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A systematic review of artificial intelligence techniques for collaborative learning over the past two decades

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A R T I C L E I N F O

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A B S T R A C T

This systematic review focuses on publications related to studies of the use of artificial intelligence (AI) for collaborative learning. The use of AI for collaborative learning is a recent phenomenon and a systematic review of such studies is lacking. Following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol, 41 journal articles were shortlisted. These articles were analysed in terms of the contexts of study (year, group size, platforms of interaction, and types of learners). Using a thematic approach, two broad foci and five sub-categories of use of AI for collaborative learning were identified: (1) learning outcomes – (a) collective performances, and (b) content of learning; (2) social interactions and processes – (c) sentiments and emotions, (d) discourse patterns and talk moves, and (e) learner characteristic and behaviours. The AI techniques were coded according to three broad purposes (discovering, learning and reasoning) and nine techniques: clustering, ensemble, regression algorithms, deep learning, decision trees, natural language processing, instance-based, fuzzy logic, and agents. A Sankey diagram was used to depict the relationships among the nine AI techniques to the five sub-categories of how AI was used to support collaborative learning. The gaps in the selected articles and limitations of the current review were discussed to suggest future areas of study.

1. Introduction

In the past few decades, artificial intelligence (AI) has been increasingly applied to advance various fields that permeate many aspects of our lives (e.g., Burleson & Lewis, 2016; Kaplan & Haenlein, 2019; Zdenek, 2003). In recent years, the resurgent interest and increasing use of AI in educational contexts have led to the emergence of the research field "AI in education", or AIED in short. AIED refers to the use of AI technologies in educational settings that facilitate teaching and learning by simulating human intelligence at various degrees to infer, judge, predict, and make decisions (Hwang et al., 2020). These may take the form of providing personalized feedback to students and teachers, guidance for policymakers, or assistance in decision-making processes (Miao et al., 2021; Seldon & Abidoye, 2018).

AIED has promising potential and is likely to play a key role in influencing teaching and learning in the near future (Loeckx, 2016; Seldon & Abidoye, 2018). Further, as AI is often considered a tool that can leverage technical capacities to resolve difficult and complex problems, the study of how AI can be used to support students' learning in complex computer-supported collaborative learning (CSCL) contexts is gaining traction (Ludvigsen & Steier, 2019; Rosé & Ferschke, 2016). This development will have an impact on how students frame and investigate problems, explore multiple perspectives, and leverage multiple resources via collaboration and social interactions with one another. Such learning contexts require students to develop advanced agency and cognitive, social-emotional, and behavioural capacities for working in knowledge societies.

How can institutions, teachers, researchers, instructional designers and content creators contribute to the development of AIED? Answering this question requires a more detailed scan of how studies are achieving collaborative learning goals and conducting research studies with existing AI techniques. A search for literature using EBSCOhost information services and comprehensive search terms (see Section 2) and the key term "review" did not lead to the identification of any article. To address this gap and contribute to the effort of understanding how AI has been used for collaborative learning, this systematic review examined studies related to collaborative learning that are supported by AI techniques published over the past two decades. This systematic review is guided by the following research questions:

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1. What are the main characteristics of studies focusing on collaborative learning supported by AI in terms of publication year, interaction platforms, group size, and learner types?
2. What are the aspects of collaborative learning supported by AI and what are the corresponding major AI techniques used to achieve these goals?
3. What are the gaps arising from the findings, limitations of the review, and future work?

2. Methods

This systematic review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) for the selection of items (Moher et al., 2015; Page et al., 2021) a 4-phase flow diagram to ensure the quality and rigor of reporting a systematic review. PRISMA was selected for this review's search strategy as it is widely endorsed and adopted as a guideline for systematic reviews (Page et al., 2021). This section presents the search strategy, selection inclusion and exclusion criteria with explanations, and how data coding was conducted.

2.1. Data sources and search strategy

A wide range of databases was used as our primary source. The databases included Academic Search Complete, British Education Index, Computer Source and Education Source. These databases were selected based on their relevance to education (e.g., Education Source) and AI (e.g., Computer Source) to ensure comprehensive coverage for the review. We used EBSCOhost information services to search the database concurrently. Scopus was included as an additional database to detect other literature that could be relevant to our study.

A search was conducted in May 2022 using three sets of search terms as shown in Table 1. The first set of search terms consists of different variations of the term collaboration. The second set of search terms includes terms relevant to artificial intelligence. The third set of search terms includes terms related to learning. In total, 2810 papers that contain the three sets of search terms within the title and abstract were identified in the search.

2.2. Selection inclusion and exclusion criteria

The overview of the search protocol is summarized in Fig. 1. This protocol was conducted following the PRISMA statement (Moher et al., 2015).

Inclusion and exclusion criteria were used to select suitable studies for this review. First, we limited the publication period to the past two decades, from January 2002 to May 2022, to ensure the relevance of the literature (Tang et al., 2021, pp. 1–19). This reduced the set to 2759studies. Next, we limited the search to peer-reviewed journal articles for quality assurance. Duplicate copies of the studies were also removed. Based on this criterion, trade publications, editorials, books, conference proceedings and review articles were also excluded from the search. The search was further limited to papers published in English to match the authors' language proficiency, reducing the search to 2074papers. Next, the titles and abstracts were scanned to ensure that the chosen articles were relevant to collaborative learning involving AI technologies. By this criterion, we excluded studies such as collaborative filtering (e.g., collaborative filtering for recommender systems by Zhang et al., 2020), non-education contexts (e.g., collaborative editing of websites by Chen et al., 2018) and use of non-AI technologies for collaborative learning (e.g., use of learning analytics by Saqr et al., 2020). This reduced the short-listed items to 67 studies. In this review, we included studies ranging from K-12 to higher education and noted that we found no studies from the pre-school contexts. The full text of each study was reviewed to verify that the focal point of the study resides in the use of AI for collaborative learning activities. Our final set consisted of 41 studies. Table 2 presents the inclusion and exclusion criteria and the number of studies remaining after assessing the criteria for fit.

Table 1
Search terms used in each category.

Categories	Search terms in the category
Collaborative learning	Collab*
Artificial Intelligence	Artificial intelligence, AI, machine learning, ML, machine intelligence, intelligent support, intelligent agent, automated tutor, deep learning, neural network, natural language processing, NLP, expert system
Learning	learn*, stud*, educat*, school, university

2.3. Aspects of collaborative learning supported by technologies including AI

This review focuses on the use of AI to support collaborative learning. Theoretically, collaborative learning can be traced to the social-cultural theory of learning (Vygotsky, 1978) which regards social interactions as necessary processes of learning. It starts with interactions between a more knowledgeable person (e.g., a tutor) with the learner (interaction in the inter-mental plane) that results in cognitive changes within the learner (changes in the intra-mental plane). Collaborative learning or CL (Laal & Laal, 2012, p. 491) refers to

An educational approach to teaching and learning that involves groups of learners working together to solve a problem, complete a task, or create a product. In the CL environment, the learners are challenged both socially and emotionally as they listen to different perspectives, and are required to articulate and defend their ideas. In so doing, the learners begin to create their own unique conceptual frameworks and not rely solely on an expert's or a text's framework.

Dillenbourg (1999) explained that there are many variations in the situations for collaborative learning, including group size, group composition, nature of collaboration, and communication media; these collaborative learning situations are arranged such that "particular forms of interaction among people are expected to occur, which would trigger learning mechanisms, but there is no guarantee that the expected interactions will actually occur" (p. 5). In other words, how the learning environment is structured and which aspect of collaborative learning is supported are critical; as well, multiple factors are involved for effective learning to occur. Thus, researchers have been exploring both the processes and the learning outcomes of collaboration.

In addition to the variations in the concept and situations of collaborative learning, a close concept is cooperative learning (Johnson & Johnson, 2009). Differences between collaborative learning and cooperative learning have been proposed; for example, collaborative learning focuses on coordinated effort on shared goals and tasks, whereas cooperative learning emphasizes the interdependence among learners, often in the form of division of roles (Davidson & Major, 2014; Dillenbourg et al., 1996); collaborative learning is for mature learners who are self-directed whereas cooperative learning caters to younger students who learn under teacher-directed activities (Bruffee, 1995). Cooperative learning involves more structural guidance or scripting, which is more teacher-directed, whereas collaborative learning prizes students' agency and working towards common goals. Regardless, common attributes of collaborative and cooperative learning (Davidson & Major, 2014, p. 29) include common tasks or activities for group work, group interactions on the shared tasks or activities, helpful group processes to jointly accomplish the tasks or activities, learning task, accountability and responsibility exhibited by individuals, as well as interdependence among individuals who are working together.

In addition to interactions with others, the theory of distributed cognition (Hutchins, 1995) suggests that cognition involves interactions with others with different expertise as well as tools in the environment that provide additional cognitive resources for learning. External tools

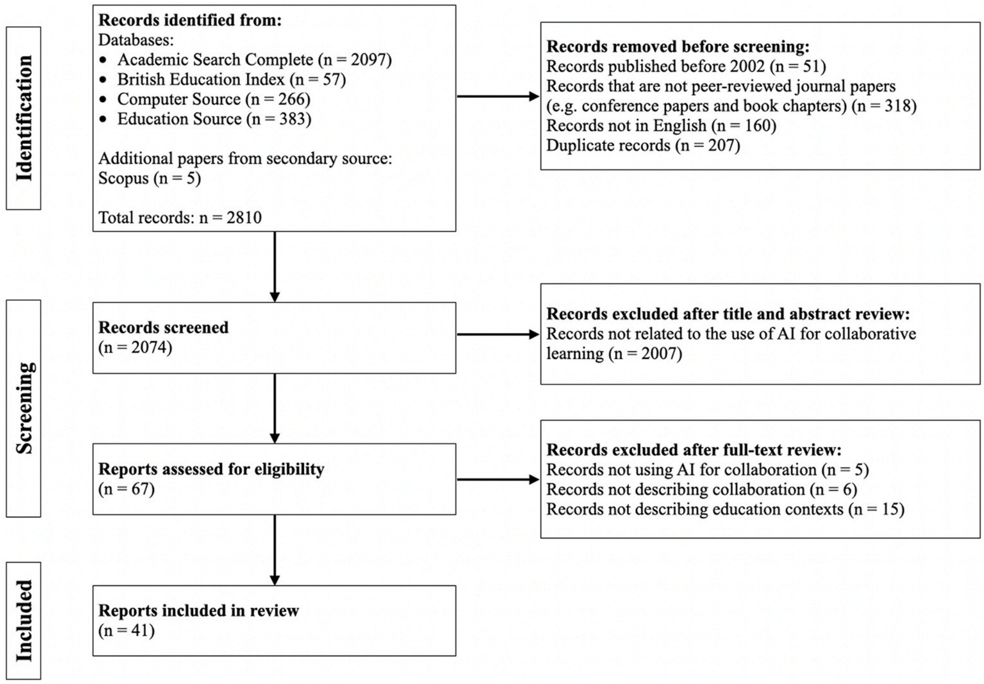

Fig. 1. Overview of search protocol.

Table 2
Inclusion and exclusion criteria.

	Inclusion criteria	Exclusion criteria
Publication year	Papers published from January 2002 to May 2022	Papers published before 2002
Source types	Peer-reviewed journal papers	Non-peer-reviewed journal papers, trade publications, editorials, books, conference proceedings and review articles
Language	English language	Other languages (e.g., Spanish, Chinese)
Context	Education (e.g., K-12, higher education)	Non-education contexts (e.g., corporate settings)
Topic	Use of AI for collaborative learning	Collaborative AI systems, use of AI for independent learning

may include computer-based resources such as the internet or learning management systems. Computer-supported collaborative learning (Stahl et al., 2014), or CSCL, has emerged as a prominent field of research in the past three decades. Researchers have studied how students interact and learn around a computer (e.g., Stahl, 2006) while interacting with shared computer resources, as well as how students learn by communicating through networked computers and interacting with online resources (e.g., Scardamalia & Bereiter, 2014). In a CSCL environment, students' adaptiveness and self-directedness are critical because they are not learning from a fixed-sequence tutorial program but learning with others mediated by network computers, with fluid and dynamic interactions and evolving roles and tasks. In such a situation, students' agency to engage with others and resources is prized (Scardamalia, 2002).

CSCL (e.g., online forums) not only support communication among learners but also scaffold learners for more productive interactions and meaning making. For example, researchers have explored the use of Knowledge Forum, an online forum, to support students in collaborative knowledge building (Scardamalia & Bereiter, 2014) and various features, such as scaffolds for productive discourse, are used to encourage productive interactions among learners. Research studies involving CSCL have explored students' learning outcomes, such as ideas discussed (Lee & Tan, 2017) or performance in learning tasks, as well as the processes such as discourse moves (e.g., argumentation moves by Weinberger & Fischer, 2006), ways of grouping students (Moore et al., 2019), and students' interaction processes (e.g., Hernández-Sellés et al., 2020).

Besides CSCL, in the late 2000s, the emergence of Massive Open Online Courses (MOOCs) has rapidly gained traction as an educational revolution that promises to provide an inclusive quality education that can create an impact in education. The rapid advancement in MOOCs has seen their enlistment in many universities globally (Sharrock, 2015). The availability of students' interaction and outcome data in CSCL and MOOCs provides fertile ground for leveraging AI to support collaborative learning. AI applications have been used to explore students' ideas and contents (Lee, 2021), students' collaborative interactions (Järvelä et al., 2020), and students' emotions (Zhu et al., 2019). This review focuses on collaborative learning because the applications of AI build on the availability of data with technological supports (e.g., CSCL) for the collaborative processes as elaborated below.

Based on the literature, this systematic review will examine the selected papers on the followings: (1) contexts of learning (e.g., types of learning environment, group size), (2) group learning outcomes (e.g., content or ideas expressed by learners), and (3) group interaction processes (e.g., grouping of or connecting students, promoting productive discourse, promoting positive behaviours for collaboration). Recognizing that there could be many variations in collaborative learning (Dillenbourg, 1999), sub-categories of these three broad factors will be identified through thematic coding of the short-listed articles. These are presented in the Findings section.

2.4. Framework and coding for AI techniques

Although there are varying definitions of AI (Murphy, 2019), it has often been referenced to be part of an approach, method, or algorithm that resides in a system and serves the purpose of doing the work in place of human intelligence. As Murphy (2019) noted, a precise definition is not necessarily critical in the study of AI, and therefore the prevalence and application of AI techniques across fields and disciplines can still be generally categorized.

2.4.1. Guiding framework for thinking about AI fields and techniques

A common query within the field of AI is whether AI and machine learning are the same. We use a guiding framework (Fig. 2) as a reminder about the nuances of the definitions and how they relate to our review of AI techniques that are used for collaborative learning. Briefly, AI is understood to be an intelligence that is exhibited through machines to address problems that used to be part of human prerogative. Hence, AI is designed and implemented to emulate human thought processes, human actions, and resulting desirable outcomes, with the eventual goal of conducting tasks that will otherwise require human intelligence. In the past, specific rules guiding decision-making were used for AI, such as in expert systems (Turban, 1995). Such rule-based systems did not involve machine learning with empirical data. Machine learning is a subset of AI that consists of a large suite of techniques that enable machines to conduct a range of functions including identification and recognition of features, understanding of subject matter, prediction of trajectories and providing answers to complex problems. The outcomes from machine learning may, however, still contain errors and will require human intervention for adjustments toward the desired objectives. Deep learning represents a smaller subset of techniques in machine learning that uses neural networks to evaluate factors and process data in a manner inspired by the human neural system. Leveraging multiple layers in the neural network, deep learning systems do not require human intervention in the machine learning process.

2.4.2. Coding of AI techniques

Fig. 2 clarifies the broad concepts of AI, machine learning and deep learning. For this review, we found it appropriate to categorize and code techniques found in the selected studies into three main categories (Fig. 3), each with its purpose and role in advancing collaborative learning. Each category contains several main families of AI techniques, which are by no means an exhaustive list but encompasses most techniques that are prevalently and predominantly used in educational studies related to collaborative learning. The final codes that are used are: clustering, ensemble algorithms, regression algorithms, deep learning, decision trees, natural language processing (NLP), instance-based, Bayesian, fuzzy logic, and agents.

First, to aid the *discovery of knowledge and inquiry* when learning with others, it is necessary for appropriate techniques and algorithms to retrieve information from databases and identify valid and potentially useful information. Subsequently, patterns and models for decision-making will be evaluated and interpreted to distinguish between data that are useful and relevant and those that are beyond the context studied. By achieving a deeper understanding of the area of study, techniques for data mining and learning often involve the identification of dependencies between variables, detection of anomalies, usage of regression, classification, and clustering processes to make sense of big data. Examples of such techniques include centroid-based clustering algorithms such as *k-means* as well as other main ensemble algorithms such as boosting, stacking, and bagging.

Apart from the discovery of knowledge and inquiry, learners *learning from knowledge and inquiries* is often a necessary step towards the acquisition and subsequent demonstration of skills, whether through study, experience or being taught. Hence, most AI techniques were inspired by learning techniques to let machines automatically learn with little or no assistance. However, the learning processes, whether inductive or deductive, do not stray away from the need for a large quantity of data that is required for training models (like humans studying and experiencing for learning) and the need for good data quality to achieve accuracy in terms of sensitivity and specificity. Some examples of learning-related AI techniques are artificial neural networks (ANN) for deep learning, support vector machines (SVM) and decision trees for classification, regression and outlier detection.

Finally, the use of heuristics can guide *reasoning from knowledge and inquiries* in complex problems and situations, allowing mediation and for solutions to be more precise, effective, and reliable. Through inductive and deductive reasoning, one could generate feasible conclusions from prior and available knowledge. There are several important elements in AI techniques that conduct reasoning, such as inferring from existing works, gathering the necessary information to formulate rules for problem solving, constructing a knowledge base to facilitate reasoning and preparing for future build-on that can handle emergent problems. Examples include natural language processing (NLP) related techniques that seek to make sense of discourse, and case-based and rule-based reasoning (CBR and RBR) build on current knowledge to increase the accuracy of AI systems. The use of fuzzy logic in techniques helps to deal with computing problems that are currently vaguely assessed but can be solved with an imprecise spectrum of data and heuristics to achieve a range of accurate conclusions. Agents are representations that aid and make decisions as a system, machine, software, or even as a technological human surrogate, by perceiving the environment using sensors and acting upon the environment using actuators but may still be unable to discern consequential effects.

For the coding scheme, two researchers first coded 12 of the selected studies and discussed the coding results to reach a consistent frame of thinking and understanding of the code. Thereafter, both researchers

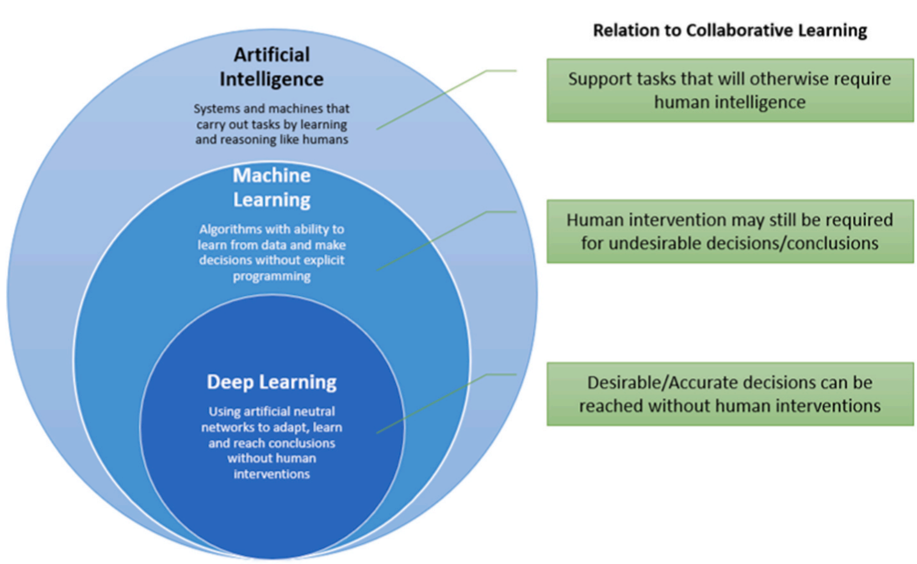

Fig. 2. The guiding framework for relating AI fields during learning with others.

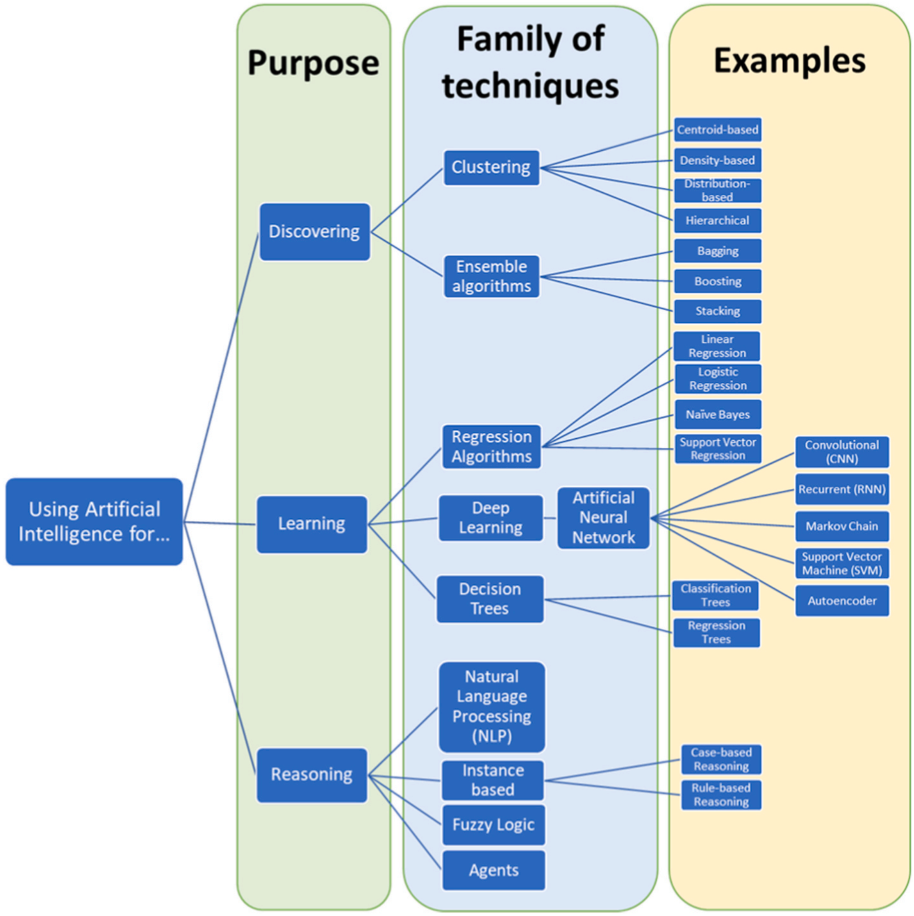

Fig. 3. A hierarchical tree showing the purposes for AI being used, followed by the main families of techniques that serve the respective purposes, and examples of the techniques that were found within the reviewed studies.

independently coded the remainder of the selected articles. Cohen's kappa (Cohen, 1960) was then calculated to measure the inter-rater reliability, which was 0.88 and considered almost perfect agreement (Stemler, 2004). Any remaining discrepancies between the researchers were thoroughly discussed again before reaching a common consensus across all codes and samples.

3. Findings

3.1. Contexts of study

To answer research question 1, contexts of study of the selected articles were analysed in terms of publication year, group size for collaborative learning, types of platforms for interactions, and types of learners. These are presented in Figs. 4–7.

Fig. 4 shows the number of publications in 5-year intervals, starting from 2002. It shows the emergence of AI for collaborative learning publications after 2002, a slight decline after 2011, followed by a general steady trend from 2012 to 2021. In 2022, just within the first 5 months, there is an apparent increase when seven articles were found.

Fig. 5 shows the group size of collaborative learning in the studies across 5-year intervals. Overall, small groups (less than 10) were the most common group context being explored, followed by massive groups (more than 100), small classes (between 11 and 30), and dyads. Over the years, there is an increasing trend for studies involving massive group sizes because of the gaining traction of the use of MOOCs while interest in studies involving small groups seems to have diminished.

Fig. 6 shows the types of interactive platforms used in the studies across the years. Overall, CSCL is the most frequent platform used,

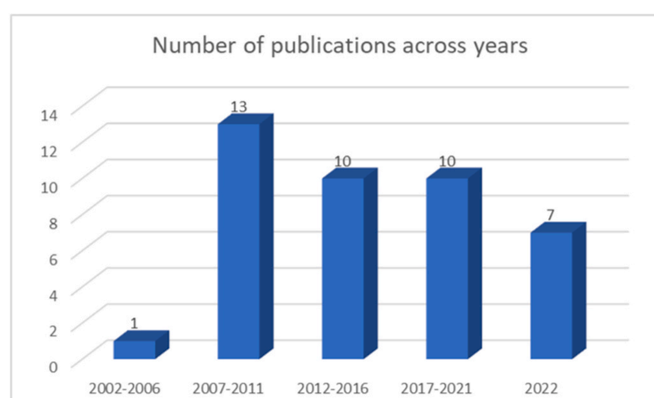

Fig. 4. Number of AI for collaborative learning publications across years.

followed by online interaction systems (e.g., online inquiry, online argumentation, online forum, etc.), and online learning systems (e.g., learning management systems). Over the years, there seems to be increasing use of MOOCs whereas CSCL is decreasing.

In terms of types of learners (Fig. 7), most studies involved university students, followed by K-12 students, while three studies involved both types of students. The youngest group in K-12 studies was fifth-grade students. Four studies did not specify the learners because they were either simulations or studies focusing on the development of a system or approach (e.g., methods of AI analysis of discourse types). Four studies involved other types of participants, including adult learners or

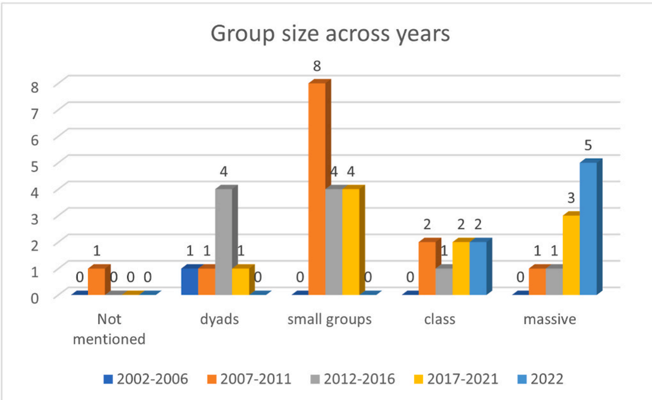

Fig. 5. Group size across years of studies.

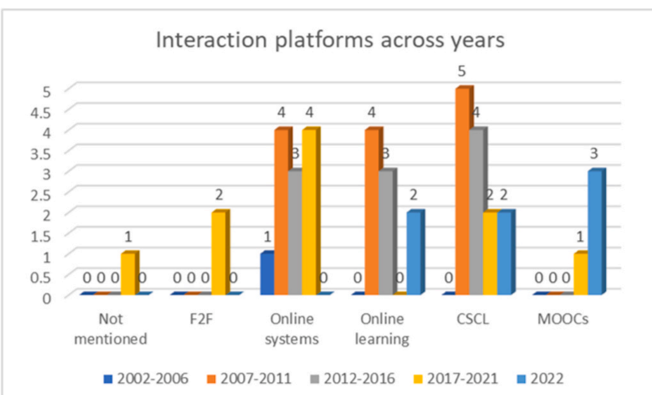

Fig. 6. Interaction platforms for collaboration across years.

university faculty. The absence of K-12 in 2022 is likely related to the trend of studies conducted in MOOCs that are mostly used in higher education.

3.2. *Aspects of collaborative learning supported by AI*

To answer Research Question 2, two general categories emerged when analysing the aspects of collaborative learning supported by AI techniques: group outcomes and social interactions and processes. Five sub-categories of AI-supported studies for collaborative learning can be identified and will be discussed in the following sections. Some studies contributed to more than one category (see Table 3).

3.2.1. *Group outcomes*

The first category is group outcomes, where studies utilised AI to gather insights into the outcomes of learners' joint activities. As the studies in this review span a wide range of disciplines, different assessment metrics were used to assess collaborative learning in different contexts. Despite the broad range of assessment methods, the goals of the studies could be distilled into two types: assessing collective performance (9) and assessing the content of learning (10).

3.2.1.1. Collective performance. Collective performance refers to goals focusing on the groups' overall performance from the collaborative activity. While some studies used AI techniques to evaluate group performance in the form of quality contributions based on metrics such as tone, coverage, relevance and plagiarism (e.g. Ramachandran et al., 2017; McLaren et al., 2010, others used AI to predict group performance based on interaction data of students collaborating in an online learning environment (e.g. Cen et al., 2016; Schneider & Pea, 2014).

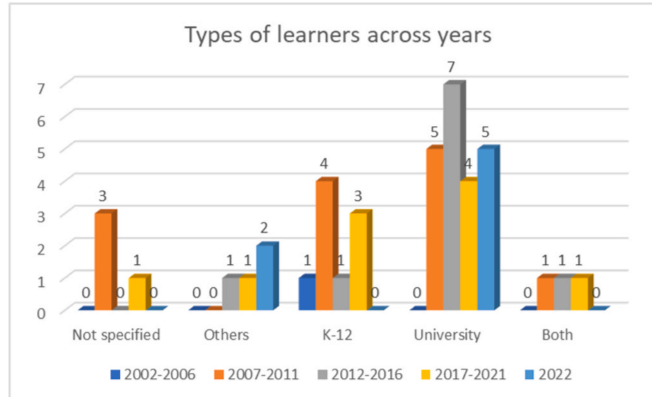

Fig. 7. Types of learners across years.

3.2.1.2. Content of learning. Content of learning refers to goals that focus on the contents of students' text generated during the collaborative activity. These papers examine the content of the students' contributions through different lenses, including analysis of differences in students' perspectives (Chen & Tsao, 2021), examination of topic relevance (Zheng et al., 2021), examination of keywords and topics covered (Calvo et al., 2011), and encouraging divergent ideas through feedback provided by an AI agent (Huang & Chuang, 2008; Huang et al., 2010).

3.2.2. *Social interactions and processes*

Goals in the social interactions and processes category focused on the exchanges and interactions learners made while working with each other to achieve more effective discourse during collaborative learning. We identified three types of goals in this category: understanding sentiments and emotions (6), uncovering discourse patterns and talk moves (15) and understanding learner characteristics and behavioural actions (3).

3.2.2.1. Sentiments and emotions. Sentiments and emotions refer to goals that address the affective dimensions of collaborative learning. Studies examined students' emotional states in the form of valence (Ammar et al., 2010; Casamayor et al., 2009; Liu et al., 2022; Zheng, Zhong, & Niu, 2022), epistemic emotions (Capuano et al., 2021; Liu et al., 2022) and level of urgency (Capuano et al., 2021). For instance, Ammar et al.'s study (2010) used video analysis of learners' facial expressions to detect their emotional states and incorporate this affective state information into an intelligent tutoring system.

3.2.2.2. Discourse patterns and talk moves. Learners' discourse patterns and talk moves used during collaborative activities can influence the extent of productive discourse (Mercer, 2000; Scardamalia & Bereiter, 2010). Most studies use AI to optimize the analysis of discourse patterns and talk moves during collaboration (e.g., Casillas Santillán et al., 2014; Rosé et al., 2008; Zheng et al., 2019). Three articles employed AI techniques for auto-coding of students' discourse. These include auto-labelling part-of-speech trigrams for diagnosis, query, regulation, argumentation and problem definition (Huang et al., 2011; Sullivan et al., 2019), analysis of part-of-speech for argumentative knowledge construction (Mu et al., 2012), and automatic coding of students' argumentation (McLaren et al., 2010). While there were studies focused on discourse analysis, some studies extended the analysis to provide interventions to improve students' talk moves (Adamson et al., 2014; Huang & Chuang, 2008; Zheng et al., 2021).

3.2.2.3. Learner characteristics and behaviours. Learner characteristics and behaviours refer to goals that focus on the learner's attributes and behaviours during collaborative activities. Most studies with this goal utilised data on learners' characteristics and behaviors to connect learners for collaboration. Studies were found to use students' academic performance (Garshasbi et al., 2019; Wang & Wang, 2022), interest (Wang & Wang, 2022; Yang et al., 2007), behavioral data (Elghomary et al., 2022; Kumar & Rose, 2010; Wang et al., 2022) and demographics (Garshasbi et al., 2019) to develop grouping strategies for collaboration. A few studies focused on the analysis of learners' behaviors to provide corrective feedback to improve their collaborative learning experience. For instance, Diziol et al. (2010) analysed learners' problem-solving behaviours and used an agent to guide the learners towards productive problem solving, while Troussas et al. (2020) analyzed students' collaborative styles to recommend types of activities they can participate in

3.2.3. Types of AI support

AI techniques used were coded into different types of support to provide a more nuanced analysis of the goals of the studies. Studies are broadly classified into four types: descriptive, diagnostic, predictive and prescriptive. In this review, studies describing more than one type of analytics will be coded following the analytics with the greatest level of complexity (Akerkar, 2013; Houtmeyers et al., 2021; Lepenioti et al., 2020). The figures and percentages listed in this section were computed for unique entries.

The applications of AI for most studies were prescriptive (21 studies, 51.2%), illustrating that most studies work towards achieving the highest level of analytics complexity where data-driven interventions were provided. As the stakeholders of education may not possess high levels of data literacy, these studies work towards providing more clarity on the actions to be made for collaborative learning through decision automation. For instance, several studies centre their study on the assigning of students into optimal groups for collaboration (Elghomary et al., 2022; Garshasbi et al., 2019; Kumar & Rose, 2010; Wang et al., 2022; Wang & Wang, 2022), while other studies developed agents to provide feedback to improve interaction patterns for more effective collaborative discourse (Adamson et al., 2014; Dyke et al., 2013; Kumar & Rose, 2010). In addition, a few studies provided recommendations of actions to tutors for pedagogical interventions for collaborative learning (Anaya et al., 2013; Casamayor et al., 2009; Gerard et al., 2019; McLaren et al., 2010).

Descriptive analytics is also well adopted in the studies (16 studies, 39%). Contrary to prescriptive analytics, these studies focused on the lowest level of analytics complexity where the involvement of AI remained at the provision of insights into collaborative learning. Many studies dedicated their goals to testing novel AI techniques or optimising existing AI techniques for assessing discourse (Nistor et al., 2015; Sullivan & Keith, 2019; Yang et al., 2022), content (Capuano et al., 2021; Chen & Tsao, 2021; Mu et al., 2012), emotions (Ammar et al., 2010; Huang & Chuang, 2008) and collective performance (Anaya & Boticario, 2011; McLaren et al., 2010; Spikol et al., 2018).

Comparatively, there were three studies on predictive analytics (7.3%) and one study on diagnostic analytics (2.4%). These studies utilised AI to provide analytics that increases decision support, enabling more effective data-driven decision-making. For instance, Thompson et al. (2014) used diagnostic analytics to identify the stages of group collaboration to aid teachers in identifying instances to provide appropriate interventions to facilitate collaboration. Three papers in this review used predictive analytics to predict learning achievement (Liu et al., 2022), group performance (Cen et al., 2016) and quality of collaboration (Schneider and Pea, 2014).

The cross-analysis of goals and types of analytics demonstrates that prescriptive analytics were widely used to achieve all goals in group outcomes and social interactions and processes. Relative to the other goals, sentiment and emotions and collective performance were found to have fewer studies providing prescriptive analytics.

3.3. AI techniques that support collaborative learning

3.3.1. Breakdown of AI techniques that support collaborative learning

A variety of AI techniques from the selected studies were coded, with some studies using a combination of techniques to achieve their goals. Out of the 41 studies, 13 studies (31.7%) adopted Natural Language Processing (NLP) techniques to investigate and support collaborative learning; 11 studies (26.8%) chose to use deep learning techniques that are predominantly neural networks, with a few studies using autoencoders and self-organizing maps; another 11 studies (26.8%) used agents to take autonomous actions that help to improve performance with learning and achieve goals; 6 (14.6%) studies used instance-based reasoning while another 6 studies (14.6%) created decision trees to be part of the decision analysis process; 5 studies (12.2%) applied clustering to their respective studies, three (7.3%) studies used regression algorithms and two (4.9%) study used fuzzy logic.

3.3.2. Recognition and potential mapping of learning goals with AI techniques

From the earlier findings, nuances of AI-supported collaborative learning were categorized into different learning goals and subgoals. The AI techniques that are utilised in the studies can be mapped to discover potential usage patterns. Since several studies may encompass multiple learning goals, the appearances of the studies in the following table are not unique and may be repeated for the purpose of recognizing usage patterns. The detailed information is presented in Table 4.

4. Discussion

4.1. Technology-supported learning platform as a key factor for students

From the findings to the first research question (see Section 3.1), no journal publication before 2004 was identified, which shows the nascent state of studies on the use of AI for collaborative learning. The number of publications has been steady from 2007 to 2021 but in 2022 alone, six studies were identified. It could be an early indication of increasing interest in the study of AI for collaborative learning. There is also an increase in the study of massive group sizes. One factor that could explain these trends is the expanding influence of MOOCs, which are used mostly by university students or adult learners and afford the big data for the application of AI techniques. In terms of platforms of interactions, besides MOOCs, researchers have been exploring the use of AI with CSCL, online learning systems (e.g., Learning Management System) and other dedicated online interaction platforms (e.g., online science inquiry). Only two studies were conducted in face-to-face settings. Logically, the digital traces in technology-supported learning

Table 3
Goals and type of analytics cross-analysis.

Categories of Goals	Sub-goals	Descriptive	Diagnostic	Predictive	Prescriptive
Group outcomes	Content of learning	<u>7</u>, 8, <u>15</u>, 24		<u>2</u>	<u>6</u>, 10, 27, 30, 32
	Collective performance	12, 13, <u>28</u>, 40	18	14, 17	16, 23
Social interactions & processes	Sentiment & emotions	<u>7</u>, 29, 31		<u>2</u>	<u>36</u>, <u>37</u>
	Discourse patterns & talk moves	4, 9, <u>15</u>, 20, <u>28</u>, 33, 39, 41			<u>6</u>, 19, 22, 25, 35, <u>36</u>, <u>37</u>
	Learner characteristics and behaviours				1, 3, 5, <u>6</u>, 11, 21, 26, 34, 38

Notes. Studies are coded based on their paper IDs (refer to Appendix A). Paper ID underlined contributed to more than one goal.

Table 4
Details of selected studies that use AI techniques to support collaborative learning

Learning goals	AI Techniques								
Subgoal categories	Discovering		Learning			Reasoning			
paper ID	CL	EN	RE	DL	DT	NL	IB	FL	AG
Group Outcomes									
Content of learning									
2						x			
6				x					
7				x					
8						x			
10						x			
15						x			
24						x			
27						x			
30						x			x
32			x				x		
Collective performance									
12						x			
13	x				x				
14				x	x				
16							x		
17				x					
18						x			
23	x				x				
28	x								
40			x	x					
Social interactions & processes									
Sentiment & emotions									
2						x			
7				x					
29									x
31							x		x
36				x					
37				x					
Discourse patterns & talk moves									
4	x				x				
6				x					
9						x			
15						x			
19							x		x
20						x		x	
22							x		x
25						x			x
28	x								
33					x				
35							x		x
36				x					
37				x					
39			x	x	x				
41								x	
Learner characteristics & behaviours									
1				x					
3						x			x
5				x					
6				x					
11	x								
21							x		x
26									x
34									x
38				x					

Notes. *CL* = clustering; *EN* = ensemble algorithms; *RE* = regression algorithms; *DL* = deep learning; *DT* = decision trees; *NL* = natural language processing; *IB* = instance-based; FL = fuzzy logic; *AG* = agents. Underlined paper ID indicates paper appears in more than one instance.

provide a fertile ground for the application of AI.

In terms of learners, most studies were conducted with university students (21 out of 41, 51.2%) followed by K-12 (8 out of 41, 19.5%) and 3 studies included both. This could also be related to the use of technological platforms. As explained in Section 2.3, unlike computer-based tutorial programs, collaborative learning with technologies requires the learners to exhibit a higher degree of self-directedness and maturity because interactions with others could be fluid and dynamic and the topics of discussion emergent. Also, it is in such a context that the prescriptive use of AI could also better support the learners (see the next section).

4.2. *Foci of study and types of AI action*

Analysis in Section 3.2 shows two broad categories of study: learning outcomes versus processes, with more devoted to processes of collaboration. Among the processes, a substantial number of studies focus on discourse patterns and talks, indicating the importance of language and communication in the collaborative process. There was no study that emphasized the interdependence of tasks or resources commonly associated with cooperative learning (Johnson & Johnson, 2009).

Our findings show most of the studies fall under the category of prescriptive actions, either in providing feedback or taking actions. It reflects the values placed on the use of AI aiming to create a real impact on learning. Examples of prescriptive actions include how to optimize group formation with inter-homogeneity and intra-heterogeneity (Garshasbi et al., 2019) and providing real-time feedback on members' social network interactions (Zheng et al., 2021). While only one article focused on the diagnosis of problems as the end goal (Thompson et al., 2014), some of these articles (e.g., Zedadra & Lafifi, 2015) involve the diagnosis of students' learning problems followed by providing advice. There is also nuanced differentiation in the prescriptive actions. For example, Zheng et al. (2021) provided users with advice (e.g., do not veer off-topic) and Zedadra and Lafifi (2015) have messages sent to users who were taking ineffective paths, but others (e.g., Zheng, Niu, & Zhong, 2022; Zheng, Zhong, & Niu, 2022) provided advice and leave some degree of decision making to the users. There could be a further exploration of the effects of the degree of agency given to the users. From a pedagogical perspective, there are values of empowering the students with epistemic agency (Scardamalia & Bereiter, 2010). Regardless, the investigation of human-computer partnership for better learning outcomes is an area that is worthy of further investigation.

4.3. Relating aspects of collaborative learning with AI techniques

During the review, researchers recognised from data analysis certain usage patterns of specific AI techniques for different nuances of collaborative work. Although this conjecture is not entirely theory-based but rather evidence-driven as shown in this review, there is always a larger question that is awaiting to be answered: What AI techniques do studies of specific learning goals tend to gravitate towards? Table 4 has a detailed part of these findings and together with the coded learning goals for each study, a Sankey diagram (Riehmann et al., 2005) can be constructed to visualise the aggregated findings. The Sankey diagram (Fig. 8) illustrates the flow of goals and techniques that studies tend to gravitate towards within an educational setting for collaborative learning.

There are several key observations from the Sankey diagram. First, it was noted that when studies are predominantly focused on a better understanding of content, discourse patterns, talk moves, and collective performances, natural language processing (NLP) emerges as a key important "Go-to" technique. This is a logical move because NLP, as a suite of methods, can help resolve ambiguity in language, and provide structure for coding and making sense of language, thus allowing downstream applications such as text analytics and speech recognition to happen.

Next, the use of artificial neural networks (ANN) in deep learning has become a more prevalent technique across the board for the analysed goals relevant to collaborative learning. Compared to initial use cases such as computer vision, image processing, machine translation, medical imaging and information processing (Alom et al., 2018), the use of deep learning has evolved beyond imitating brain processing to develop algorithms, into modelling of patterns and prediction problems that can aid better understanding of how students learn in complex computer-supported collaborative learning contexts.

Finally, the use of agents is noticeable within studies that focus on learner characteristics, including how students behave and talk. As with all kinds of agents, there needs to be the capability to perceive, think, and act in order to understand student learning characteristics. Different from intelligent agents that act on behalf of information provided by

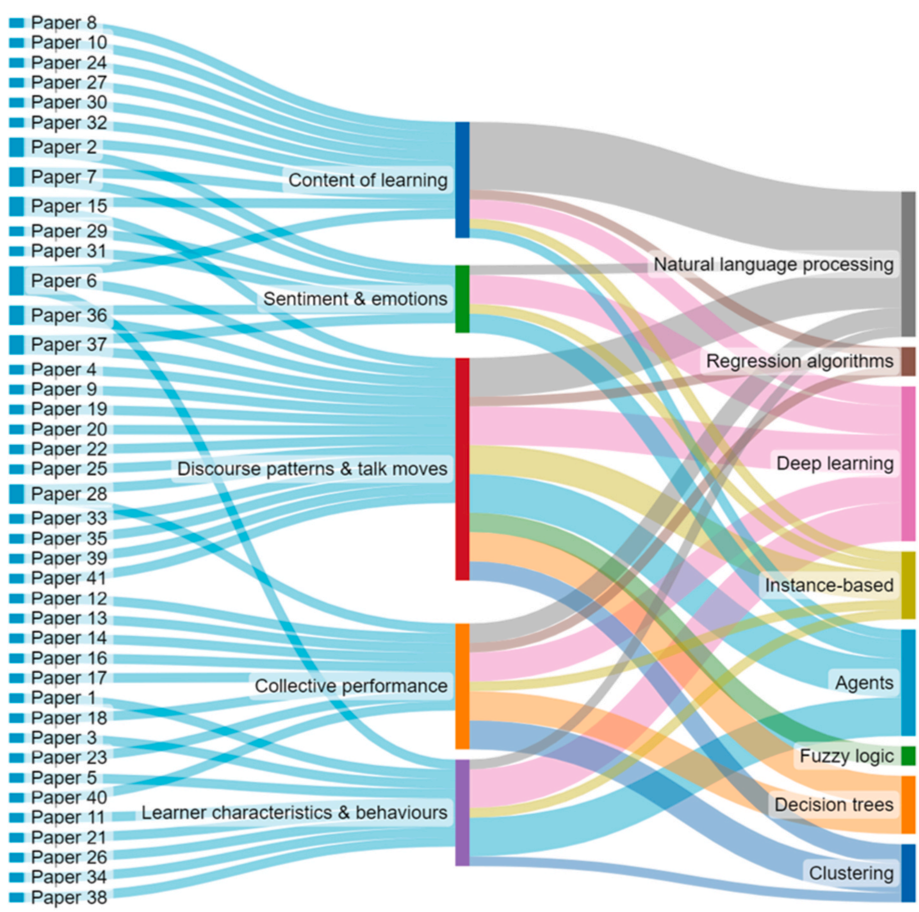

Fig. 8. Sankey diagram showing tendency of AI techniques being used for specific learning goals.

programmers for autonomous activities, learning agents in the reviewed studies essentially execute tasks and conduct analysis to achieve learning goals, and often focus on building up mental properties of the agents, such as detection of learners' beliefs, identification of intentions, and creation of new or improvement of existing knowledge bases.

4.4. Gaps arising from the findings

At least two gaps were found among the shortlisted papers. First, in terms of the theoretical underpinning of collaborative learning, researchers (e.g., Dillenbourg, 1999) have suggested variations in the definitions for collaborative learning, and how collaborative learning is different from cooperative learning. It is thus critical for researchers to declare how collaborative learning is defined in their studies and which aspects of collaboration are the focus of the study. There were 27 papers (65.8%) that did not provide the theoretical underpinning of collaborative learning and 13 papers (31.7%) did not provide a clear description of the situations of collaborative learning. A few studies cited cooperative learning theories (e.g., Israel & Aiken, 2007) while the terms collaborative learning and cooperative learning were used interchangeably. The lack of clarity in theoretical underpinning has several implications:

1. Some situations may not be regarded as collaborative learning to some researchers, for example, simply putting learners to learn together.
2. The nature and approaches of scripting for collaboration can be very different for dyads and participants in MOOCs. For example, the strategies for identifying and connecting participants of similar interests dynamically will not be relevant for dyads.
3. Successful group structuring and processes for learning in a MOOC, learning in a class, and learning in pairs may be different. Lack of clarity of what is regarded as collaborative learning will create challenges in generalizing the findings.

In addition, from the perspective of ethical and responsible use of AI, the degree of agency of learners to decide how to make sense of the AI results decreases from descriptive to predictive and to prescriptive actions, and the impact on the learners increases correspondingly. Given that most of the AI algorithms still carry some degree of errors, whether it is acceptable to the users to have prescriptive actions is in question. Also, communicating with and educating users about the margin of error is still a missing piece in most studies.

4.5. Limitations of this review

There are several limitations in this review. First, this review utilised the PRISMA protocol to select articles to answer the research questions. Due to the search pattern and strategy, there may be AI-relevant conference articles that were omitted during the narrowing of the review's scope. Next, this review used the search term 'collab*' to represent the scope of collaborative learning. However, the analysis shows variations in the definitions of collaborative learning. It is possible that some authors may have used other terms (e.g. cooperative learning) in the title but still refer to collaborative learning in the study. It is suggested that future reviews can cast the net wider to include search terms although it will require greater effort to screen through the articles to retain the focus of the review. Also, we limit our search to databases related to non-disciplinary-specific learning environments because specific disciplines could have certain instructional approaches that are more prominent (e.g., problem-based learning for medical education) that could skew the findings; moving into specific disciplines (e.g., medical education, engineering education) could broaden the scope extensively.

Regarding the presented choice of techniques, this review has also attempted to classify and categorize the vast range of AI techniques at this opportune time juncture where emergent methods and techniques have stabilised without significant upheavals to the range of techniques that are available to the larger research community. Although this review may not have included an exhaustive list of all AI techniques, efforts were made to ensure it touches on most families of techniques, whether existing or emergent, that would be present in most, if not all, studies that one will encounter in the academic field.

5. Conclusion and future work

This systematic review of AI for collaborative learning sets out to answer three research questions specified in the Introduction. In terms of the characteristics of studies, journal publications on AI for collaborative learning only emerged in 2004 with about 5–7 publications every 5 years. An increased frequency was found in 2022 and there is a trend toward the use of MOOCs. This review shows the great variations in research contexts, goals and approaches to using AI to support collaborative learning. Most studies were conducted with university students, supported by technologies such as MOOCs, CSCL, online learning or online platforms dedicated to specific purposes (e.g., inquiry or problem solving.

In terms of foci of research learning supported by AI, two broad categories and five sub-categories were found. First, AI was used to assess learning outcomes, including group performances and the content of students' discussions. Second, AI was used to support collaborative learning processes, including students' sentiments and emotions, students' collaborative discourse and talks, and students' characteristics and behaviors. The majority of AI applications were taking prescriptive actions, followed by providing descriptive information, providing prediction and diagnosing problems. A few patterns of the use of AI techniques can be detected. First, NLP was related to understanding content and discourse patterns and making sense of text data. Second, the use of ANN in deep learning has broad applications across the analysis of various situations in collaborative learning. Third, noticeable use of intelligent agents to provide actions.

The main contribution of this paper is addressing the research gap of the lack of systematic review on the use of AI techniques to support collaborative learning. For teachers, instructional designers, and content creators, this review provides information about applications that have been researched and could possibly be deployed in teaching and learning. For example, the use of CSCL and MOOCs as learning platforms, and the use of AI to assess learning outcomes and support students in the collaborative processes.

Several implications for researchers can be derived from the findings of this systematic review. For interested researchers, a few aspects of studies could demand more attention: (a) the importance of declaring the theoretical underpinning of collaborative learning and providing clear descriptions of situations of collaborative learning in the study; (b) the ethical and responsible use of AI, especially in taking prescriptive actions, needs further exploration; (c) the applications of diagnostic and predictive analytics are relatively less explored. Diagnostic analytics could alert teachers and learners to potential areas of weakness and strengthen prescriptive recommendations, and predictive analytics could suggest potential trajectories for teachers and learners to take preemptive actions.

Through this review, we have presented a clearer understanding of the distribution and usage of AI techniques for various goals and purposes. This will help the research community to better manage resources and select approaches and techniques that can potentially out-perform human-level executions in collaborative classrooms and learning environments. Further, by identifying complex tasks that can be efficiently achieved by AI, it will free up human resources and workforce that can be better equipped to complete other tasks in collaborative learning that require creativity and empathy.

Besides the gaps found in the shortlisted papers, certain constraints were imposed for scoping of this review. Moving forward, a wider net could be cast to search for articles that may use other terms to describe collaborative learning situations, and for quality conference articles.

Declaration of competing interest

The authors confirm there are no conflicts of interest.

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The views expressed in this paper are the authors' and do not necessarily represent the views of the host institution.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.caeai.2022.100097.

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