (Holmes et al., 2019; Hwang et al., 2020). Specifically, AIEd has provided new opportunities, potentials, and challenges for educational innovations, e.g., the change to personalized learning, the challenge of the instructor's role, and the development of complex educational system (Baker et al., 2019; Holmes et al., 2018; Starčič, 2019). Varied AIEd techniques (e.g., natural language processing, artificial neural networks, machine learning, deep learning, and genetic algorithm) have been implemented to create intelligent learning environments for behavior detection, prediction model building, learning recommendation, etc. (Chen, Xie, & Hwang, 2020; Rowe, 2019). AIEd has becoming the primary research focus in the field of computers and education, which has the potential to foster a transformation of knowledge, cognition, and culture (Hwang et al., 2020).

Although AI has the potential to transform education (Holmes et al., 2019), good educational outcomes typically do not occur by the virtue of merely using advanced AI computing technologies (Castañeda & Selwyn, 2018; Du Boulay, 2000; Selwyn, 2016). More importantly, the use of distinct classes of educational technologies generally imply different philosophical and pedagogical perspectives, which in turn pose critical influences on the quality of learning and instruction (Hwang et al., 2020). Although relevant work has reviewed AIEd categorizations (Holmes et al., 2019), approaches (Baker et al., 2019; Luckin et al., 2016), research issues (Hwang et al., 2020), challenges (Baker et al., 2019), and future visions (Pinkwart, 2016), few studies explicitly examine what are the different roles of AI in education, how AI are connected to the existing educational and learning theories, and to what extent the use of AI technologies influence learning and instruction (Hwang et al., 2020).

To address this gap, this position paper makes a critical reflection of theoretical, pedagogical, and computational aspects of AIEd by proposing three AIEd paradigms that use AI techniques in varied ways to address the learning and instructional issues in education. The main objective of this position paper is to summarize the major paradigms with the descriptions of relevant theoretical foundations, conceptual research, and

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practical implementations. Particularly, this position paper offers a reference framework for future AIEd practice, research, and development, that has potential to foster learner-centered learning, human agency, and lifelong learning in the current innovation-driven knowledge age.

2. Review of relevant work

AIEd faces the essential problems in the general education field, e.g., how to meet learners' needs, what to provide to the learners and when, and how to empower learners to take agency for their own learning (Du Boulay, 2000). Although AIEd integrates advanced computing and information processing techniques in education, it does not guarantee the good educational outcomes and high quality of learning (Castañeda & Selwyn, 2018; Du Boulay, 2000; Selwyn, 2016). The use of technology should be tightly connected with educational and learning theory to inform instructional design and technological development (Bower, 2019). A series of systematic reviews have been conducted by different research teams to point out the common problem in AIEd, i.e., the lack of connection between AI techniques and theoretical underpinnings, which in turn critically influence the effect of implementations of AI in education. For example, after reviewing 146 articles of research on AI applications in higher education, Zawacki-Richter et al. (2019) concluded that there was a lack of critical reflection of theoretical, pedagogical, and ethical implications with the implementation of AI applications in higher education. Chen, Xie, Zou, and Hwang (2020) conducted a systematic review of 45 influential AIEd studies and summarized that only several studies used learning theories to ground AIEd research, including the situated learning theory, collaborative learning theory, and adapting learning theory. Deeva et al. (2021) conducted a review of 109 articles on automated feedback systems and concluded that the applied learning theories or educational frameworks had not been reported in most cases, even though the theories played an important role in understanding the context in which a system was implemented. Since the distinct classes of educational technologies generally imply different pedagogical perspectives, it is essential to examine the different roles of AI technologies in education by considering the existing educational and learning theories (Hwang et al., 2020). As a consequence, this position paper summarizes the major paradigms with the descriptions of relevant theoretical foundations, conceptual research, and practical implementations, and offers a reference framework for future AIEd practice, research, and development.

3. Methodology

The research purpose is to summarize the major paradigms with the descriptions of relevant theoretical foundations, conceptual research, and practical implementations. The research questions are *what are the different roles of AI in education, how AI are connected to the existing educational and learning theories, and to what extent the use of AI technologies influence learning and instruction*. In order to locate and summarize relevant papers, the systematic procedures of literature selection and categorization are used as followings:

1) The academic databases used to collect papers are Web of Science, Scopus, Science Direct, Wiley Online Library, ACM, IEEE, Taylor & Francis, EBSCO.
2) The keywords used to search in the literature are: ("artificial intelligence" OR "AI" OR "AIED" OR "machine intelligence" OR "machine learning" OR "intelligent tutoring system" OR "expert system" OR "recommender system" OR "recommendation system" OR "feedback system" OR "personalized learning" OR "adaptive learning" OR "prediction system") AND ("theory" OR "theoretical" OR "theoretical framework" OR "behaviorism" OR "cognitivism" OR "constructivism" OR "connectivism" OR "complexity").
3) The time period under review is mainly from 1990 to 2021.
4) The selected articles are categorized with respect to the theoretical underpinnings or frameworks used to support AIEd in the articles. A categorization strategy has been employed to group articles into main education and learning theories, e.g., behaviorism, cognitivism, constructivism, connectivism, complexity, etc.
5) To answer the research questions, the selective articles are characterized in terms of the educational and learning theories used to underpin the design and implementation of AI technologies, different roles AI technologies play in the learning and instruction processes, and the influences of AI technologies on education. In terms of this research question, three paradigms are identified as described below.

4. Results

AIEd has been undergoing several paradigmatic shifts, which are characterized into three paradigms in this position paper: AI-directed, learner-as-recipient, AI-supported, learner-as-collaborator, and AI-empowered, learner-as-leader (see Table 1). In Paradigm One *AI-directed, learner-as-recipient*, AI is used to represent and direct cognitive learning while learners are recipients of AI services; in Paradigm Two *AI*-supported, learner-as-collaborator, AI is used to support learning while learners work as collaborators with AI; in Paradigm Three *AI-empowered, learner-as-leader*, AI is used to empower learning and learners take agency of their learning.

4.1. Paradigm One: AI-Directed, learner-as-recipient

Paradigm One is characterized as *AI-directed, learner-as-recipient*, that is AI represents the domain knowledge and directs the learning processes while the learner acts as recipients of AI service to follow the specific learning pathways. The theoretical underpinning of Paradigm One is behaviorism, which emphasizes the construction of carefully arranged sequences of content leading to the learner's correct performance (Skinner, 1953). Paradigm One views learning as a reinforcement of knowledge acquisition through programmed instructions that introduce new concepts in a logical, incremental fashion, offer the learner immediate feedback about incorrect responses, and maximize the positive reinforcement (Greeno et al., 1996; Schommer, 1990; Skinner, 1958). The learner acts as recipients to react to pre-specified sequences of knowledge, follows learning procedures and pathways and executes learning activities set by AI to achieve predefined goals (Burton et al., 2004; Holmes et al., 2019; Koschmann, 2009). In Paradigm One, the AI systems inherit the characteristics of the teaching machine (Skinner, 1958), to make logical presentations of subject knowledge, require the learner's overt responses, and present immediate knowledge of correctness (Burton et al., 2004). The AI systems neither model the learner's emerging, incoming knowledge and skills, nor do they adjust its feedback to that learner as an individual, or at least as a representative of a class of individuals. Paradigm One is the least learner-centered paradigm.

A typical implementation of Paradigm One is the earlier work in Intelligent Tutoring Systems (ITSs). For example, ACT Programming Tutor set a database of production rules for the programming knowledge, used basic statistics to estimate the probability of students' learning of the rules, and presented the individualized sequences of exercises to students based on the estimated probability (Anderson et al., 1990). Another example is the non-intelligent version of Stat Lady, a statistics tutor. The Stat Lady presents all curriculum content in a fixed order and requires learners to solve a predefined set of problems before mastery is presumed to move on to the next step (Shute, 1995). In addition to the system's and expert's representation of the knowledge, an intelligent version of Stat Lady assesses students' incoming knowledge based on an online pretest, uses various methods to represent students' current learning states, and makes mastery or remediation decisions accordingly (Shute, 1995). AI based on statistical relational techniques are typically used in Paradigm One to represent knowledge as a set of production rules, to detect certain student behavior patterns, or to provide automatic

Table 1
Three paradigms of AIEd.

	Theoretical underpinning	Implementations	AI techniques	Examples
Paradigm One: *AI-directed, learner-as-recipient*	Behaviorism	Earlier work of Intelligent Tutoring Systems (ITSs)	AI based on statistical relational techniques	ACT Programming Tutor (Anderson et al., 1990); Stat Lady (Shute, 1995)
Paradigm Two: *AI-supported, learner-as-collaborator*	Cognitive, social constructivism	Dialogue-based Tutoring Systems (DTSs); Exploratory Learning Environments (ELEs)	Bayesian network, natural language processing, Markov decision trees	An exploratory environment QUE (Metzler & Martincic, 1998)
Paradigm Three: *AI-empowered, learner-as-leader*	Connectivism, Complex adaptive system	The human-computer cooperation; Personalized/adaptive learning	The brain-computer interface, machine learning, deep learning	A real-time MOOC predictive modeling (Le et al., 2018)

feedback or hints. In Paradigm One, overall, AI serves as a director of the entire learning processes and learners receive AI services to conduct cognitive inquiry, solve problems, and achieve learning goals.

A main issue in the first AIEd paradigm is *how much* and *what* kind of information about a learner is required to adequately represent, diagnose, and guide knowledge and skill acquisition? In Paradigm One, although some systems collect the learner's information to diagnose the learning state, it is the system to define learning content, procedure, and goal, while the learner is coerced along a particular learning path provided by the AI system (du Boulay, 2019). The system's or the expert's view may cause a stereotype regarding the knowledge and skills the AI system might expect the learner to achieve (Kay, 2000), since the individual learners' characteristics, needs, and goals are not taken into consideration. It also is a challenge in Paradigm One to address domains and tasks that include ill-defined problems (Pinkwart, 2016). To address the over-dominance of AI as a "black box" for learners in Paradigm One, learners are treated as collaborators in Paradigm Two.

4.2. Paradigm Two: AI-Supported, learner-as-collaborator

Paradigm Two is characterized as AI-supported, learner-as-collaborator, that is the AI system relinquishes its controlling power to serve as a supporting tool, while the learner works as collaborators with the system to focus on the individual learner's learning process. The second AIEd paradigm is grounded upon a cognitive and social constructivism view of learning, which reflects a notion that learning occurs when a learner interacts with people, information, and technology in socially situated contexts (Bandura, 1986; Liu & Matthews, 2005; Vygotsky, 1978). Correspondingly, in Paradigm Two, the AI system and the learner should build active, mutual interactions to optimize the learner-centered, personalized learning. Specifically, the AI system collects learners' emerging, individualized information as input to adaptively optimize the student model, while the learner acts as collaborators to communicate with the AI system in order to achieve better or more efficient learning (Baker et al., 2019; du Boulay, 2019; Rose et al., 2019). Overall, comparing to Paradigm One, Paradigm Two makes a critical move toward the learner-centered human learning through mutual interaction and sustained collaboration between the learner and the AI system.

Multiple AI implementations, such as the dialogue-based tutoring systems (DTSs) or the exploratory learning environments (ELEs) have been developed in Paradigm Two to achieve mutual interactions between the system and the learner. On the one hand, the AI system collect and analyze emerging, multimodal data from the learner to make accurate understanding of the learner's learning status. For example, Stamper (2006) used a Markov decision process to automatically generate production rules using previous learner data on a problem set and to continue refining the production rules as new data was generated by the learners. In this way, the learner's data is collected to make a more accurate representation of knowledge and skills in the system, than the knowledge model completely defined from the expert's or system's view. Moreover, Käser et al. (2017) used the dynamic Bayesian network models to represent multiple skill hierarchies of students and the relationships between the different skills, which improved the accuracy of the representation of the learner's knowledge. On the other hand, the learner can communicate with the system to understand the system's decision-making process and to make better choices for further learning. For example, an exploratory environment named QUE was designed for learners to explore the discrepancies between the incorrect responses of a student and the system's knowledge of the "correct" line of reasoning in the rule-based intelligent tutoring systems (Metzler & Martincic, 1998). In this way, the learner explored the intelligent system's reasoning processes by asking "why not" and "what if" questions which were critical to explaining or understanding reasoning processes in an interactive learning situation (Metzler & Martincic, 1998). AI algorithms, such as Bayesian network, natural language processing, Markov decision trees, have been used to analyze large data volumes from multiple sources, achieve reliable results with high accuracy, and generate visualizations for communication (UNESCO, 2019). In summary, in contrast to Paradigm One where AI systems predefine the cognitive learning path while learners receive AI services to follow the learning, in Paradigm Two, the AI system and the learner build mutual interactions, which moves toward a more learner-centered learning.

A main issue in Paradigm Two, however, is *to what extent and how* learners' information is integrated in the AI system to optimize the student model, reflect varied aspects of the learning status, and to develop adaptive, AI-supported learning and instruction. The general problem is a lack of continuous communication or synergetic human-computer interactions. This interaction is complex because neither the learner's information and data nor the system's state is static or simple. Both have complex, hierarchical structures and both change dynamically during the learning process. In other words, it is critical for the AI systems to offer real-time data analysis and immediate feedback to learner and for the learner to use those feedback to enhance the ongoing, emergent learning processes. Therefore, it would be beneficial if the AI system maintains continuous learner-generated data collection and analysis, and provides learners with real-time, exploratory opportunities to make decisions about learning. To further foster learner agency, learners are treated as leader in Paradigm Three.

4.3. Paradigm Three: AI-Empowered, learner-as-leader

Paradigm Three is characterized as *AI-empowered, learner-as-leader*, which holds learner agency as the core of AIEd (Bandura, 2006) and views AI as a tool to augment human intelligence (Law, 2019). Paradigm Three reflects a perspective from the complexity theory that views education as a complex adaptive system (Mason, 2008), where a synergetic collaboration between multiple entities (e.g., the learner, the instructor, information, and technology) in the system is essential to ensure the learner's augmented intelligence. In this complex system, AIEd needs to be designed and applied with awareness that AI techniques are parts of a larger system consisting of learners, instructors and other human (Riedl, 2019). To achieve the synergetic collaboration in the complex system, concepts like human-computer cooperation (Hoc, 2000), human-centered AI and ML systems (Riedl, 2019), human-AI collaboration (Hwang et al., 2020), human-centered artificial intelligence in education (Yang et al., 2021) are proposed to approach AI from a human perspective by considering human conditions, expectations, and contexts. Within Paradigm Three, AI assists the learners and instructors to achieve the augmented intelligence by providing a high level of transparency, accuracy, and effectiveness (Riedl, 2019; Yang et al., 2021). The instructor is equipped with understandable, interpretable, and personalized supports by AI systems to foster learner-centered learning (Baker et al., 2019; Holmes et al., 2019; Roll & Wylie, 2016). The learner takes agency to work as the leader of her own learning, manages the risks of the automation of AI decision, and develops better or more efficient learning (Gartner, 2019). Overall, Paradigm Three, as the developmental trend of AIEd, reflects the ultimate goal of the application of AI in education, that is to augment human intelligence, capability, and potential (Gartner, 2019; Law, 2019; Tegmark, 2017).

The human-computer cooperation system, integrating advanced AI techniques and human decision-making, has potential to achieve the AI-empowered, learner-as-leader goal in Paradigm Three. On the one hand, advanced techniques (e.g., brain-computer interface, machine learning, deep learning) has potential to achieve continuous data collection and analysis to ensure data accuracy, transparency, and interactiveness (Baker et al., 2019; Gartner, 2019; Kay & Kummerfeld, 2019). For example, the development of advanced interaction techniques, e.g., smart wearable devices, cloud computing, Internet of Things change the way human interacts with AI systems (Pinkwart, 2016; Xie et al., 2019). In turn, the role of AI in the education system also changes with the development of human-artificial cognition (Hwang et al., 2020). On the other hand, with personalized information supported with the AI techniques, the human can make better decision about teaching and learning. For example, Le et al. (2018) build a deep learning model with the recurrent neural network classification to make a real-time MOOC predictive modeling and provide personalized communication affordances to allow direct communications between the instructor and learners. Cukurova et al. (2019) put forward an idea of human intelligence argumentation supported by AI techniques. They used prediction and classification algorithm models to increase the transparency of the decision-making processes of expert tutors for advanced reflections and feedback. Those innovative work attempts to use human-computer cooperation to enable instructors to make a more accurate prediction and analysis of learners' further participation, and further provide individualized guidance to the learner. In summary, in Paradigm Three, it is the synergetic interaction, integration, and collaboration between the AI system with human intelligence that need to be fostered in order to produce adaptive, personalized learning (Blikstein, 2018; du Boulay, 2019; Tang et al., 2021).

A main challenge in Paradigm Three is *how to* address the complexity, i.e., how to match the complexity of learning process to the complexity of AI systems and the complexity of educational contexts. To develop the AIEd field, the future AIEd should be designed and operated such that it offers constant communication means to gather values and interpretations from all stakeholders, to align AI models with human values throughout their operations, and to make the goals compatible with the learner-centered learning (Knox et al., 2019; Rowe, 2019; Segal, 2019). Addressing these challenges not only requires AI systems to support the emergent, changing learning processes, making use of learners' tendency and behavior while providing learners with interpretable and actionable output, but also empowers the learners and instructors to reflect on the learning and instructional processes and goals, informing AI systems to adapt accordingly and leading to an iterative cycle of learning development. Emerging concepts abovementioned, such as human-centered AI and ML systems (Riedl, 2019), human-AI collaboration (Hwang et al., 2020), human-centered artificial intelligence in education (Yang et al., 2021) serve as frameworks for Paradigm Three. Moreover, a sustainable development of AIEd needs to deal with various pedagogical, social, cultural, technical, and ethical dimensions, e.g. inclusion and equity in AIEd, teacher preparation for AI-empowered education, inclusive data collection and use systems (Hwang et al., 2020; Pedró et al., 2019; Zawacki-Richter et al., 2019). In summary, Paradigm Three aims to empower learners to take full agency of learning, optimize AI techniques to provide real-time insights about emergent learning, and rethink learning changes brought by AI in complex, interconnected learning systems.

5. Discussion

Since educational and learning theories have seldom been adopted in AIEd research to underpin learning and instruction, it is suggested that there is a need for a close combination of AI technologies with educational and learning theories (Chen, Xie, & Hwang, 2020; Hwang et al., 2020; Hwang & Tu, 2021). Grounded upon main learning theories, this position paper proposes three AIEd paradigms to systematically summarize how AI techniques are used to address educational issues. Paradigm One AI-directed, learner-as-recipient and Paradigm Two AI-supported, learner-as-collaborator are primary AIEd paradigms in the last three decades to provide learning services for learners to follow and collaborate in learning. Paradigm Three *AI-empowered, learner--as-leader* indicates the developmental trend of AIEd, that is, to promote human intelligence to be integrated in artificial intelligence, and to address issues such as biases in AI algorithms, lack of governance, and non-transparency of why and how an AI decision is made (Hwang et al., 2020; Hwang & Tu, 2021).

To facilitate the AIEd development towards Paradigm Three, essential factors including: multimodal data collection techniques, real-time AI algorithm models, and multidimensional attributes of AIEd. First, multimodal data collection enables the richness and complexity of human learning to be better interpreted, evidenced, and supported (Cukurova et al., 2019; Giannakos et al., 2019; Yang et al., 2021). The development of advanced interaction techniques has potential to transform the multimodal data collection techniques (Xie et al., 2019). For example, a variety of multimodal data collection, including physiological sensing data, eye-tracking, electroencephalography, helped obtain a multifaceted understanding of the learners' status and achieved a good learning performance prediction (Giannakos et al., 2019). Second, real-time AI algorithm models have potential to collect and feedback information to human in a timely fashion, which can better facilitate learner or teacher agency in education. Human-Computer interaction (HCI) can integrate real-time AI algorithm models as well as multimodal input data to pursue multi-pronged approaches and the combination of complex, multimodal data, as well as the identification of the most important features of those data-streams to foster Paradigm Three *AI-empowered, learner-as-leader*. The real-time AI models assure the way researchers collect and make-sense of the user-generated data to provide a deeper understanding of the real time interaction between humans and technologies (Giannakos et al., 2019; Xie et al., 2019). Third, in addition to the techniques, multidimensional attributes of AIEd, such as social, cognitive, emotional, philosophical, ethic dimensions, are critical considerations in the educational contexts. When AI technologies can make better computing and logic decision-making than humans, humans have some characteristics that AI cannot match regarding perceptions, emotions, feelings, and cognitions (Yang et al., 2021). Therefore, Paradigm Three moves towards a human-centered AI (HAI) should approach AI from a human perspective by considering multidimensional attributes, conditions, and contexts of human. It is worth mention that the use of advanced techniques per se do not guarantee the development of the AI-empowered, learner-as-leader paradigm. For example, researchers used the brain-computer interface technology to capture the learner's electroencephalography information in order to detect the learner's psychological, emotional, or attention levels (e.g., Verkijika & De Wet, 2015). Although in this case the state-of-art technique is used, like many other AI applications, the old paradigm of education remains, i.e., the learner's need and learning goal are not considered, the learner is not informed with how data is used and for what purpose, and the learner is not empowered to take agency for their own learning. Overall, an integration of human intelligence and machine intelligence can help AIEd move from Paradigm One and Two towards Paradigm Three; particularly, designing real-time AI models that can embed multimodal data collection and analysis techniques and integrate human cognition, thinking, reflective judgments is a way to realize Paradigm Three.

Overall, the development of AIEd has been undergoing Paradigm One AI-directed, learner-as-recipient and Paradigm Two, AI-supported, learner-as-collaborator, and currently moving towards Paradigm Three AI-empowered, learner-as-leader to facilitate learner agency, empowerment, and personalization, enable learners to reflect on learning and inform AI systems to adapt accordingly, and lead to an iterative development of the learner-centered learning.

6. Conclusions

In this position paper, we propose three AIEd paradigms, AI-directed, learner-as-recipient, AI-supported, learner-as-collaborator and AI-empowered, learner-as-leader to systematically summarize how AI techniques are used to address learning and instructional issues in education. AI techniques have potential to significantly stimulate and advance instructional and learning sciences, which, in turn, would offer evidence-informed opportunities for developing AI technologies (Hwang et al., 2020; Pedró et al., 2019). More importantly, it is crucial to emphasize that AIEd is not only about implementation of AI technology; it is an integration of pedagogical, social, cultural, and economic dimensions during the technology application processes (Castañeda & Selwyn, 2018; Selwyn, 2016). Based on existing educational theories, researchers can derive new interpretations or ideas on the pedagogy and the learning sciences steaming from AIEd applications (Hwang et al., 2020; Hwang & Tu, 2021). Consistent with previous work (e.g., Deeva et al., 2021; Holmes et al., 2019; Hwang et al., 2020), we argue that the future development of the AIEd field must lead to the iterative development of the learner-centered, data-driven, personalized learning in the current knowledge age.

Declaration of competing interest

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

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