Exploring Group Discussion with Conversational Agents Using Epistemic Network Analysis

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Abstract. Conversational agents—dialogue systems that provide learning support to students in real time—have shown promise in facilitating science discussion. To enact conversation norms, the appearances, personalities, or tones of the agents often resemble personas that students are familiar with, such as peers or mentors. This study uses epistemic network analysis (ENA) to explore how students interacted with two personas agent (a peer and an expert) in collaborative settings. Data came from chat logs of three student groups with low, mixed, and high ability. The groups interacted with both prototypes. The chat logs received qualitative codes for discussion types, including claim-making, reasoning, building on prior ideas, and responsiveness to the agents. ENA visualized the differences in discussion between groups and between the agent conditions. Overall, the higher-ability groups engaged in more claim-making in tandem with building on prior ideas when interacting with the peer agent, compared to the expert agent. Meanwhile, the low-ability group showed more syntheses of previous ideas when responding to the expert agent. Findings illuminate the design space for adapting agent personas to group settings to facilitate productive exchange.

Keywords: Collaboration · Conversational agent · Epistemic network analysis · Case study

1 Introduction

A fundamental challenge in science education in the United States is promoting students' sustained interest and participation in scientific practices [1]. Engaging in collaborative discussion offers ways for students to build on the knowledge of others, gain agency, and develop interest in science [2–4]. Conversational agents, or chatbots in this study, have shown particular promise in facilitating discussion [5–7]. These agents use natural language understanding of text and speech to provide suggestions that enrich students' idea generation, argumentation, and conceptual knowledge [5, 6].

A key goal in designing conversational agents is to make them more conducive to discussion and subsequent learning [8–10]. The agent's appearances, tones, and gestures may enact human characteristics such as friendliness, competence, or sociability, to prime users to demonstrate conversational norms as if they were interacting with human partners [11, 12]. Agents can adopt the appearance and lingo of a mentor,

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teacher, or peer in educational contexts to simulate classroom norms [8, 13–15]. Learners with limited understanding may seek help from a mentor agent, whereas more capable learners may deepen their knowledge through giving help to a peer agent [13].

However, considerations of agent design have mostly been applied to individual interactions between a student and an agent and not to collaborative contexts. In the latter case, students' interactions with the agents may vary with group dynamics [16]. This is because the hints and questions from the agent may get ignored in groups where elaboration is not the norm [6]. A factor that may influence such group dynamics is ability composition [17, 18]. For example, students with low or average knowledge may not participate as much when the conversation is dominated by high-ability peers.

The current research explores how students' interactions with conversational agents vary in three student groups of low, mixed, and high abilities within a high school science curriculum. The author draws from prior agent designs in individual tutoring settings to test two prototypes: a peer and an expert agent [8, 13–15]. In a within-subject design, student groups (each consisting of two to three 9th graders) interacted with both prototypes in randomized orders, as they built a concept map of the marine ecosystems. The following questions guide the research:

RQ1. How do students' collaborative discussion patterns vary with different group composition?

RQ2. Within student groups, how do discussion patterns differ when interacting with the peer versus the expert agents?

Overall, students in the mixed and high-ability groups showed more connection between making claims, providing reasoning, and building on prior ideas, compared to the low-ability group. The groups also showed distinct patterns when interacting with the peer versus expert agents. Students in groups with higher levels of prior knowledge appeared to engage in more reasoning and claim-making when interacting with the peer version. Meanwhile, individuals in the group with lower knowledge levels showed more reasoning and reflection on prior ideas when responding to the expert agent.

These findings illuminate how responses to agent designs vary with group composition. This understanding has important design and learning implications. From a design perspective, findings contribute to research on developing agent personas that can be perceived as natural social partners and encourage productive conversational norms. From a learning perspective, learning systems and facilitators may examine the diverse patterns that student groups display. Such consideration helps to identify patterns that are conducive to knowledge construction. It also assists the development of adaptive learning scaffolds for different student groups.

2 Background

2.1 Collaborative Conversational Agents

Engaging in knowledge building efforts, where students collaboratively share ideas and build on one another's knowledge, is an important process to enrich students' science understanding [2–4]. Through exchange, individuals outline their personal and sociocultural experiences, discuss, negotiate, and develop a shared understanding of learning phenomena [4, 19].

Students engage in a range of knowledge building discussion moves, from stating claims to elaborating on and expanding shared knowledge [20]. This wide array of discussion moves presents opportunities for teachers to support different participation structures [20]. For example, teachers can decide on which students may initiate questions or propose actions, ask questions to redirect student attention, or propose tasks for students to build on one another's ideas and artifacts [3, 21, 22]. These participation structures shift knowledge building from teachers as the sole transmitter of knowledge to students and the tools or systems that they engage with [3, 22].

Conversational agents can play an analogous role to teachers in fostering knowledge building communities. These agents use natural language understanding to process students' talks and provide in-time support for conceptual understanding and participation [5–7]. More than tools to enrich student discourse, agents are active participants in the group conversations. Agents can propose prompts for the groups to explain, contrast, and support their ideas, thus fostering different discussion moves.

2.2 Peer and Expert Agent Designs

Agent designs that replicate human behaviors or social norms can influence users' perceptions. In turn, users subconsciously display social behaviors when interacting with the computer agents [11, 12]. Users may enact social norms such as gender stereotyping or reciprocating help with the machines, even with minimal interface cues or when they acknowledge that machines may not have motivation or feelings [11].

Researchers have thus underscored the importance of designing agents to foster more natural human-computer interactions. Two distinct agent profiles have emerged in learning contexts: peer and expert agent. The peer agent profile is based on the similarity-attraction effect [23], which suggests that learners would be attracted to agents that parallel them in appearance, knowledge, or interest [14, 15]. In a study where researchers assigned students to work with computers whose characteristics either aligned with or mismatched students' personalities, students conformed more to the personality that was similar to their own and found it more attractive and intelligent [24].

The similarity-attraction effect gives rise to the peer agent design: human-like characters that appear close to the target groups in age and knowledge level [14]. A related design is the learning-by-teaching model [26], where student users are responsible for explaining target concepts to the agent, who presumably has limited prior knowledge.

Meanwhile, learners may attribute more trust to agents whom they perceive to possess higher knowledge levels [27], in ways that are similar to how they would interact with a teacher or domain expert. This conjecture has led to the designs of expert-like agents—characters that are more knowledgeable, with talk moves that simulate the human instructors [14, 15, 28].

User perceptions and responses to agent designs can be leveraged in designing agents to produce optimal learning and domain interests. For example, choices of agent designs could adapt to learners' domain knowledge [13]. Learners with limited understanding and skills may benefit from interacting with the expert-like agent. Meanwhile, more capable learners can attempt to teach the peer agent. Such interactions provide opportunities for learners to acquire alternative viewpoints and deepen knowledge.

2.3 Agent Designs Influence Human-Agent Interactions

The content of user replies also varies with how users perceive the agent [14, 28–31]. For example, users rated a casual tone agent as friendlier and provided more elaborate survey responses to the agent than one that relied on a formal questionnaire style [30]. In exchange with learning robots, learners who interacted with a robot that behaved as a peer showed more affective displays, compared to a robot that resembled a tutor [31].

Research from human-human tutoring interaction lends further insights into potential differences in the content of students' responses to the different agent profiles. In inquiry-driven classrooms, teachers tended to use questions to elicit students' thinking, and students replied to teachers' elicitations, elaborated on their thinking, or offered argumentation [32]. In peer tutoring, rather than only focusing on providing explanations, students may also express emotions such as triumph, anger, and confusion around the learning problems [33]. They also pose provoking questions to their partners [34]. Thus, we may expect different discussion patterns with the agent profiles. Students may engage in more explanation and argumentation with the expert agent, while being open to brainstorming ideas when it comes to discussing with the peer agent.

In addition, embedding the agents in group discussion introduces an interesting dynamic, since students with different levels of prior domain knowledge may interact with each other and with the agents in varied ways. In mixed-ability groups, students with a higher level of domain knowledge tend to become the "mentors" who provide help and explanations to lower-ability students. In turn, the lower-ability peers can benefit from spontaneous help-seeking [17, 18]. We can thus explore whether high-ability students will dominate the conversations in interactions with the peer agent, or if other students will also see the agent as lower-ability and may engage in elaborative talk.

How can we analyze the content of student discussion to reveal differences in interactions between the agent profiles? Education researchers have focused on the types of argumentative discourse students make, vocabulary, conversational topics, and contributions to the group's discussion [35–37]. Researchers have also examined how several discussion moves can co-occur within the same conversational window to formulate the epistemic structure of the discussion [35]. Analyses of co-occurring moves can reveal key insights to compare the discussion structures between student groups and agent prototypes. Such analyses can explore questions such as: In which agent condition do students brainstorm ideas while responding to the agent more frequently?

3 Methodologies

This study presents a qualitative discourse analysis of students' discussion moves with one another and the conversational agents. The analyses focus on three purposefully sampled student groups of low, mixed, and high prior knowledge in science. The study applies ENA [38] to examine the differences between group compositions and agent conditions. The choice of ENA builds on understanding of collaboration and learning not as isolated cognitive elements, but the associations of those elements to form systemic understanding [38].

3.1 Study Setting

This research is situated in a high school environmental science programs called Marine Science Exploration (MSE). The program represents a multi-year partnership between a local state park, education and biology researchers, and local school districts in southwestern United States. The state park has been working for several years on a marine protected area to study how habitats respond to reduced human impacts.

Early in the curriculum (lesson 3 out of 8), students receive an introduction to the marine protected areas and are asked to brainstorm the elements and processes that may affect the marine habitats. In classroom observations of those lessons, the park educators and teachers noticed that not all students participated in the group discussion. Furthermore, students tended to get fixated on certain ideas and linear relationships, instead of thinking about more complex processes. The idea of a collaborative conversational agent came as a potential solution to improve students' conceptual understanding and participation.

3.2 Agent Design

Conceptual Nudges. The agent, nicknamed Kibot, can embed itself in student text-based discussion and provide nudges. Figure 1 presents examples of Kibot's dialogues. The nudges build on key aspects of scientific reasoning when learning about systems, namely Elements, Evidence, and Causal Coherence [39].

Element captures the components and processes in the ecosystem. The agent thus monitors and gives hints for students to consider key terms from organisms (e.g., fish, plankton), human activities (e.g., plastic pollution, fishing regulation), and processes (e.g., salinity). Evidence describes how students use data or observations to warrant their claims. Causal coherence, meanwhile, refers to whether students can use a coherent and logical chain of reasoning to connect observable concepts to scientific ideas.

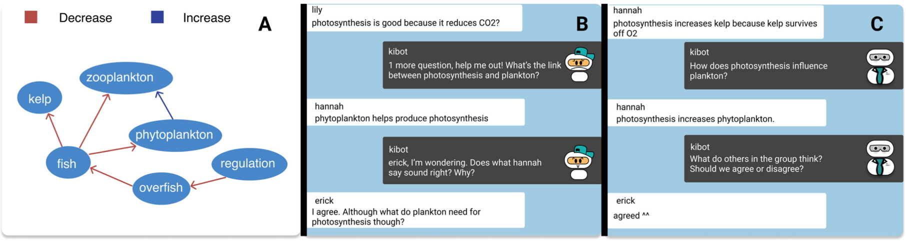

Fig. 1. Examples of co-constructed concept map (Panel A); the peer agent (B); and the expert agent (C). The agents send similar types of nudges, but their wording and expressions differ.

The pipeline for Kibot's causal coherence hints is as follows. The agent first applies the dependency parser from the Python's package "spaCy" [40] to segment students' chat into subjects and objects. For example, a sentence such as "fish are dangerous because it eats other fish" would yield a link between "fish" (the subject) and "other fish" (the object). As the students' conversation unfolds, the overlapping connections form a concept map of connected terms. Next, Kibot compares the students' concept map with an "expert" concept map. The expert map is created in three feedback sessions with four state park educators and six marine biology researchers. Kibot uses two algorithms to compare the student answers and the expert map: (1) Levenshtein-based string similarity to capture instances where students' answers closely resemble expert concepts, and (2) word embedding [40], where shorter distance between the respective word vectors for students and experts' answers serves as a proxy for higher similarity.

If there exists a missing link between a term that the students already mention and a term in the expert map, Kibot provides a hint, for example, "I see. **Does plankton [term students have mentioned] play any other roles in this system**?" After seven chat turns, if the students still have not mentioned the target missing term, Kibot provides more explicit prompts, for example, "I am wondering if **plankton [term students have mentioned] and photosynthesis [missing term]** can be linked in any ways?".

Finally, Evidence describes the extent to which students apply reasoning from scientific data or their own observations to back up their claims. The agent asks students to elaborate on their reasoning by explaining their ideas or whether they agree with statements from their peers. These nudges draw from research on transactive exchange where students build on prior ideas with reasoning and elaboration [5, 10]. To encourage equal participation, Kibot alternates between asking students to elaborate on a claim they just make and nudging those who have participated the least in the discussion.

Agent Design. The activity with the conversational agent takes place when students just watch an overview video of the marine protected areas (MPA) at the state park. In groups of two to three, students engage in a chat with each other and with the two Kibot prototypes. The goal of the chat is to build a concept map of the marine ecosystem and to reason through the connections in the map. The interaction order with the agents is randomized: Half of the student groups start with the peer agent, while the other half start with the expert agent, and switch halfway through the activity.

The Peer Agent. The agent is designed to resemble a peer with equivalent levels of knowledge, building on the similarity-attraction theory [23]. The peer agent is not presented as knowledgeable, but is learning from the chat. The agent eagerly participates in the discussion, often using colloquial expressions to ask the students to "explain" concepts in ways that benefit its learning. Similar to work in one-on-one tutoring [8, 14], the peer agent expresses emotions through changing its facial expressions, such as showing a frown when confused or a lightbulb when asking questions.

The Expert Agent. The expert agent, who showcases mastery of the content knowledge, generally speaks in a formal tone and does not use colloquial phrases [8]. Contrary to the peer agent that changes its expression, the expert agent keeps the same expression throughout its interactions with the students.

In sum, the agent prototypes (peer and expert agent) send the same conceptual nudges to students at similar frequencies. However, their design and vocabulary vary to give impressions of different levels of competence.

3.3 Participants

Participants were ninth grade students in two classes (51 students) taught by the same science teachers in a public high school in southwestern U.S. The school served a diverse student population that was majorly White and Hispanic/Latino in the 2019–20 school year. The students were participating in the MSE program during their science class time. The school had one-to-one laptop policy, and students were familiar with using chat windows to converse with one another. Because of social-distancing measures due to COVID-19, students were sitting far apart from each other and mostly used the chat interface to communicate with one another. Students had experiences with collaborative groupwork in their science class, but reported limited experiences with learning chatbots prior to the lessons.

Prior to seeing the agent interface or interacting with the agents in groups, all participants individually answered a pretest. The pretest aimed to capture students' science domain knowledge of the MPA. In the pretest, students answered three open-ended questions about the marine ecosystem and the role of regulation, e.g., "How do marine protected areas affect fish populations and other things in the ocean". Consistent with the curriculum's focus, student responses were scored as the sum of number of correct elements, correct causal relationships, and evidence. The scores were then rank ordered, and student groups were categorized as low-ability (all three students scored below average), mixed (at least one above average), and above-average (all above average). Using purposeful random sampling [41], the author randomly selected one group from each ability category. Group *Plankton* (low-ability) consisted of a female and two male students. Group *Fish* (mixed-ability) had three female students, and group *Whale* (high-ability) had one female and two male students.

3.4 Data Sources

The main data source came from the three groups' chat logs with the agents. Each chat per prototype (peer or expert) lasted 12.5 min on average, SD = 1.2 min (Group Plankton: 12 min with peer; 11 min with expert; Fish: 14 min with expert; 12 min with peer; Whale: 14 min with peer; 12 min with expert).

The unit of code was a single chat message (total N = 407 utterances; each group had 136 messages on average, SD = 23.5 messages). The messages went through two coding iterations. In the first iteration, the author used a priori codes for the types of contribution to group's knowledge building [19, 42]. Although there were other codes included in prior frameworks [19], such as emotion or making hypotheses, these codes had fewer than three occurrences each and were thus excluded from the final analyses. In the second iteration, the author conducted close reading of the group chats to devise emergent codes. An additional code (*Respond to Kibot*) emerged in this stage to note whether student's utterance was self-initiated or in response to the agent's nudges. Table 1 provides examples of the codes.

Table 1. Coding scheme for student discussion.

Code	Definition	Example
Claim	Statement links systems elements	Kelp provides habitat
Reasoning	Statement draws from pre-existing knowledge, scientific facts and data, or evidence in the lesson	Plastic pollution reduces fish population **because it contaminates their habitat**
Build on self	Statement draws on previous ideas a student has stated	A: Sea urchins increase kelp A: Sea urchins decrease kelp because they eat a lot of kelp
Build on friend	Statement draws on previous ideas that peers have stated	A: Plastic pollution should be banned B: Yes, because it harms the animals
Respond to Kibot	Statement in response to the agent's nudges	Kibot: What do you think, A? Do you agree or disagree? A: I agree because a ban should let fewer people into that area and there will be less overfishing

To establish reliability, the author and a research assistant separately coded 20% of the chat and showed substantial agreement with the original codes, Cohen's κ = .96. The author coded the rest of the data. Each chat message received a dichotomous code for whether the code was present (coded as 1) or not (coded as 0). This means that a message can receive more than one code if multiple discussion moves existed, for example, if the student built on friends' ideas while making claims.

3.5 Procedures

This study applied Epistemic Network Analysis (ENA) in the rENA package [43] to examine the co-occurrences of codes within a moving chat-window of three.

Discussion types were considered associated if they appeared in the same sliding text window (e.g., a window of size three measures co-occurrences within three consecutive texts).

In ENA, co-occurrences of discourse types formed a binary matrix (1: occur; 0: not occur). Then, the matrix was normalized and singular value decomposition (SVD) was applied to reduce the dimension of vectors to two dimensions that explained the most variance in the data. ENA allowed for visualizations of the discussion network for each group. Each code (e.g., claim, reasoning, respond to Kibot) became a node in the diagram, with lines indicating that the two nodes co-occurred within the chat windows. ENA also allowed for visualizing subtraction networks, that is, the differences between the epistemic networks for each condition per group. The visualization subtracted the connection weight of each node in the networks, and indicated larger connection between discourse types by showing thicker, darker lines.

To answer RQ1 about potential differences in students' interactions with the conversational agents between the low, mixed, and high ability groups, this study first ran ENA with students in groups as the unit of analyses over all utterances (i.e., both agent prototypes). Analyses plotted the subtraction networks for group pairs (e.g., low-mixed, mixed-high, high-low) to highlight differences between their discussion networks.

To answer RQ2 about how student's discussion may differ when interacting with the bot prototypes, the author conducted ENA within each group. Individual students' chat occurrences within group within conditions constituted the unit of analyses.

4 Results

4.1 Between-Group Differences in Discussion Networks

The first research question examines the extent to which group discussion networks varied with ability compositions. The author created subtraction networks (Fig. 2) and compared the connections between discussion types between groups. Each dot in the figure represents an individual student, and the colors denote the groups they belong to (i.e., black for Plankton, purple for Fish, and blue for Whale).

Overall, students in the higher-ability groups appeared to show more complex discussion moves. For example, when comparing groups Fish and Plankton (left panel, Fig. 2), the purple line in Fig. 2 suggests a link between *Reasoning* and *Building on friends' ideas*. This indicates that individuals in group Fish (the relatively higher ability group) showed more connections in these discussion moves. Similarly, the blue lines in the central and right panel (Fig. 2) shows that group Whale, the high-ability group, showed more connections between *Claims* and *Building on prior ideas* in comparison to the other two groups. To illustrate, consider the following excerpt from group Plankton (low).

Kibot: What would happen if kelp increases?
S1: Fish increase/zooplankton increase/phytoplankton increase.
S2. Pollution increases/fish increases.
S1: Global warming increases/water temperature increases.

Kibot: Why do you think so?

S3: When the temperature rises it affects the fish.

In this exchange, students were mostly making claims without providing reasoning for their answers. They also did not explicitly mention previous ideas to build on. In contrast, the following excerpt from group Whale illustrates how S5 built on his friend's idea ("regulation increases fish") to give explanations and inquired about a related relationship (breeding-fish).

Kibot: What would happen if regulation increases?

S4: Regulation increases fish.

S5: Regulation increases fish because it protects the fish from overfishing.

S5: Does breeding increase fish?

In sum, group comparisons reveal that students in higher-ability groups appeared to show more connection between making statements, reasoning, and engaging in transactive exchange, compared to the low-ability group.

4.2 Within-Group Differences in Interactions with Peer Versus Expert Agents

The observed differences in interactions between groups suggest that there may exist variation with group composition. The second research question explores these differences using another grain size: within-group shifts in interactions between the peer and expert agents. To answer this question, this study used ENA to compare the discussion networks between the two agent conditions for each group (Figs. 3, 4 and 5; red lines = more connections for expert agent; blue = peer agents).

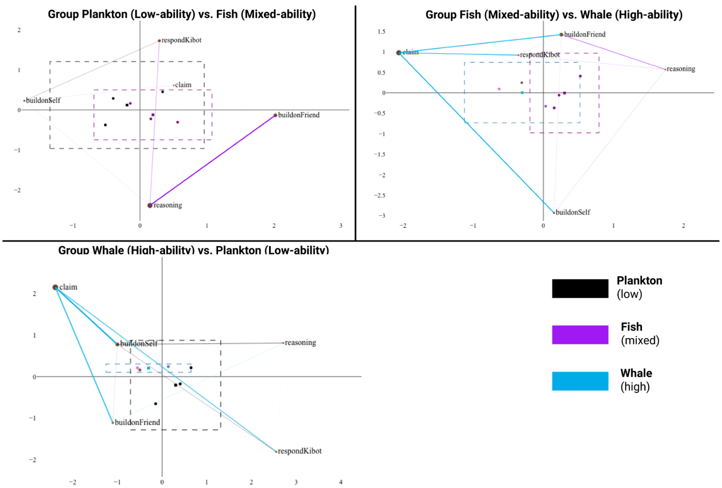

Fig. 2. Between-group comparisons (ENA subtraction networks) of the overall discussion in groups Plankton (low-ability; black), Fish (mixed ability; purple), and Whale (high-ability; blue). (Color figure online)

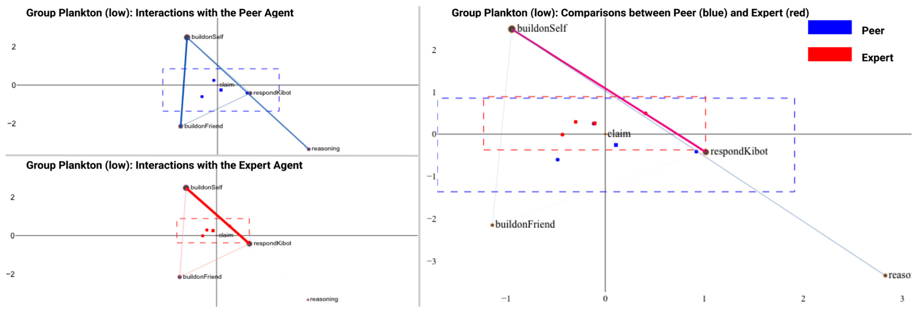

Fig. 3. Comparisons of group Plankton (low ability) between expert (red) and peer (blue) agents. (Color figure online)

Overall, the most noticeable difference between the peer and expert discussion networks for group Plankton (low ability) is the connection between *Build on self* and *Respond to Kibot* in the expert condition, compared to the peer condition (Fig. 3). While this group mostly stated simple claims, the students more frequently built on prior claims when responding to nudges from the expert agent than those from the peer agent.

Meanwhile, group Whale (high ability; Fig. 4) demonstrated more discussion connections in the peer condition, compared to the expert agent. Individuals in this group made more links between *Claim – Respond to Kibot; Claim – Build on self;* and *Respond to Kibot – Build on friends*, as highlighted by the blue lines for the peer condition. Take the following excerpt from group Whale as an example of code co-occurrences for *Respond to Kibot – Build on friends*:

S6: Regulation decreases plastic pollution.

Kibot (peer): Ah, regulation can reduce plastic pollution! S5, what other ways do human influence the ecosystem?

S4: Co2 emissions increase global warming.

S5: Other ways we influence the ocean ecosystem is burning of fossil fuels, so there should be regulation for that too.

In this excerpt, the peer agent was encouraging S5 to build on S6's idea around regulation. In response, S5 brought up another related concept ("fossil fuel burning") and linked the two ideas under the discussion on regulation.

Interestingly, group Fish (mixed ability; Fig. 5) showed mixed patterns in comparisons of the agent prototypes. Similar to group Whale, this group showed more connections between *Respond to Kibot – Build on friends* and *Respond to Kibot – Reasoning* in the peer condition. At the same time, individuals in this group showed more links between *Building on self – Building on friends* in the expert condition.

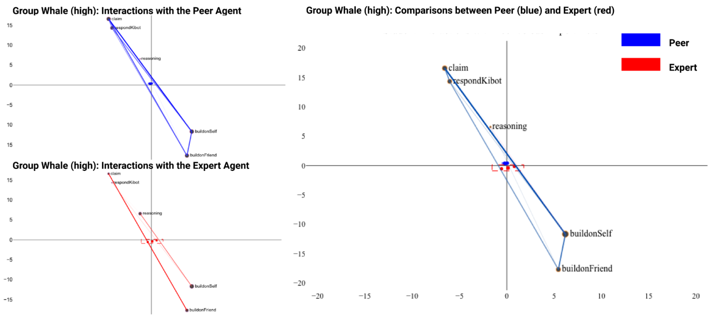

Fig. 4. Comparisons of group Whale (high ability) between expert (red) and peer (blue) agents. (Color figure online)

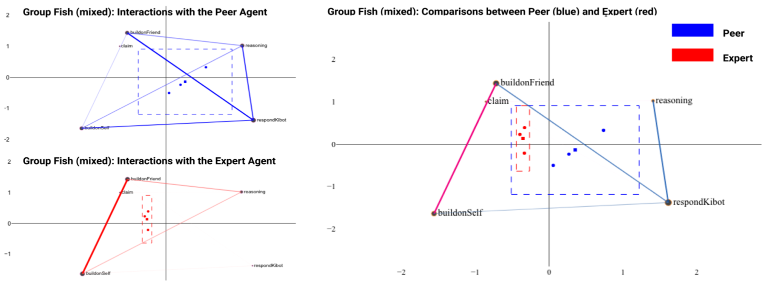

Fig. 5. Comparisons of group Fish (mixed ability) between expert (red) and peer (blue) agents. (Color figure online)

Notably, the coordinates of individual students within each condition (e.g., red dots for expert agent; blue for pee) were close to one another. This suggests that between-agent differences might have been driven by the group as a whole, instead of by an individual.

5 Discussion

5.1 Grouping Arrangements Show Different Discussion Patterns

This research examines ability grouping as one factor that may be associated with group interactions. Overall, students in the higher-ability groups showed more reasoning and claim-making, in combination with elaboration on prior ideas from the group. Transactive exchange, where students build on each other's knowledge to co-construct ideas, is a key principle in knowledge building [22]. Such exchange allows students to discuss the concepts at hand in depth to advance individual learning [22, 44, 45].

Finding of the different interactive patterns between the groups suggests the design need to provide further scaffolds on knowledge building for certain groups, instead of providing nudges at similar intervals across groups. Scaffolds can be reflective prompts that explicitly guide students to think about how they are putting their ideas together and present the group as a community [45]. These prompts may help students to focus on knowledge building goals and improve the quality of the group discussion [45].

Another direction is to provide prompts that adapt to the group's ongoing discourse. In this study, the agents gave conceptual hints that were adaptive to the groups' knowledge states, through comparing their ongoing concept maps with an underlying expert map. In addition, to emphasize equal participation, the agents constantly directed its nudges at less active participants. However, students' uptake of the nudges varied. It is possible that the agents' nudges were not opportune or sufficient to prompt the lower-ability groups to engage in other forms of discussion. Other systems have attempted to address this issue through using natural language processing to categorize students' chats and dynamically select the agents' messages from candidate talk moves [46, 47]. Prior work has compared the impact of such dynamic conversational systems among different age groups, including high school and college students [47]. Future empirical work can explore how these systems can support learners within the same classrooms or discussion groups.

5.2 Group Interactions Diverged with the Agent Designs

Findings around grouping arrangements warrant the need for investigating how student groups' exchange varies with agent designs. Both designs are assumed to elicit scientific discourse from students. Each agent's introductions frame students' role as an explainer (expert agent: "*I'm testing you. Show me what you know*"; peer agent: "*I'm here to learn with you.*"). Explicit framing of students' role discussion may encourage engagement and improved outcomes across ability groups [17].

Interestingly, the current study reveals that interactions with the two agent designs were not similar across groups with different ability compositions. Students in the low-ability group more frequently provided reasoning when responding to the expert version. Meanwhile, those in the high-ability groups engaged in more transactive exchange with the peer agent. These findings overlap with hypotheses around student-agent interactions in one-on-one tutoring systems [13]. Students with higher levels of understanding may engage in deeper elaboration of ideas when they are trying to provide help for a peer agent, and those with emergent domain knowledge may more frequently respond to the nudges from the expert agent.

Analyses of data from the mixed-ability group suggest that these patterns were likely taken up by the group. This means that the lower-ability students in this group also became explainers to the peer agent. Thus, combining the peer and expert agents may result in a richer set of discussion patterns in the mixed ability group. A follow-up analysis can follow a larger sample of heterogeneous ability groups, to explore which types of social dynamics may support shared interaction norms.

6 Conclusions

Prior work has explored design paradigms in learning exchange between individual students and conversational agents [8, 14, 15]. Interactions likely diverge in group settings, where individuals are influenced by the participation norms from others in the group. The current study illustrates how interactions are embedded within social structures such as ability composition. Analyses suggest the affordances of ENA in comparing group interactions across dimensions of group compositions and agent designs.

A limitation to the current research is that it only presents a small sample of cases. Future research can examine whether these patterns exist in a larger sample, particularly in groups with mixed ability. Iterations of this work will apply other research designs, such as between-subject designs, to examine the pathway between varied group interactions and student learning. These analyses can also account for variables such as students' gender, social status, and participation tendency.

In addition, student interactions with the conversational agents were brief because they were constrained within one class period. A direction for future exploration is to track how the observed interactive patterns evolve over time, as students gain more exposure to the agents' nudges. Another direction is to examine whether students transfer the discussion moves to another task without the appearance of the agents.

Finally, the current research focuses on students' ability (as indicated by prior understanding of element, evidence, and causal links within systems). Future work can explore other dimensions that may influence student learning, such as different preferences for engagement in collaborative work.

Overall, this study reveals interaction dynamics when collaborative agents are embedded in group discussion. The patterns that this research uncovers broaden the design space for learning systems. They also suggest the learning moments that facilitators (whether teachers or conversational agents) may consider to develop appropriate support for productive discourse and subsequent learning.

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