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Artificial Intelligent Robots for Precision Education: A Topic Modeling-Based Bibliometric Analysis

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ABSTRACT: As a human-friendly system, the artificial intelligence (AI) robot is one of the critical applications in promoting precision education. Alongside the call for humanity-oriented applications in education, AI robot-supported precision education has developed into an active field, with increasing literature available. This study aimed to comprehensively analyze directions taken in the past in this research field to interpret a roadmap for future work. By adopting structural topic modeling, the Mann-Kendall trend test, and keyword analysis, we investigated the research topics and their dynamics in the field based on literature collected from Web of Science and Scopus databases up to 2021. Results showed that AI robots and chatbots had been widely used in different subject areas (e.g., early education, STEM education, medical, nursing, and healthcare education, and language education) for promoting collaborative learning, mobile/game-based learning, distance learning, and affective learning. However, a limited practice in developing true human-centered AI (HCAI)-supported educational robots is available. To advance HCAI in education and its application in educational robots for precision education, we suggested involving humans in AI robot design, thinking of individual learners, testing, and understanding the learner–AI robot interaction, taking an HCAI multidisciplinary approach in robot system development, and providing sufficient technical support for instructors during robot implementation.

Keywords: Artificial intelligence robots, Topic modeling, Bibliometric analysis, Precision education, Research topics, Future of human-centered artificial intelligence

1. Introduction

Alongside the prevalence of artificial intelligence (AI) applications in personalized learning (e.g., robots and chatbots) is a shift from technology-driven to humanity-driven applications (Yang et al., 2021).

1.1. Human-centered AI and its use in education advancement

According to Yang et al. (2023), human-centered AI (HCAI) is interpreted as "AI taking humanities as the primary consideration, which requires explainable and trustworthy computation for continuously adjusting AI algorithms through human context and societal phenomena to augment human intelligence with machine intelligence, thereby enhancing the welfare of human kinds" (p. 1).

A robust, trustworthy HCAI system, when being applied in education, should have the capabilities of understanding individual learners' prior experiences, needs, interests, relevant emotions, and social structures, adapting to complex real-world learning contexts, and appropriately interacting with individuals (Li et al., 2021). This is commonly achieved by allowing humans to seamlessly interact with and guide AI and enrich the AI system with human capabilities, knowledge about the world, and users' personal perspectives (Renz & Vladova, 2021). HCAI also bridges the gap between machines and learners by leveraging emotional and cognitive input from learners and allowing machines to understand learners' language, emotions, and behaviors (Shneiderman, 2020).

HCAI's capabilities of understanding individuals, adapting to contexts, and appropriate interaction are particularly important in advancing education. This is because learning involves teaching and interaction with humans; thus, AI-supported learning technologies should be human-centered, focusing on both performance and learners' emotions, feelings and outcomes, interaction, and learning contexts. (Shneiderman, 2020).

1.2. Precision education and HCAI

In HCAI, AI design is undergoing a transition from one-size-fits-all to precision approaches (Yang, 2021). As a core component of HCAI, precision education involves “the use of machine learning and learning analytics of AI to improve teaching quality and learning effectiveness” (Yang et al., 2021, p. 1-2) by “identify[ing] at-risk students as early as possible and provid[ing] them with timely intervention through [the four steps of] diagnosis, prediction, treatment, and prevention” (Yang, 2021, p. 106). For instance, in the case of poor performance and learning disabilities, learners’ learning behaviors, learning contexts, and learning strategies can be analyzed by following the four steps to identify solutions (Lu et al., 2018).

As precision education focuses on providing prevention and intervention to individuals, learning systems’ capabilities of integrating knowledgeable instructors’ expertise and intelligence into decision-making are essential (Hart, 2016). Developing such intelligent systems requires the ability to simulate educational experts’ intelligence (Hwang et al., 2020).

Currently, few AI systems for precision education have explicitly considered HCAI approaches. One mere example is provided by Weitekamp et al. (2020), in which instructors designed computerized lessons based on insights generated by an AI tutor. Although with limited human capabilities, such AI systems share similarities with HCAI design in caring for individuals’ needs and emotions, real-world contexts, and human-machine interactions (Renz & Vladova, 2021).

1.3. AI robots for precision education

AI robots or human-friendly systems are increasingly important for precision education by allowing personalized, natural interaction with real-life physical environments through practical demonstrations and hands-on experiences (Chen et al., 2020b). Practices regarding AI robots’ use in precision education are available. In Zhong et al. (2020), a quasi-experimental design was implemented with 84 junior high school students to show virtual and physical robots’ effectiveness in promoting students’ higher-order thinking in resolving complex problems and reducing cognitive load. In Santos et al. (2020), children shared their experienced emotional events to a chatbot, which then provided personalized scaffoldings accordingly.

Advantages of AI robots for precision education (Edwards et al., 2018) include (1) facilitating one-to-one learning by adapting instruction and communication to individual learners’ knowledge levels and learning styles, (2) promoting the shift of teachers’ roles toward overseers responsible for designing and selecting machine-oriented instruction, monitoring learner progress, and providing pastoral support, (3) turning abstract concepts into real-world problems adapted to individuals’ learning needs to promote all-in-one learning experiences where learners put theoretical knowledge into practice, and (4) supporting students to learn at their own pace with personalized materials through interactive experimental learning individually and collaboratively.

There are also disadvantages concerning AI robots’ use for precision education (Xia & Zhong, 2018; Tlili et al., 2020; Chen et al., 2022). First, it would be time-consuming and challenging to create, rebuild, and repair AI robots that are complex, with personalized learning objectives being considered. Second, robots with the same protocols for behavior analysis and pattern recognition and without the sense of humor or real-time life experiences cannot make personal connections to learners with things in life apart from the assigned work. Additionally, it is challenging to carry out robot cultivation on a large scale due to high requirements for cultivation resources and supporting facilities.

Despite the disadvantages, the available literature regarding AI robots used to promote precision education generally shows their positive effects on learning motivation, participation, and engagement, understanding of science processes and mathematical concepts, achievement score improvement, and development of creativity, designing, problem-solving, and teamwork (Tegos et al., 2011; She & Ren, 2021; Edwards et al., 2018; Kubilinskienė et al., 2017). Consequently, AI robot-supported precision education has developed into an active field of research.

1.4. Reviews on HCAI and educational robots

Discussion on HCAI in education is available. Renz and Vladova (2021) demonstrated the need for HCAI practice to promote the human condition for precision and smart learning. However, there is currently no literature review on HCAI in education due to very limited pedagogical practices. Regarding AI robot-supported precision education, based on a review of 22 empirical studies concerning robotics education in K-12, Xia and Zhong (2018) identified the prevalence of LEGO robots and non-experimental design and highlighted instructional suggestions about open environments, targeted design, appropriate pedagogy, and timely support. Guided by activity theory, Tlili et al. (2020) analyzed 30 studies about robot-supported special education, identifying research gaps, challenges, and contradictions. These reviews have advanced knowledge about educational robots; however, they mainly adopted systematic review methodologies that are prone to error and coding inconsistencies. Additionally, considering the increased research on AI robots' applications in education, a comprehensive examination is needed to understand the directions taken in the past to enlighten a roadmap for future work.

1.5. Research aims and questions

This study analyzes extant literature regarding AI robot-supported precision education using topic modeling and keyword analysis. We mainly focus on research topics and their dynamics by looking at research topics' evolution across four chronological sub-periods of time during the past 20 years and relating them to technological, pedagogical, and methodological advances. Given the low number of papers in the early years, according to López-Robles et al. (2019), a suitable way is to divide the time span into comparable periods. For example, López-Robles et al. (2019) divided the study period (1988–2017) into 1988–1997, 1998–2007, 2008–2012, and 2013–2017 with 144, 970, 2,083, and 3,195 papers, respectively. In Cobo et al. (2011), five non-equidistant periods of time (i.e., 1978–1989, 1990–1994, 1995–1999, 2000–2004, and 2005–2009) were used because there were few papers in the former years, which could lead to a low number of keywords being used as input in co-words analysis to detect main themes. Accordingly, this study uses non-equidistant periods of time (i.e., 2001–2010, 2011–2017, and 2018–2019, with 26, 40, and 49 papers, respectively) to ensure a good input for data analysis. We additionally include the sub-period 2020–2021 to understand the most recent research topics in the field. Findings can help educators understand AI robots' potential to promote precision education. Based on the updated information on the present research, we provide insights into future research and pedagogical practices in this field. There are four research questions (RQs).

RQ1: What were the major research topics during 2001–2010?
RQ2: What were the major research topics during 2011–2017?
RQ3: What were the major research topics during 2018–2019?
RQ4: What were the major research topics during 2020–2021?

2. Methodology

2.1. Data collection

On 24 October 2021, Web of Science and Scopus databases were searched to identify articles about AI robot-supported precision education. Figure 1 shows the flowchart of data collection. There were two search strategies. The first strategy involved search terms concerning AI, robots, personalization, and education. The search terms were decided with reference to Chen et al. (2021) and Zawacki-Richter et al. (2019) by considering both personalized learning and the use of AI robots. The second strategy considered personalization-, education-, and chatbot-related terms determined by referring to Chen et al. (2021) and Smutny and Schreiberova (2020) by considering both personalized learning and the use of chatbots. Data were limited to journal articles or conference papers written in English.

After duplication, 5,112 papers were included for screening based on exclusion criteria presented in Figure 1. When deciding to include a paper or not, we started from the first criterion and directly excluded 4,784 papers irrelevant to instruction and learning. Subsequently, for the remaining 328 papers, we checked whether they provided detailed information about robots' use for educational purposes. Accordingly, 73 papers were excluded. We further excluded 81 reviews or survey papers. Finally, 174 papers remained for data analysis. Figure 2 shows the number of papers by year, which indicates two stages of development, that is, a slow-growth trend from 2001 to 2017 and a fast-growth tendency since 2018.

2.2. Data analysis

We analyzed the 174 papers using keyword analysis, structural topic models (Roberts et al., 2019), and the Mann-Kendall trend test. For keyword analysis, we extracted key phrases from titles and abstracts and calculated their frequencies in four sub-periods of time. For topic modeling, we first collected terms from titles and abstracts, then used term frequency-inverse document frequencies to filter unimportant terms. Exclusivity and semantic coherence criteria were used to facilitate model selection (Figure 3). A manual comparison of models with 13 and 15 topics based on associated papers and terms was further conducted, which indicates that the model with 13 topics produces "the greatest semantic consistency within topics and exclusivity between topics" (Chen et al., 2020a, p. 4). Two experts then examined the statistical results to determine topic labels. Among the 13 topics, one was excluded as it mixes up robot motion and learner motivation. The remaining 12 topics were included for analysis, with their changes in prevalence being examined using a trend test.

Figure 1. Flowchart of data collection

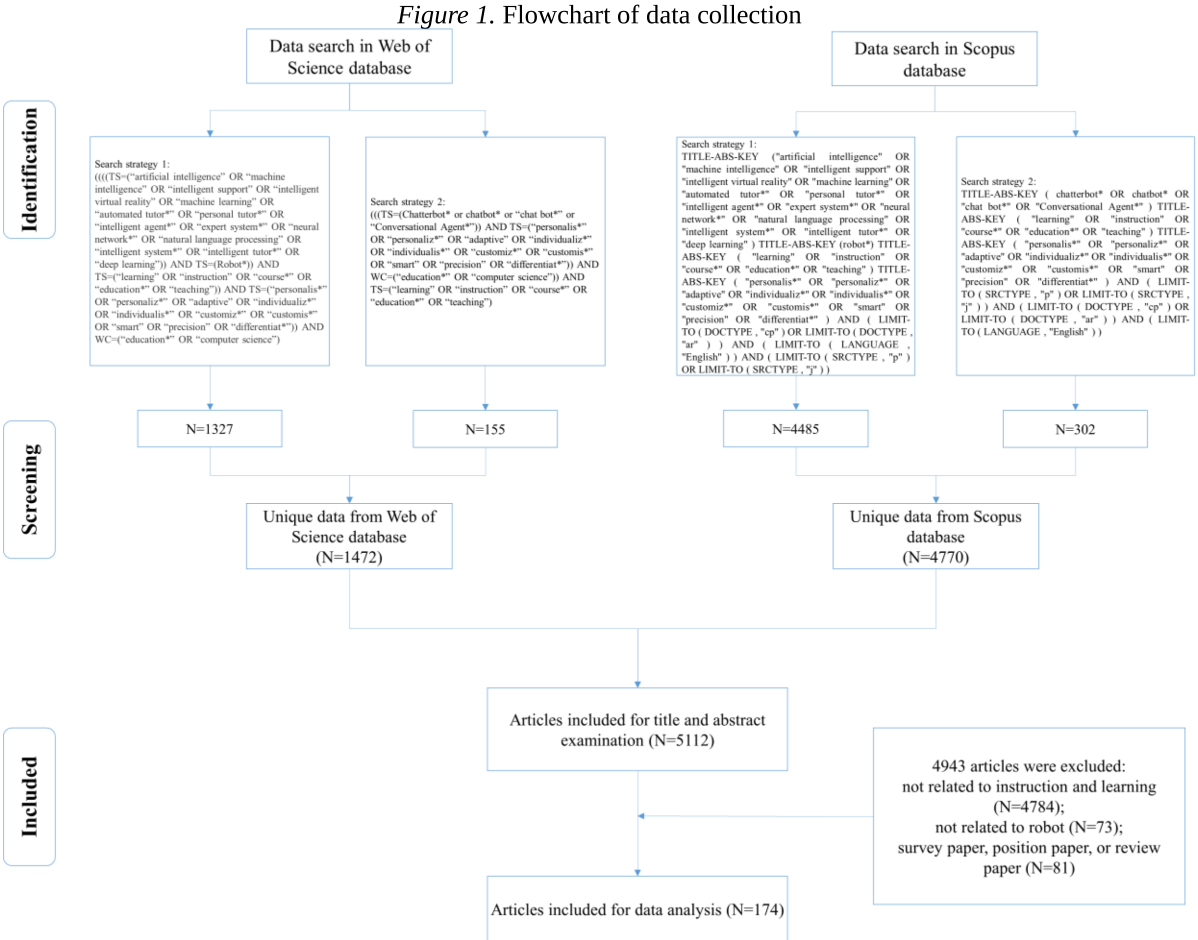


Figure 2. Number of papers by year

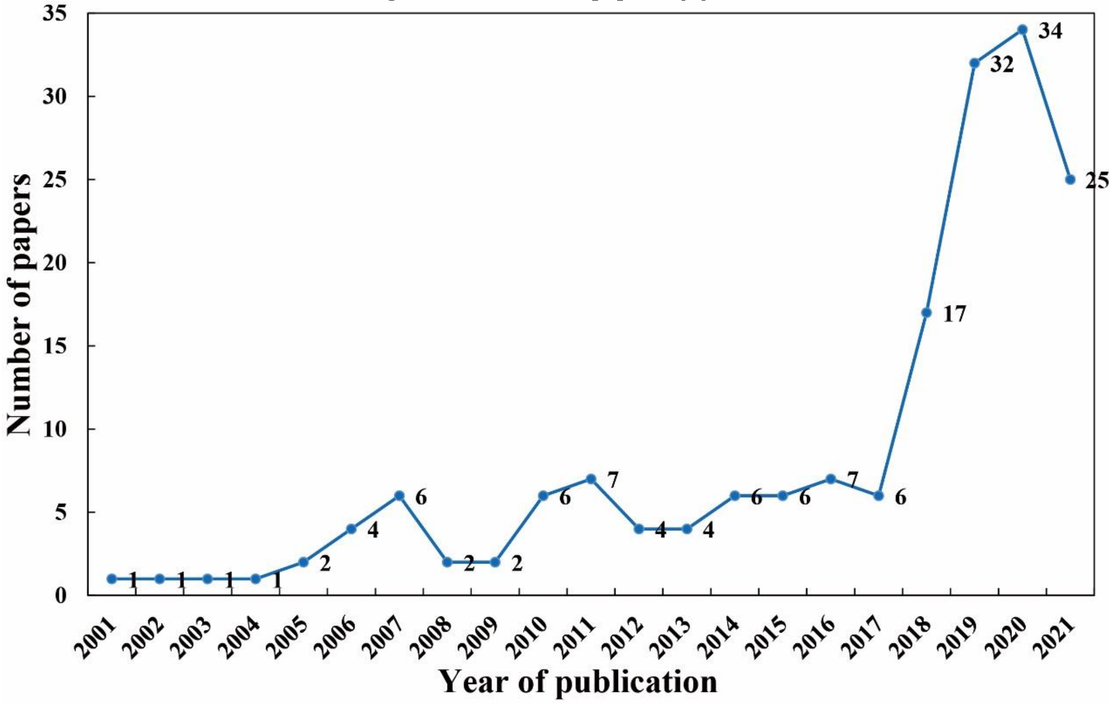
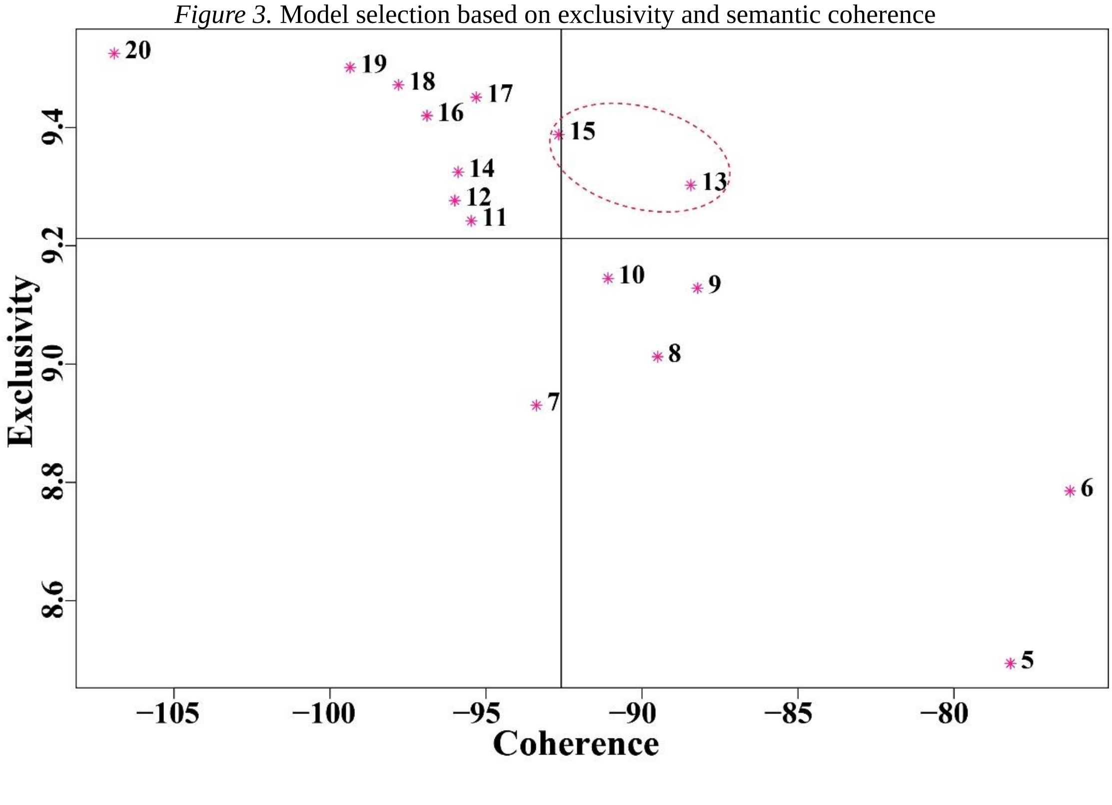


Figure 3. Model selection based on exclusivity and semantic coherence



3. Results

Figure 4 visualizes key phrases in the four sub-periods. Figure 5 visualizes emerging phrases during 2020–2021. During 2001–2010, researchers mainly focused on the conversational agent's pedagogical use, especially in language learning (see Figure 4(a)). Subsequently, AI, collaborative learning, learning style, serious games, human-robot interaction, learning process, and adaptive learning received a growth of research interest among scholars (see Figure 4(b)). During 2018–2019, there was a growing research interest in neural networks, social robots, educational chatbots, young children, and machine learning (ML) (see Figure 4(c)). During 2020–2021, there was a trend in research on humanoid robots, natural language processing (NLP), deep learning, speech recognition, argumentation skill, mental model, emotion recognition, dialog-based form, emotional engagement, adaptive writing support system, and cognitive load (see Figure 4(d) and Figure 5). Figure 6 presents the topic modeling results, and Figure 7 visualizes topic proportions by year, which clearly shows how the prevalence of each topic changed with time going on. The two most popular topics were *conversational agents* and *chatbots for education*, and four topics were increasingly researched, including *robots for early childhood education*, *chatbots for education*, *robots for STEM education*, and *chatbots for distance learning*.

Figure 4. Key phrases during sub-periods (a) 2001–2010, (b) 2011–2017, (c) 2018–2019, and (d) 2020–2021

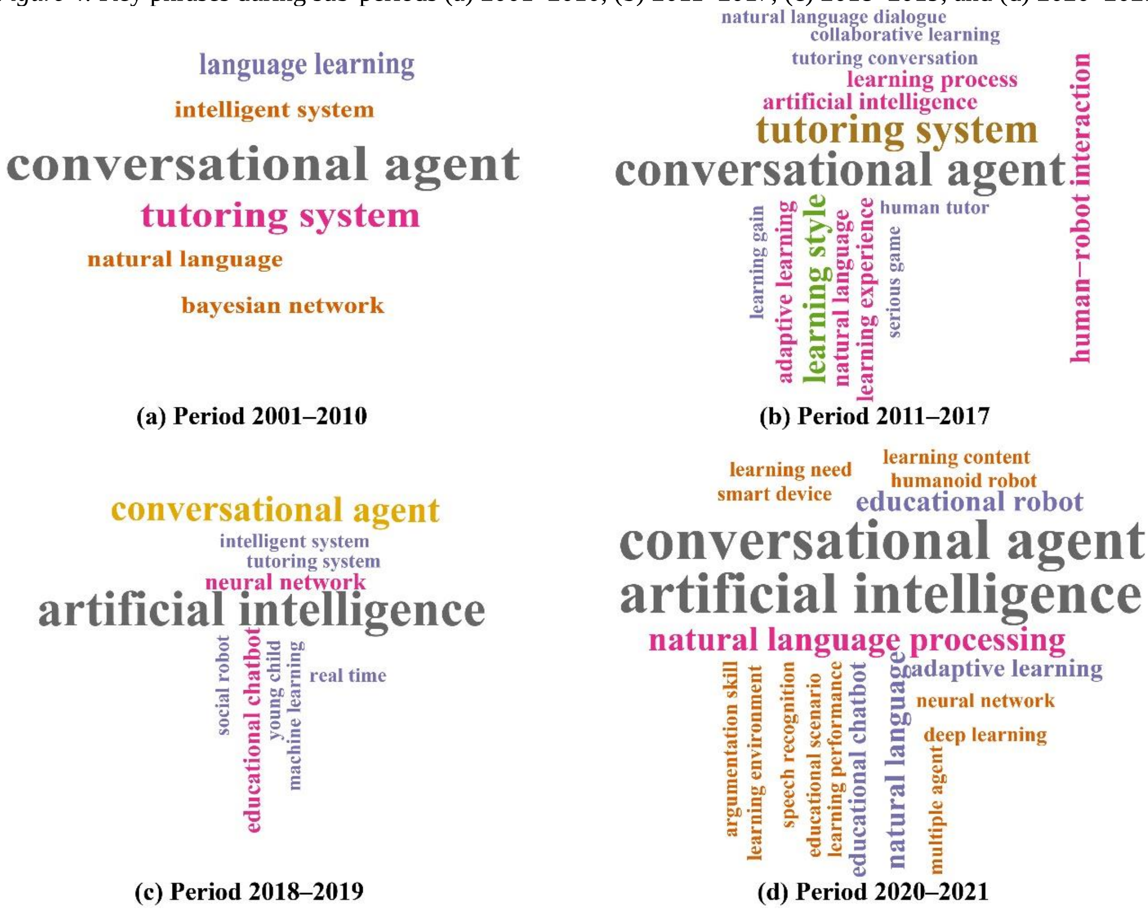


Figure 5. Emerging phrases during 2020–2021

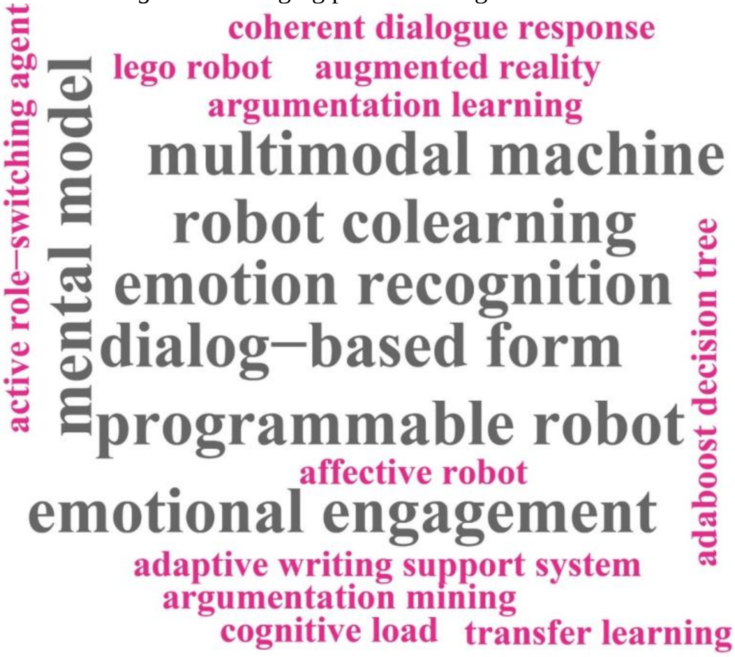


Figure 6. Topics with suggested labels, topic proportions, and developmental trends

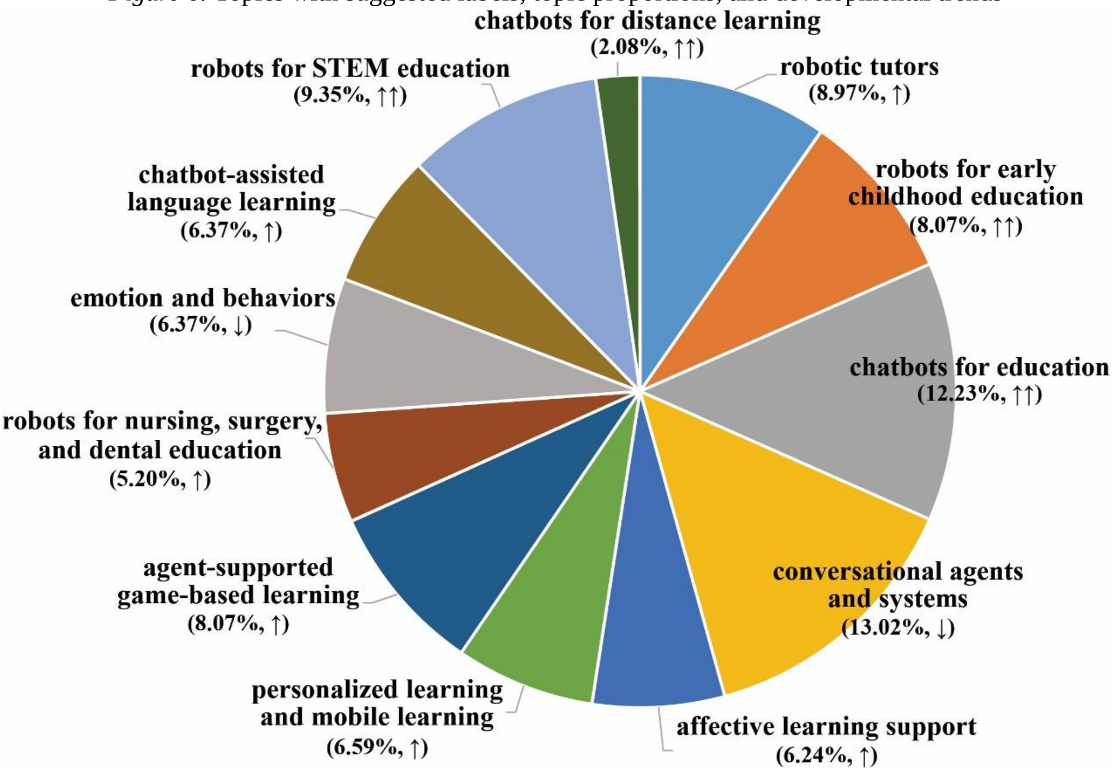
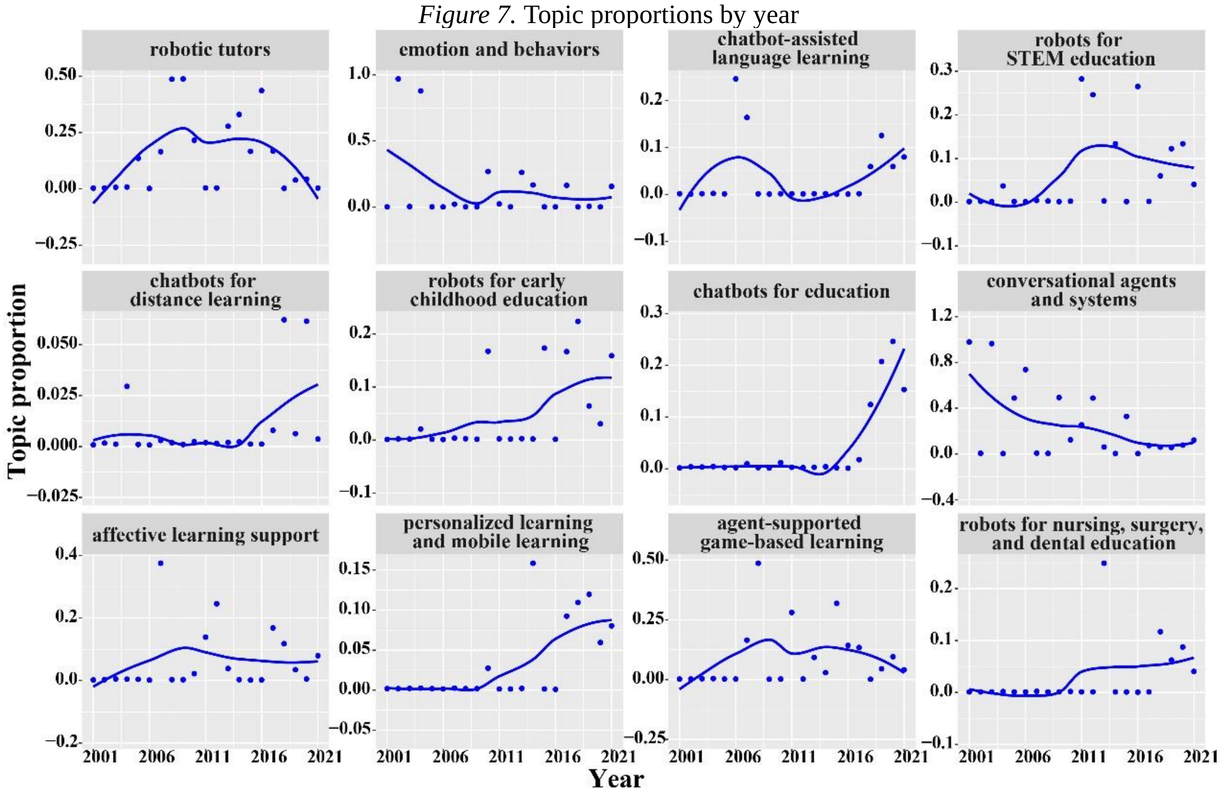


Figure 7. Topic proportions by year



4. Discussion

This study provides a topic modeling-based bibliometric analysis of literature related to AI-supported robots for precision education to understand the most frequently studied topics in the field during the past 20 years. Results showed rapid growth of interest in AI robot-supported precision education research because of advances in computers, information communication technologies, and analytical innovations like AI and ML, alongside educators' increased interest in exploring AI robots' potential for personalized education (Chen et al., 2021). In line with the four RQs, the following sub-sections present a discussion on the findings of research topics in the four sub-periods. We further discussed the challenges and directions to advance the development of HCAI and its application in educational robots.

4.1. Research topics during 2001–2010

In this period, the main topics centered on conversational agents for educational use and embodied conversational agents for affective learning, evidenced by the high frequencies of phrases such as conversational agent, language learning, intelligent/tutoring system, and the topic of *emotion and behaviors*, as indicated in Figure 4(a) and Figure 7.

4.1.1. Conversational agents for educational use

Conversational agents, which allow humans to interact with computer systems using natural language socially and effectively, endorse sociocultural theory's emphasis on learning through social participation and interaction (Vygotsky, 1978). This is particularly important in language learning, where learners need direct and frequent social interaction for target language practice in authentic exchanges, accordingly to language socialization and situated language learning. Intelligent tutoring systems integrated with conversational agents, by extending "communication and interactive opportunities beyond [the] lecture experience" (Gosper et al., 2008, p. 1), offer enormous opportunities to cultivate learners' spontaneous productive skills and second language fluency. Alongside the advances in AI, and especially NLP and speech recognition technologies, conversational agents' use for supporting social learning has become affordable. For example, CALMsystem (Kerly et al., 2008) supported a learner's reflection by inferring a knowledge level for the learner depending upon his answers and encouraging him to involve in a dialogue to reflect on his performance.

4.1.2. Embodied conversational agents for affective learning

Alongside conversational agents' prevalence in education is an attempt to exploit their emotional capabilities to deal with learners' affects productively. The correct identification of learners' emotions is essential to learning endeavors and outcomes because emotions expressed during social interaction can affect attention, meaning creation, and memory, thus influencing learners' cognitive and affective development. This task can be achieved by using embodied conversational agents, which, with a virtual animated body that produces both verbal and non-verbal signals, can show empathy and emotions and support learners' emotional states productively. According to De Waal (2009), conversational agents programmed with natural language that includes emotions and empathy promote stronger relationships and collaboration and more complex learner–conversational agent interactions. Increasingly, embodied conversational agent is employed as an interaction metaphor in education. Morton and Jack (2005) integrated speech recognition with embodied conversational agents and virtual worlds to construct immersive, contextualized environments where learners conversed in the target language and obtained feedback from embodied conversational agents.

4.2. Research topics during 2011–2017

In this period, issues related to embodied conversational agents' integration into digital games, conversational agents for computer-supported collaborative learning, AI robots in medical, nursing, and healthcare education, and AI robot-supported STEM education became popular, with phrases such as collaborative learning, serious games, and topics of *agent-supported game-based learning*, *robots for STEM education*, and *robots for nursing, surgery, and dental education* appearing increasingly, as shown in Figure 4(b) and Figure 7.

4.2.1. Embodied conversational agents' integration into digital games

The increasing interest in integrating embodied conversational agents into digital games is driven by the need to make digital game-based learning more interactive. Embodied conversational agents and digital games have close relationships. First, interactivity and believability are salient characteristics in digital game-based learning to fully engage learners, which are affordable by embodied conversational agents. Second, gamification's ability to appreciate users' motives, cognition, and emotions to optimize their feelings, motivations, and engagement corroborates embodied conversational agents' capabilities to provide affective and emotional support. Furthermore, both digital games and conversational agents promote social skill development. Additionally, embodied conversational agents enrich learning experiences in gamification through active experimentation and multimodal interaction (e.g., gaze, facial expressions, and gestures), thus making learning more experiential (Colpaert, 2006). Consequently, embodied conversational agents are increasingly integrated into digital games to enrich verbal and non-verbal interaction, especially for social communication skill promotion. For example, a serious game, ECHOES, adopted an embodied conversational agent as autistic children's social companion to help them develop social communication skills (Bernardini et al., 2014).

4.2.2. Conversational agents for computer-supported collaborative learning

Alongside the call for socio-cognitive learning (Vygotsky, 1978) that emphasizes learning through socialization and collaboration is the increasing use of conversational agents as personalized tutoring aids to promote computer-supported collaborative learning. In computer-supported collaborative learning, a temporary appearance of a suitable degree of misunderstanding is beneficial; thus, a supportive conversational agent should intelligibly elicit peer dialogue to foster learning beneficial conditions during collaboration. An agent represented as a three- or two-dimensional human-like avatar or interface in computer-supported collaborative learning environments can (a) trace learning processes, (b) stimulate interaction and collaboration, and (c) inform learners about interaction status. For example, a conversational agent in a web collaborative learning system (Tegos et al., 2011) intelligently facilitated and triggered discussion among partners by allowing instructors to define agent interventions when an important concept was detected in learners' dialogue.

4.2.3. AI robot-supported medical, nursing, and healthcare education

In medical and healthcare education, simulated training provides valuable opportunities for students to acquire required skills and rehearse skills learned for future careers. In simulated training, high-fidelity simulators are a necessity. There are two common types of simulated patients as the recipient of students' skills, including stationary manikins and human simulated patients. However, stationary manikins cannot reproduce human movements or respond to trainees' commands, and human simulated patients have difficulties in exactly imitating real patients, which usually leads to ineffective and inefficient simulations. To provide effective simulated training, educators increasingly exploit robots' ability to simulate required actions in supporting medical and clinical simulated training.

Due to the shortage of qualified nurses while the ever-aging population, simulator robots are increasingly popular in nursing training, particularly regarding the patient transfer, to simulate patient's limb movements to help nursing students learn nursing skills. Researchers also exploit robots' ability to express emotions and feel pain like humans via visual-based feedback. In Lee et al. (2021), a robot's pain level was calculated using fuzzy logic and displayed in real time by a projector and a three-dimensional facial mask during nursing training. Regarding emotion expression, by exploiting embodied conversational agents' capability of engaging in natural interaction with humans through dialog and non-verbal expressions, Bickmore and Gruber (2010) used embodied conversational agents as virtual counselors to offer problem-solving skill training and emotional support for caregivers.

4.2.4. AI robot-supported STEM education

In an increasingly complicated world, it is essential for youth to foster contextualized knowledge and skills covered by STEM to resolve complex problems and make sense of information. With the advances in robotics and automation, robots have become accessible for school-age children to facilitate their STEM learning by allowing them to explore their ideas using technical- and computational-oriented tangible objects. Robots' effectiveness in STEM education corroborates the idea of "making", which, rooted in constructionism, is increasingly brought into classrooms to engage children in various technology-enhanced making activities like building robotics inventions. Making with robotics is student-centered with a focus on constructionist learning, where "students engage in manipulating, assembling, and reassembling materials while going through the design learning process and problem-solving program errors through trial and error" (Eguchi, 2017, p.16). Such experience promotes transdisciplinary learning where learners encounter different concepts in STEM contextually; in this way, abstract concepts become visible and tangible for learners to comprehend when they test their ideas with robotics inventions.

4.3. Research topics during 2018–2019

In this period, the major topics included robots' use in early education, AI robots' integration into mobile learning, and neural network-based educational robots, witnessed by the increasing use of phrases such as neural networks, social robots, young children, and topics of *personalized learning and mobile learning* and *robots for early childhood education*, as indicated in Figure 4(c) and Figure 7.

4.3.1. Robots' use in early education

Prior to this period, robots' pedagogical affordances were mostly demonstrated in primary, secondary, and higher education, whereas this period has witnessed considerable interest in robots' use in early education. This is driven by the need to cultivate technology and innovation literacies at an early age. However, the traditional early childhood curriculum pays little attention to developing early knowledge about the artificial world. There is thus a call for systematic educational reform by encompassing technology with creative thinking and problem-solving in early childhood education to prepare children as future citizens in a fundamentally technology-driven society. Alongside advances in novel interfaces, programming languages, and robotics engineering, educational robotics kits that developmentally fit young children are increasingly available for them to engage in "learning by designing" and "learning by programming" activities through hands-on experiences. Fachada (2018) confirmed smart toy robots' effectiveness in promoting children's social engagement and conversation skills. Williams et al. (2019) highlighted that allowing young children to construct, program, test, and interact with their social robots through hands-on experiences promoted their understanding of how AI works.

Affordances of robots in early education included: (1) enabling young children to understand things they meet in daily life through playful, practical hands-on activities, (2) exploiting computational thinking-focused activities to facilitate active learning, enhance motivation, and maintain engagement, and (3) serving as emotionally learning companions to promote their social and language skills. The last affordance is especially important in the education of children with special needs, a field that has gained increased attention as our society aims to provide equal opportunities to these children to develop skills and improve their quality of life (Moyi, 2019). Particularly, intense concern has been attached to autistic children's education using intelligent robots. Most autistic children have difficulties socializing with others, but they have no problem communicating with objects like robots that offer human-like social cues, which, together with the simplicity of an object, can facilitate their social skill learning.

4.3.2. AI robots' integration into mobile learning

Alongside the global trend in ubiquitous mobile learning and the need for ever-present hands-on learning opportunities (Axelsson et al., 2019), educators attempt to involve learners in learning by developing robot-supported pedagogical models around mobile devices. Mobile robots have been popular in remote laboratories to allow students to explore and interact with the real world through sensors and actuators to learn a wide range of knowledge in programming, electronics, and robotics and enable resource sharing without time and space constraints.

Researchers have also coupled multimodal conversational interfaces to improve mobile applications with intelligent, communicative capabilities and adaptation to learners' requirements by enabling learners to interact directly with mobile conversational agents to accomplish tasks. In Kim et al. (2019), students conversed with and answered questions raised by a mobile chatbot via text to practice English grammar skills.

4.3.3. Neural network-based educational robots

The increase in adopting advanced neural network-based algorithms is driven by the need for "smart services" with cognitive and intellectual abilities that are more scalable to satisfy personalized learning needs. For example, in an intelligent learning assistant for autistic children (Vijayan et al., 2018), a deep conventional neural network model processed brain image patterns to make predictions about children's behaviors, a recurrent conventional neural network analyzed facial images for decision making, and a reinforcement learning module analyzed children's speech to make responses accordingly. In an educational chatbot developed by Sreelakshmi et al. (2019), a question-answering module used neural networks to extract suitable answers from the knowledge base, and a quiz generation module identified key sentences and generated question-answer pairs to generate quizzes for learners.

4.4. Research topics during 2020–2021

In this period, the major topics included chatbots' use in distance education, AI robots for argumentation skill acquisition, and integration of physiological sensors and advanced deep learning into educational robots, witnessed by the increased use of phrases such as deep learning, dialog-based form, argumentation skill, adaptive writing support system, mental model, emotional engagement, and cognitive load, and topics of *chatbot-assisted language learning*, *chatbot for distance learning*, and *chatbot for education*, as indicated in Figure 4(d), Figure 5, and Figure 7.

4.4.1. Chatbots in distance education

In the era of "Education 4.0", the call for integrating innovative AI technologies into blended and flipped classrooms results in the proliferation of distance education. Distance education is the fastest-growing educational modality driven by the wide affordances of digital and handheld devices and global Internet access. However, online learning is criticized for lacking support, feedback, and interaction and causing learners' sense of isolation. These limitations became apparent during the COVID-19 pandemic when there was a rash transition from traditional face-to-face classes to complete online education, thus urging educators to effectively tackle the limitations. Chatbots appear as an alternative to this impasse, as they can minimize manual effort and provide immediate user-friendly assistance, human-like interaction, and continuous psychological and pedagogical support anytime and anywhere. Consequently, scholars are attempting to integrate chatbots or virtual assistants into distance education platforms to enable greater interactivity, facilitate sociability, and make online learning more interactive and dynamic. In a personalized dialogue-based system (Rajkumar & Ganapathy, 2020), a chatbot scaffolded learners' learning by answering frequently-asked questions, recommending tutorials, and planning learning paths. In Seering et al. (2020), a social chatbot in online communities "grew up" from "birth" through its teenage years, interacting with community members and "learning" vocabularies from their conversations. By taking the personalization and interaction levels to a new height, chatbots ultimately reduce dropout rates and increase educational achievements and satisfaction among distance learners.

4.4.2. AI robots for argumentation skill acquisition

Compared to previous periods when chatbots in language education mostly centered on basic conversation and language skill development, in this period, there is an increase in using robots to facilitate the development of metacognition skills such as arguing in a reflective and well-formed manner, which are beneficial to cultivate communication, collaboration and problem-solving competencies (Wambsganss & Rietsche, 2019). To cultivate such skills as argumentation, individuals need to receive constant tutoring and feedback during learning. However, it is hard for instructors to offer adaptive support and feedback to individual learners, particularly in large-scale lectures or distance education. The recent advances in NLP and ML promote new pedagogical human-computer interaction by implementing adaptive personal computer assistants with argumentation mining approaches to access individuals' argumentation levels and provide adaptive feedback and step-by-step guidance to intelligently support argumentation learning, thus enabling individuals to learn autonomously and independently of instructors, time, and place.

4.4.3. Integration of physiological sensors and advanced deep learning into educational robots

Driven by the rise of Robotics 4.0 with prevalent disruptive technologies like the internet of robots, AI of Things, and deep learning, there is a trend in integrating physiological sensors like eye-tracking and advanced deep learning into educational robots. For example, eye-tracking signals can be collected from learners during their interaction with educational robots to understand changes in their workload, dynamics of emotions, and physiological state. In a Dinus intelligent chatbot (Majid & Santoso, 2021), sentiment analysis was adopted to identify learner emotions in textual-based conversation, and recurrent neural networks were used to classify the emotions based on current conversations. In a robot system for supporting autistic children (She & Ren, 2021), a neural network as a generative conversational agent generated meaningful and coherent dialogue responses, and a transfer learning module learned dialogue characteristics to resolve the limitation of insufficient dialogue corpus.

4.5. Challenges regarding AI robots' application in education

Regarding challenges about AI robots' application in education, researchers have noted instructors' acceptance of AI robots and technological challenges.

4.5.1. Instructors' acceptance of AI robots

Instructors are the keystone to AI robots' pedagogical implementation. Although many instructors could appreciate robotics' benefits, they are reluctant to use it. This is especially true for instructors who lack experience with information technologies and struggle to execute effectively on-the-spot responses to analytics from AI systems, thereby hindering robotics' application in education. To promote AI robots' pedagogical practice, it is essential to improve instructors' acceptance by showing them AI robots' pedagogical benefits via longitudinal experiments based on educational theories. Currently, the advantages of most AI-supported educational robots commonly exist in theory without evidence showing their effectiveness in real-world teaching and learning. This is because the experimental design for AI system assessment is challenging as large samples are needed to produce probabilistic results (Chen et al., 2021). However, such experiments should be promoted to improve instructors' acceptance and verify AI robots' true effectiveness in the long term rather than due to novelty effects. By putting theoretical advantages demonstrated in literature into practice, the pedagogical applicability of AI robots to realistic educational scenarios can be evaluated.

4.5.2. Technological challenges

One advantage of AI robots is the rich interaction with real-life environments. Although physical exercises or objects can be exploited to facilitate instruction as robots are physically present, currently, motor activities with robots are rarely integrated into learning tasks owing to their feasibility. This is because the more robots act and move through space, the more likely they are to induce technical issues, e.g., falling over or overheating. Nevertheless, as robot technologies advance, it is promising that motor activities would become feasible to integrate to trigger higher learning gains.

Although AI robots are intensively applied to facilitate language learning, their technological capabilities have limitations centering on inappropriate interpretation and response (e.g., failed communication when learners input incomplete sentences and chatbots respond with nonsense outputs and diminished learning interest due to limited emotion and visible cues) (Huang et al., 2022). To make robots autonomous in natural interaction, there is a need for effective action selection based on the understanding of learners' abilities and progress to trigger appropriate actions to scaffold their learning. Although many AI robots allow learners to learn conveniently by self-deciding what and how to learn, troubles arise when they cannot handle learning tasks or use robots appropriately. Thus, instructors need to monitor learners throughout their interactions with AI robots and provide scaffoldings when necessary.

4.6. Future of HCAI in education and its application in educational robots

To address the technological challenges of AI robots to promote a higher level of personalization and enhance instructors' and learners' acceptable of AI robots, there is a need to consider higher-level HCAI capabilities in educational robots.

4.6.1. Benefits of HCAI systems compared to traditional AI systems

Compared to traditional AI systems with difficulties in guaranteeing non-discrimination, due process, and understandability in decision-making, HCAI systems have unique benefits of informed decision-making, reliability and scalability, personalized learner experiences, and more inclusive outcomes (Shneiderman, 2020). First, by leveraging the power of humans and machines, HCAI contributes to more precise AI algorithms built from human input and values, thus enabling instructors to make highly informed decisions and design more adaptive support to promote students' better learning. Second, by exploiting technology's computational abilities and simultaneously leveraging emotional and cognitive inputs from humans, HCAI contributes to expanding processes and information to a larger volume without threatening data integrity or increasing human resource costs. Third, by considering learners' characteristics, needs, and learning behaviors during AI system development, HCAI contributes to personalized, fulfilling learner experiences. Additionally, by keeping humans in the loop while building AI, HCAI enables humans to monitor for bias in algorithmic decisions, thus contributing to checked and balanced systems that make outcomes more inclusive.

However, HCAI's benefits can be constrained due to a high requirement of expertise and a lack of holistic assessment of HCAI approaches (Xu et al., 2022). As our results showed, although AI robots and chatbots have been widely used in different subject areas (e.g., early education, STEM education, nursing education, and language education) for promoting computer-supported collaborative learning, mobile/game-based learning, distance learning, and affective learning, limited practice on developing true HCAI-empowered educational robots is available. The limited practice of HCAI for educational purposes is also indicated in previous studies (e.g., Renz & Vladova, 2021).

4.6.2. Future of HCAI and its application in educational robots

To advance HCAI specifically to the community of AI robot-supported precision education, the concept of "co-learning" is important, which focuses on humans' interaction with, learning from/with, and growing with AI (Huang et al., 2019). Specifically, AI needs to learn how to explain the learning, reasoning, and planning process to humans; humans need to learn how to include human intention and values in AI, explore ways to seamlessly interact with and teach AI, and adapt rules to enrich AI with uniquely human capabilities, knowledge about the world, and specific user's personal perspective (Stephanidis et al., 2019). Future efforts on developing true HCAI systems for educational purposes are listed below.

Humans as part of a continuous feedback loop with AI. Being involved in the training, testing, and tuning processes of AI model construction, humans can validate AI decisions' precision and offer feedback to AI in case of a wrong decision (Nakao et al., 2022). An example is given by Weitekamp et al. (2020), who allowed an instructor to teach an intelligent tutor who then taught learners. Specifically, a human instructor demonstrated to the tutor how to resolve problems. When the tutor provided wrong solutions, it showed to the human instructor learners' trouble spots as ML systems usually encountered similar problems as learners.

Think of individual learners. To ensure that the end result enhances and positively augments the learning of individual learners, there is a need to clearly understand their backgrounds, needs, locations, and the ways they are going to utilize AI systems (Xu et al., 2022). This can be achieved by involving a sample of end learners in the model training, validating, and testing during system construction to capture their feedback.

Test and understand learner–AI robot interaction. Understanding and testing learner–AI robot interaction in real-world situations is essential for successful learner experiences (Xu et al., 2022). To promote AI robots' capabilities in perceiving and interpreting complex real-world environments, human actions, and interactions (Li et al., 2021), there is a need to include more human-like world understanding and common-sense knowledge grounded in physical reality into AI robots by leveraging social and cultural theories (e.g., activity theory and actor-network theory) to frame the relationships between AI robotics and learning (Oliver, 2011) into social and cultural contexts. These frameworks help to see how learners make personal, social, and cultural meanings from interaction with robots, instructors, and peers to understand their learning trajectories and make sense of their learning experiences. The process of tracing learners' interactions also helps understand how AI robots can be associated with their perspectives, interests, needs, and situated contexts to inspire feasible pedagogical implications for personalized instruction.

Take an HCAI multidisciplinary approach. As a multidiscipline, the successful HCAI design for learning objectives requires close collaboration among AI engineers and professionals, educational experts, psychologists, designers, sociologists, etc. to consider pedagogical innovations and learners' learning styles, analyze learners' behaviors during their interaction with AI robots in different contexts, and build technologically and pedagogically sound HCAI robots (Chen et al., 2021). For instance, for the development of an interactive intelligent tutoring system, which presents results related to classification, clustering, and prediction to learners via learner interfaces, educational experts can support the mental modeling of target learners (Xu et al., 2022).

Sufficient technical support. Training programs that emphasize well-balanced interactions among knowledge of contents, pedagogies, and technologies, can be provided to instructors with varied linguistic, instructional, and technological skills to guide them in effectively integrating AI robots into classrooms. During instruction, according to Bers et al. (2014), every instructor ought to have trained assistants to support troubleshooting technology issues, tracking children's progress, and offering one-on-one help to achieve the optimal combination of human and AI robot instruction to best support students' learning.

4.7. Limitations of this study

This study has limitations. Firstly, our analysis was based on records retrieved from Web of Science and Scopus. Although Web of Science and Scopus are multidisciplinary databases of academic output and are commonly adopted for literature reviews, there might still be articles related to AI robot-supported precision education that were not included in the two databases. Future research may consider exploring how research trends in AI robot-supported precision education vary when including articles from more journal sources and even from relevant conference proceedings. Furthermore, although topic models are acknowledged for their abilities to uncover thematic structure within large-scale literature data, they might not bring about strict conclusions. Future work can be conducted to combine text mining technologies with systematic and qualitative analysis methodologies to achieve a more fine-grained understanding. This would require developing techniques that allow systematic analysis of a large dataset to be conducted in an automatic way.

5. Conclusion

This study examined research on AI robots for precision education during 2001–2021 using structural topic modeling and keyword analysis. Results showed that AI robots and chatbots are widely used in different subject areas for promoting computer-supported collaborative learning, mobile/game-based learning, and affective learning. We also identified a lack of practice and research on true HCAI educational systems. Findings obtained contribute to identifying the main topics and gaps in the extant literature with implications for future practice and research on AI robots. Based on the findings, we propose suggestions for advancing HCAI and its application in educational robots from the perspective of "co-learning" between humans and AI. These suggestions include (1) involving humans as part of a continuous feedback loop with the AI model, (2) thinking of individual learners, (3) testing and understanding learner–AI robot interaction, (4) taking an HCAI multidisciplinary approach in system development, (5) providing sufficient technical support for instructors during AI robots' implementation for educational purposes.

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