How Virtual Agents Can Shape Human-Human Collaboration: A Systematic Review

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Abstract. Virtual agents have demonstrated considerable success in fostering learning experiences. Existing literature reviews of the field have found that in the context of virtual agent support for individual learners, agents enhance the social and cognitive learning experience. However, these reviews have not examined how virtual agents can facilitate collaboration between two or more human learners. This systematic review addresses this gap. We identified and analyzed 55 studies reporting on virtually embodied or text-based agents that facilitate collaboration among two or more human learners. We found that researchers operationalize and measure collaboration through a variety of lenses, including academically productive talk, knowledge building, and collaborative decision-making. The analysis also revealed a set of behaviors that virtual agents perform to support collaborative learning activities, including scaffolding collaborative behaviors, consolidating students' ideas, and encouraging quieter students to participate in the conversation. We identify gaps and opportunities for refining and unifying existing frameworks and establishing shared evaluation methods. These advancements hold the potential to enhance the effectiveness of virtual agents supporting human-human collaboration.

Keywords: Collaborative Learning · Virtual Agents · Systematic Review

1 Introduction

Collaborative learning can enhance students' critical thinking skills [95], increase motivation [24], and lead to measurable improvements in learning [16, 62]. In collaborative learning, students justify their actions and provide feedback on their partner's contributions, allowing them to reflect on their answers and solidify their understanding of the material [92]. However, collaborative learning presents challenges, such as unequal participation and poor task coordination [43]. Virtual agents have shown promise in providing support to overcome these challenges, offering a unique opportunity to enhance collaboration between human learners.

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Virtual agents–AI systems designed to interact with users–have emerged as a powerful approach to support and enhance collaborative and individual learning experiences [12,100]. Virtual agents can take various forms, ranging from text-based chatbots [51] to embodied and animated avatars [91]. These versatile systems have been shown to motivate learners [65] and support the development of self-regulated learning [41]. Furthermore, virtual agents have the potential to enhance collaboration by prompting collaborative dialogue [47] and managing group dynamics [79] in real time, fostering productive learning environments.

Existing literature reviews on virtual agents have primarily focused on virtual agents that support human-agent collaboration [40,58,74]. Consequently, there is limited understanding of how virtual agents support human-human collaboration in learning contexts. This study addresses this gap by synthesizing the literature to examine the following research questions:

- **RQ1:** How do prior studies on virtual agent-supported collaborative learning operationalize collaboration, and what outcomes do they use to measure success?
- **RQ2:** How do virtual agents currently support collaboration, and what behaviors do they perform during their interventions?

2 Background

2.1 Operationalizing Collaboration

Collaboration is commonly defined as the "mutual engagement of participants in solving problems together" [66] or as "a shared effort among individuals with similar abilities, common goals, and coordinated actions" [17]. Collaborative learning is based on the idea that group efforts can achieve more than individuals working alone [48], with conversation playing a central role in socially constructing knowledge [5]. However, our review of relevant work revealed that collaboration is defined operationally, with definitions tailored to specific contexts such as decision-making [20], co-regulation [47], and knowledge-building [55]. One of the central goals of this work is synthesizing the varying operational definitions within this context, aiming to establish a more robust framework that can guide future research.

2.2 Virtual Agents for Collaborative Learning

Over the past 20 years, virtual agents have been shown to be effective in helping students learn in various domains [14,71,73], and researchers have explored different dimensions of how to design and implement them [36,101]. Understanding how to design virtual agents that support collaboration is crucial, as agents can be positioned as collaborators or facilitators during collaborative learning. For this reason, we opt to analyze them through the same lens as educators who facilitate collaborative learning in their classrooms. The Implementing Collaborative Learning in the Classroom (ICLC) framework [38] outlines five key teacher competencies that encompass the process of supporting collaborative learning: planning, monitoring, supporting, consolidating, and reflecting. This review focuses on how virtual agents exhibit behaviors aligned with four of these competencies–monitoring, supporting, consolidating, and reflecting–within agent-supported collaboration. The planning competency is excluded, as the virtual agents in this review serve only as facilitators who interact with students in predetermined ways during collaboration, not as designers of collaborative activities.

In this context, *Monitoring* refers to the process of agent systems collecting data by observing and detecting behaviors, keywords, or interaction patterns, which enables them to provide targeted support in the form of the following competencies. The *Supporting* competency can take the form of *macro-level scripting*, where agents provide hints, suggestions, or reminders to guide student interactions [19], or *micro-scripts*, which act as real-time conversational prompts to enhance dialogue [18]. For example, an agent designed to guide students through discussion phases may issue reminders to keep the group on track [77]. Similarly, an agent providing real-time feedback might prompt a student to rephrase explanations in more original terms [28].

Consolidation focuses on integrating perspectives within a group. Agents encourage participation, clarify misconceptions, and prompt students to engage with each other's ideas. This often takes the form of prompts such as "Do you think X is related to Y?" or "Do you agree with this statement?" [83]. Since consolidation often involves indirect scaffolding, there is some overlap between supporting and consolidating behaviors.

Finally, the *Reflecting* competency involves prompting students to assess their performance and learning process. Formative reflections occur during activity and encourage real-time behavior changes, while summative reflections allow students to evaluate their collaborative experience after the task [76]. By integrating these competencies, virtual agents facilitate structured, adaptive collaboration.

2.3 Related Literature Reviews

As the fields of virtual agents and collaborative learning have expanded, several review studies have helped advance our understanding of both areas. In collaborative learning, these reviews highlight its significant potential in higher education [37] and emphasize that interaction with peers increases student engagement, thereby improving learning performance [63].

In virtual agent research, recent studies show that agents can effectively scaffold learning [74] and positively impact learning outcomes [8,70]. However, researchers emphasize the importance of careful consideration when designing these agents ([61,101]. Despite the growing interest in both virtual agent and collaborative learning research, studies at their intersection are limited. Existing research primarily explores virtual agents as *collaborators* [40,74] rather than *facilitators of collaboration*, leaving gaps in our understanding of how virtual agents influence collaborative behaviors and how collaboration itself is defined in these contexts. This review addresses these gaps by analyzing how virtual agents support human-human collaborative learning and the metrics used to evaluate their effectiveness in educational contexts.

3 Methods

This study followed the standard for conducting a systematic literature review, as described by the PRISMA guidelines [59].

3.1 Literature Search

We conducted two separate searches across nine databases to identify relevant studies. The first search, performed on March 1, 2024, used the following keywords: **("pedagogical agent" OR "conversational agent" OR "motivational agent" OR "collaborative agent" OR "embodied agent" OR "interactive agent" OR "virtual human" OR "virtual character") AND (collab* OR cooperat*)**, which retrieved 1,684 studies. The second search, conducted on June 13, 2024, used the keywords: **("virtual agent" AND (collab* OR cooperat*))**, yielding 366 studies. After merging the results and removing 596 duplicate records, we identified 1,454 unique studies for title and abstract screening (see Fig. 1).

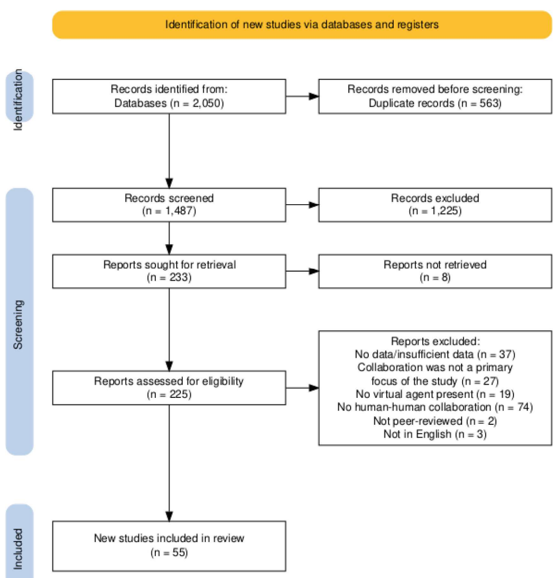

Fig. 1. PRISMA-style flow chart created with Haddaway et al.'s tool [25]

3.2 Inclusion Criteria

To be included in this systematic review, studies had to feature a virtual agent, either as a virtually embodied character or a text-based agent, with a primary focus on collaboration in human-human-agent interactions. Additionally, only studies presenting primary empirical data were considered, excluding reviews or design proposals.

3.3 Screening

The study screening was split into two phases, as depicted in Fig. 1. In the first screening phase, the titles and abstracts of each study were examined for potential inclusion. This process resulted in the exclusion of 1225 studies, leaving 233 studies for further screening. In the second phase, the full-text versions of each study were retrieved and examined to ensure they met the inclusion criteria. Eight studies could not be retrieved in full-text form, and 178 did not meet the inclusion criteria, leaving 55 studies for analysis.

3.4 Data Extraction and Coding

To address the research questions, we extracted a variety of data from each study, including participant information, study setting, and the number of students and agents present in each interaction, along with information describing the behaviors the agent performed during the study, the frameworks cited when defining collaboration in each study, and the types of outcomes measured by the researchers. The full table is available in an Open Science Framework repository[1].

Sixteen studies' full-texts (29% of the sample) were selected to be coded by a second author to establish inter-rater reliability for data extraction. The authors achieved a Cohen's kappa of 0.75, indicating substantial agreement [23].

4 Results

Fifty-five studies were included in this review, mainly conducted in undergraduate educational settings ($n = 35$). Nine took place in K-12 settings, and ten with adult participants. Most studies involved a single agent that facilitated collaborative dialogue (74%, though some utilized multiple agents with distinct roles ($n = 6$), such as providing domain expertise [54,55], communication advice [29,91], or scaffolding teamwork [30].

Across all studies, 15% utilized a Wizard-of-Oz methodology, in which researchers simulated adaptive systems by manually triggering agent responses based on participants' interactions (e.g., [39,54]. Additionally, 55% of studies featured embodied agents, often representing tutors, teachers, or peers, while the remaining studies employed text-based chat agents. Some agents were designed as near-peer mentors [97] or robots [56,57], reflecting diverse representations in human-agent collaboration research.

[1] https://osf.io/kfmg4/?view_only=67ac13b1b7454fd484af29a9a16b8eb4.

4.1 RQ1: How Do Prior Studies on Virtual Agent-Supported Collaborative Learning Operationalize Collaboration, and What Outcomes Do They Use to Measure Success?

In these studies, analytical approaches varied in how researchers examined and measured collaborative behavior. The methodological frameworks used include those described in Table 1. Some articles grounded their analysis in established theoretical frameworks ($n = 28$), while others introduced new approaches ($n = 5$). Twenty studies did not explicitly reference a theory or framework, instead discussing collaboration, collaborative learning, or CSCL more broadly. The most frequently referenced framework was Academically Productive Talk (APT) or Accountable Talk [50], cited by 14 studies. APT provides guidelines for teachers to prioritize student reasoning over correctness, and students demonstrate accountability to their learning community, accurate knowledge, and rigorous thinking.

Table 1. Frameworks used to analyze collaborative learning interactions.

Term	Definition	Studies
Academically Productive Talk	Students are accountable to the learning community, accurate knowledge, and rigorous thinking. This approach prioritizes student reasoning over correctness.	[1,2,6,7,15,21,22] [51,80–82,85,87] [78,83]
Conflict Mediation	Learners discuss or debate conflict resolution and communication strategies, focusing on the affective tone of the discussion.	[26]
Transactivity	Learners use their partners as resources, building on their earlier contributions.	[6,57,85]
Cooperative Problem-Seeking	Students creatively search for a problem to solve, focusing on mutual acceptance of problem specifications.	[11]
Group/Collaborative Decision-Making	Students work more effectively as a group than as individuals, enhancing their collective ability to understand problems through collaboration and decision-making.	[20,39,52,72]
Knowledge Building	Learning and knowledge-building occur within a community before they develop within an individual, involving joint problem-solving and building shared understanding.	[1,54]
Knowledge Construction	Students make ideas meaningful by connecting them to prir knowledge and the context in which they arise.	[57,68,87]
Knowledge Integration	When students consider different perspectives, they create opportunities to integrate knowledge, leading to a deeper understanding.	[30,31,34]
Joint Attention	The more learners focus on the same area of their screen, the more attention they pay to each other.	[30,31,33,35]
Collaborative Writing	Students collaborate on writing a single document as a group.	[45,96]
Socially Regulated/Co-Regulated /Self-Regulated Learning	Students set goals, monitor their behavior, and evaluate their progress. This process extends to monitoring peers' behavior, setting group goals, and transitioning between types of regulation.	[47,53,99]
Exploratory Talk	Learners engage in exploratory talk by expressing partly-formed ideas to forge understanding, making themselves vulnerable to peer criticism.	[97]
Task and Group Awareness	A student's awareness of social interactions within a group, such as whether another person is paying attention.	[54,99]

Knowledge building is another theory motivating the studies identified in this review and involves students not only building their understanding but also seeing themselves as part of something larger than themselves [69]. A similar but theoretically distinct framework, *knowledge construction*, was often referenced alongside knowledge building, which led to overlapping definitions and phrasing in some contexts. For example, Nguyen et al. [57] cited Scardamalia and Bereiter's work on knowledge building, though they described it as "Collaborative Knowledge Construction", merging the two terms with less emphasis on its constructivist foundations [94]. Similarly, Hayashi et al. [30] discussed Knowledge Integration, a term originally coined by Linn et al. [46], citing Rochelle et al. [67] without connecting it to foundational theory or theories on communities integrating and building knowledge [69].

Outcome Measures. The analyzed studies reported four types of outcomes: learning, self-reported information, performance, and collaboration. Learning outcomes were commonly assessed through pre- and post-tests to measure knowledge gains [81]. Self-reported measures varied between studies, capturing participants' perceptions of agent interactions and their confidence in task completion [26]. Performance outcomes were evaluated using task-specific scoring metrics to assess the effectiveness of problem-solving or decision-making processes [72]. Collaboration outcomes focused on interaction quality and team dynamics, often examining how virtual agents influenced group communication and coordination [13,15].

Although all of these studies included agents designed to facilitate collaboration between two or more participants, only **twenty-seven** of the 55 studies provided an evaluation metric directly related to collaboration (Table 2), such as participation or frequency of encouraged behaviors. This result suggests that many studies infer collaborative success through other outcome measures, such as learning or performance, rather than explicitly assessing collaboration itself. The monitoring competency is excluded from this table because all agents inherently perform this function when collecting data to inform their support, with no intervention strategies or outcome measures targeting this competency.

As shown in Table 2, collaborative outcomes were typically assessed through post-hoc analysis of learner dialogue. Researchers commonly compared dialogue between groups with and without an agent or examined different types of agent interactions. The most frequently measured collaborative outcomes include participation and frequency of specifically targeted behaviors. Participation was often quantified by turns taken or words spoken by each participant [4,15]. An example of a targeted behavior is the Explicit Response Ratio (ERR) described by Tegos et al. and analyzed in five studies [78,81,82,85,87]. The ERR examines the number of explicit positions and arguments made in response to an agent intervention. Other studies went further by annotating entire sessions to determine the ratios of different dialogue acts by each student or within a group [10,45,55,57,78,80–82,85,87].

4.2 RQ2: How Do Virtual Agents Currently Support Collaboration, and What Behaviors Do They Perform During Their Interventions?

The virtual agents exhibited behaviors that align with the monitoring, supporting, consolidating, and reflecting competencies described in the ICLC framework

Table 2. Agent behaviors that embody the Supporting, Consolidating, and Reflecting competencies, and the collaborative outcomes used to measure success

ICLC Competency	Agent Behavior	Collaboration Outcome
Supporting	Macro-Scripts ([2–4,6,7,10,11] [13,28,32–35,39,45,47,51,53] [54,55,57,68,72,77,79,86] [78,82–85,87–89,97]	Number or percentage of student utterances categorized as targeted behavior [2,11,33,35,45,51,54,56,57]
		Uptake of encouraged behavior [10,32,78,80–82,85,87,97]
		Lexical conformance/Topic similarity [35]
		Messages sent by each participant [4,51]
	Micro-Scripts [1,2,15,21,22] [27,28,30,32–35,56,68,72,79] [78,82–86,89,97]	Number or percentage of student utterances categorized as targeted behavior [1,2,15,21,22,33,35,54,56]
		Uptake of encouraged behavior [32,78,80–82,85,87,97]
		Lexical conformance/Topic similarity [35]
		Messages sent by each participant [4,51]
Consolidating	Encouraging Participation [4,10,20,26,34,35,44,47] [57,80,81,85,87] [78,82,83,90,91]	Messages sent by each participant [4,44]
		Number of words per student [44]
		Contribution Score (messages + unique words) [20]
		Quality of contribution (task relevance * informativeness of each message, rated by researchers) [20]
		Number or percentage of student utterances categorized as targeted behavior [21,57]
		Uptake of encouraged behavior [10,78,80–82,85,87]
		Lexical conformance/topic similarity [34]
		Sequences of student dialogue acts [57]
	Macro-Scripts [2,4,10] [32–35,47,51,56,57,68,72] [78,79,82–86,97]	Number or percentage of student utterances categorized as targeted behavior [2,33,35,51,54,57]
		Uptake of encouraged behavior [10,32,78,80–82,85,87,97]
		Lexical conformance/topic similarity [35]
		Sequences of student dialogue acts [57]
		Messages sent by each participant [4,50,72]
		Number of words per student [72]
	Micro-Scripts [1,2,21,22,27,30] [32–35,56,68,72,79,84,86] [78,80–83,85,87,97]	Number or percentage of student utterances categorized as targeted behavior [1,2,21,22,33,35,54]
		Uptake of encouraged behavior [32,78,80–82,85,87,97]
		Lexical conformance/Topic similarity [34]
	Acting as a Teammate [39,52,96]	–
	Summarizing Discussion [4,72]	Number of words per student [72]
		Messages sent by each participant [4,72]
	Gaze Feedback [30,32,34,35]	Gaze similarity [30,32,34,35]
		Lexical conformance/topic similarity [34]
		Number or percentage of student utterances categorized as targeted behavior [33,35]
		Facial expression pattern matching [34]
	Praise/Positive Feedback [21,27,28,30,32,33] [34,35,47,52,57,84,90,91,97]	Number or percentage of student utterances categorized as targeted behavior [21,33,35,57]
		Relevance of utterance to agent suggestion [32]
		Number of words per student [32]
		Lexical conformance/topic similarity [34]
		Sequences of student dialogue acts [56]
		Uptake of encouraged behavior [78,80–82,85,87,97]
		Gaze similarity [30,32,34,35]
Reflecting	Self-Assessment Support [98,99]	-
	Conflict Mediation [26]	-
	Macro-Scripts [54]	Number or percentage of student utterances categorized as targeted behavior [54]
	Micro-Scripts [54]	Number or percentage of student utterances categorized as targeted behavior [54]

[38] as detailed in Sect. 2. Almost all agents in this review participated in the monitoring competency, as 75% of the agent systems leveraged user data to provide feedback. The most common data source for adaptation was student

chat history, with 70% of the studies reviewed analyzing keywords or dialogue patterns to trigger interventions. Some agents prompted the students to answer questions that informed the agent's decisions [11,96], while others used eye-tracking [30,34,35] or log data [53,88,90,91] to offer relevant support.

47 of the 55 evaluated studies performed activities in alignment with the supporting competency, which entailed providing prompts such as hints, suggestions, or reminders to influence student interactions or their progress through the activity. There were two ways that agents engaged with the students in line with the *Supporting* competency: Micro-scripts and macro-scripts.

22 studies highlighted the behavior of agents providing *micro-scripting* when supporting students. This type of behavior from the agents focused on scaffolding individual behaviors or prompting the user to make behavioral changes in real time. For example, Adamson et al. [2] designed agents that requested students to expand their reasoning if the agent interpreted a statement as paraphrasing, and Hayashi et al. [27] designed agents that, among other things, asked students to use more original words in their explanations if they detected statements had been copied and pasted from the description. Nguyen et al. [57] designed virtual agents that sent prompts in the form of "conceptual nudges" to the group when they had missed a link between key terms in the discussion.

35 studies designed agents that used *macro-scripts* to fulfill the supporting competency. These agents sent interventions that guided the overall activity or overarching conversation rather than individual dialogue moves. Morch et al. [54] designed an agent that prompted students to 'divide the labor' and 'think jointly in specific terms' to be more effective collaborators. Additionally, Tavanapour et al. [77] structured the meeting, providing reminders of time remaining during each step in the meeting and synthesizing the deliverables for each stage. Many of these studies had agents that performed both micro- and macro-scripting behaviors when supporting the students, as some interventions were designed to keep the students on track with the activity, while others were specific to the behaviors the agents were trying to promote.

In 67% of the studies, 37 agents exhibited the *consolidating* competency, encouraging participation, clarifying misconceptions, and fostering discussion. While many used micro- and macro-scripts (24 and 20 studies, respectively) and overlapped with the supporting competency, they also provided positive feedback and acted as teammates to engage students.

Agents who recognized students' contributions and provided positive feedback, also known as motivational agents [49], were examined in 15 studies. For instance, Hayashi et al. [27,28,33] developed agents that motivated learners to engage more deeply with concepts using phrases like "Good! You are explaining the concept with some unique words. Keep on going!"

In two studies, the agents functioned as teammates, contributing alongside human participants. Milella et al. [52] investigated the effects of agent gender and cooperativeness on behavior and group performance, with the agent suggesting quiz answers and responding to group decisions.

Only four of the studies in this review had agents that aligned with the *reflecting* competency. Two of these studies provided students with the opportunity to self-reflect, such as asking students a set of questions before and after the collaborative task to enhance their awareness of their behaviors [99].

5 Discussion

5.1 RQ1: How Do Prior Studies on Virtual Agent-Supported Collaborative Learning Operationalize Collaboration, and What Outcomes Do They Use to Measure Success?

The studies in this review demonstrated diverse approaches to operationalizing collaboration, aligned with their specific research contexts, such as cooperative problem-seeking [11] and task and group awareness [99], reflecting the multi-faceted nature of collaborative learning. Operational definitions allow virtual agent researchers to investigate context-specific questions, but they also highlight the broader challenge of balancing specificity and generalizability. This challenge is not unique to agent-supported collaborative learning, and it reflects a larger discussion in social sciences about clarifying theoretical constructs while maintaining flexibility for different contexts [60]. Rather than viewing these variations as inconsistencies, they can be seen as complementary perspectives that enrich our understanding of collaboration. Efforts to refine and connect related concepts–such as distinguishing between knowledge construction and knowledge building [93]– demonstrate how diverse operational definitions can be organized into a more structured framework. Established theories such as Academically Productive Talk [50] can serve as examples of how well-defined frameworks can provide common ground while still allowing for contextual adaptation.

The integration of operational definitions with established theories has previously been explored. For example, the PISA 2015 framework identifies three key competencies for collaborative problem-solving: shared understanding, coordinated action, and team organization [75]. Many of the operational definitions in this review align with these competencies, suggesting an opportunity to connect new research to established theory more explicitly. Positioning new definitions within existing structures rather than developing them in isolation could enhance clarity and generalizability in the field.

The variety of evaluation metrics used in virtual agent research presents challenges for cross-study comparisons. Although different evaluation metrics can provide information, inconsistencies such as varying definitions of participation and reliance on self-reported data limit the generalizability of the findings. Although virtual agents hold promise in shaping collaborative dynamics between human learners, the field would benefit from more standardized outcomes. Some frameworks, such as Cook et al.'s 'find-predict-explain-refine' approach [11], introduced a novel collaboration framework that could be further examined with established measures. Aligning research with established measures would strengthen comparability, enabling a clearer understanding of how virtual agents influence collaborative learning.

5.2 RQ2: How Do Virtual Agents Currently Support Collaboration, and What Behaviors Do They Perform During Their Interventions?

The analysis of virtual agent behaviors reveals both significant competency and notable gaps in supporting collaborative learning. The predominance of supporting and monitoring competencies (found in 85% and 75% of studies, respectively) reflects the field's current technical capabilities and pedagogical priorities. However, this distribution also highlights areas for future development.

The prevalence of the *monitoring* competency is expected and demonstrates that data-driven adaptation is foundational to agent design. While most systems rely on chat-based dialogue for analysis, the emergence of monitoring through eye-tracking suggests promising research directions for more multimodal strategies. However, the reliance on keyword and dialogue pattern analysis may overlook more nuanced aspects of collaboration, such as non-verbal cues, emotional states, or group dynamics. While researchers have explored the use of multimodal data in adaptive systems, future research could explore how these approaches can be tailored to agent-supported human-human collaboration contexts.

While these agents primarily facilitated collaboration through the *supporting* competency in the ICLC framework [38], some agent interventions also indirectly align with the *consolidating* competency by encouraging students to build on each other's assertions, thus fostering deeper knowledge construction. Notably, 53% of studies provided both types of support, suggesting that these competencies may be interconnected and demonstrating the potential for virtual agents to address multiple facets of collaborative learning simultaneously.

In contrast, the most underrepresented competency across these studies was *reflecting*. Few virtual agents provided students with opportunities to directly reflect on their actions or the collaborative process, suggesting that this competency remains underutilized in current agent designs. This gap may stem from the inherent challenge of developing agents that can prompt meaningful self-reflection without disrupting the natural flow of collaborative dialogue. Alternatively, it may reflect a broader focus within the field on immediate, task-oriented support rather than long-term development of self-efficacy and collaborative skills. This highlights a promising area for future research, where virtual agents could be leveraged to foster deeper metacognitive engagement alongside traditional task support.

5.3 Implications for Theory and Practice

As Dillenbourg [17] suggests, the term "Collaborative Learning" is widely used across disciplines, making it difficult to establish a single, unified definition. Rather than continuously expanding the term, researchers should clarify how their operational definitions align with established frameworks such as the ICAP Framework [9] or the PISA Collaborative Problem-Solving Assessment [75]. Organizing definitions into structured categories can help distinguish key differences while maintaining coherence. Comparative analysis of related theories

[42] and hierarchical integration of frameworks could further refine terminology and reduce redundancy. Recent efforts to merge coding schemes for assessing collaboration [64] highlight the value of synthesizing perspectives to develop a more comprehensive understanding of collaborative learning.

Virtual agents supporting human-human collaboration focus on the 'support' and 'consolidate' competencies, encouraging participation and managing group dynamics. While agents are frequently used to prompt participants to engage with each other's ideas and consolidate their views, they are rarely used to provide opportunities for learners to reflect on the collaboration itself. This raises the question of how integrating more reflective components could help learners evaluate their contributions and promote the long-term development of collaborative skills.

In terms of measurement, the review indicates that collaboration is assessed in a variety of domain-specific or goal-specific ways, making it difficult to compare results across different studies. This highlights an opportunity for further research to develop more comprehensive ways of assessing collaborative success, ensuring that studies not only capture learning and performance outcomes but also the nuances of effective collaboration. Identifying shared evaluation metrics could improve the reliability of findings, while replication studies could validate these metrics. By establishing clear guidelines for assessing collaborative success, researchers can create more meaningful comparisons and enhance the practical impact of their findings.

6 Conclusion

The study of agent-supported collaborative learning spans diverse theoretical and methodological approaches. We found a variety of frameworks and theories that drive agent-facilitated collaboration, including Academically Productive Talk, Knowledge Building, and Transactivity. We found that virtual agents perform various behaviors ranging from micro-level scaffolding to macro-level coordination, but the absence of standardized metrics for assessing collaboration complicates efforts to evaluate agents and their effectiveness across studies. Our review notes that established frameworks for collaboration, such as Academically Productive Talk, demonstrate the potential to establish valuable structure while allowing for contextual refinement. By identifying opportunities to formalize connections between frameworks and establish shared evaluation metrics, we hope to enhance our understanding of how virtual agents can effectively facilitate human-human collaboration.

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