Co-Designing AI Agents to Support Social Connectedness Among Online Learners: Functionalities, Social Characteristics, and Ethical Challenges

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ABSTRACT

Due to the lack of face-to-face interactions, online learners frequently experience social isolation that negatively impacts students' well-being and learning experiences. Many text-based AI agents have been equipped with different social characteristics and functionalities to support people who are socially isolated. However, the design of agent's functionalities, social characteristics, and ethical challenges in promoting social connectedness among online learners are underexplored. Taking a co-design approach, we included 23 online learners enrolled in an online for-degree graduate program as active participants in two virtual co-design workshop studies. Through four different co-design activities, we identified online learners' preferences for AI agent's functionalities and social characteristics in promoting their social connectedness as well as potential ethical concerns. Based on our findings, we establish the role of AI agent as a facilitator to continuously scaffold online learners' social connection process. We further discuss the unique ethical challenges regarding agent-mediated social interaction in online learning.

CCS CONCEPTS

• **Human-centered computing** → **Empirical studies in HCI**; **Empirical studies in interaction design**; **Natural language interfaces**.

KEYWORDS

co-design; AI agent; online learning; social isolation; artificial intelligence; AI ethics; AI-mediated social interaction

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1 INTRODUCTION

With the growing demand for online for-degree programs across universities and colleges, online learning has become critical in shaping the landscape of higher education. However, due to the geographical and spatial disconnects, online learners have very few opportunities to directly interact with other students, which has resulted in many online learners feeling socially isolated and alone in their education journey [31, 50, 62, 73]. Frequent feelings of social isolation put online learners at a much higher risk for anxiety, depression, and withdrawal from the courses or even the online program [3, 50]. On the other hand, improving students' feelings of "social connectedness" [50], could encourage students' social belongingness, deeper learning process, and increase student retention rate [3, 50, 53].

However, adult online learners in higher education face a number of difficulties when attempting to build social connections with other students [31, 62, 72]. For example, while establishing strong social ties with others is highly desired [62, 72], online learners often juggle between their education, full-time jobs, and caring responsibilities, leaving them with limited bandwidth to invest in building social connections with other students [31, 62, 73]. Each online class typically has hundreds, if not thousands, of students enrolled. Identifying students with shared interests, background, or goals is more or less equivalent to finding a needle in a haystack—online learners would need to search through walls of texts on the discussion forums or chat groups to identify students that they want to connect with [62, 72]. Without the random run-ins or spontaneous hangouts with other students on campus, the online environment presents a social-technical gap during interactions [1, 72] that makes it more difficult and less motivating for online students to build social connections with each other [72].

Considering these challenges online learners encountered in remote social interaction, Artificially Intelligent (AI) agents [1] offer great potential in supporting online learners' social connectedness. AI agents have been widely employed in online learning context to sieve through large amounts of information to provide personalized learning resources [26, 28], class logistic information [22], and social information [72, 73] to students 24/7. Comparing to recommender systems that often operate on digital platforms [40] (e.g., shopping recommendations on Amazon), AI agents possess human-like features such as personality and natural language generation that can potentially bring spontaneity and randomness to online

[1]Unless indicated otherwise, in this paper, we use AI agents to refer specifically to disembodied, text-based AI agents.

interactions [1, 36, 72]. In fact, an increasing number of applications are already using AI agents to help members of a community connect— Slack applications such as *Donut* and *GreetBot* all use AI agents to promote social interactions within the Slack groups. AI agents are also widely used to deliver encouragement, care, and positive energy to people experiencing loneliness and social isolation [14, 33, 51]. However, the design requirements of AI agents that can support online learners' social connectedness is underexplored.

There are two crucial design factors to consider when designing AI agents in a specific context: their *functionalities* and their *social characteristics*. Functionality refers to what the AI agents can do to provide support. For example, AI agents have been designed with functionalities like offering well-being advice [33], facilitating therapy [20], or mediating social interactions [72] to provide support. Social characteristic refers to characteristics that determine the agent's social skills [9]. For example, AI agents can be empathetic [15, 18] or human-like [64] during interactions. Understanding the desired functionalities and social characteristics of the AI agent will help determine the specific design requirements of AI agents that can help online learners feel more socially connected.

Before we insert an AI agent into an online learning environment that could have irretrievable and immeasurable impact on online learners' lives, we have to consider the potential social and ethical concerns. To provide timely and personalized support, advanced AI techniques are being integrated into AI agents to detect users' emotional and mental states through analyzing user dialogues or social media [35, 46]. In online learning, there have been a plethora of AI technologies designed, developed, and implemented by leveraging the readily available data generated by online learners. Many such technologies, claiming to be developed with the goal of advancing online learners' learning experiences and outcomes, often harvest and monitor large amounts of student data, ranging from demographic information to students' social media posts, **yet have hardly engaged online learners in any of the technology design or development process.** Given the unequal power relationship [58] between online learners and institutions, online learners have little say, or even awareness, of the large-scale collection and analysis of their data [58, 59].

With the goal of designing user-centered and socially responsible AI technology that could help promote online learners' social connectedness, we take the approach of co-design [52, 54] to include online learners as active participants from the beginning of the design process. Co-design has been frequently adopted in prior literature to understand the design of AI agents across various contexts [10, 21, 48]. Through two co-design workshop studies with 23 online learners, we provide the necessary design techniques and tools for online learners to voice their preferences and concerns freely to envision a future where AI agents could help support their social connectedness. Through these co-design workshops, we seek to explore three research questions:

RQ 1: What functionalities should an AI agent possess to help online learners feel socially connected?
RQ 2: What social characteristics should an AI agent have to help online learners feel socially connected?
RQ 3: What are the potential social and ethical challenges of agent-mediated social interaction in online learning?

In this paper, we present and discuss design implications and ethical challenges of AI agents that could help promote social connectedness among online learners. We describe two virtual co-design workshops consisting of four design activities used to understand online learners' preferences of AI agents' functionalities and social characteristics. We also briefly present an AI agent mockup designed to elicit perceived social and ethical challenges of agent-mediated social interaction. Based on online learners' design preferences and concerns, we establish AI agents' roles as facilitators to scaffold online learners' social interaction process and discuss social and ethical implications of agent-mediated social interaction in online learning.

The contribution of our work is three-fold. First, we contribute a set of design implications of the functionalities and social characteristics of AI agents that could promote social connectedness from online learners' perspectives; second, taking into account online learners' preferred functionalities and social characteristics of AI agents, we establish the role of AI agents as facilitators and propose the future direction of designing agent-mediated social interaction in online learning to promote social connectedness among online learners; third, considering online learners' perceived concerns of agent-mediated social interaction, we discuss implications on designing socially responsible AI that could mitigate social and ethical concerns of agent-mediated social interaction.

Privacy, Ethics, and Disclosure. We are committed to ensure the privacy of students' data used in this study. This study was approved by the Institutional Review Board (IRB) at the researchers' institution. The demographic information, workshop video recordings, and design artifacts created by online students during the workshop were collected upon student consent and later anonymized. We offered extra credits to students participated in our studies. These extra credits could be earned in other ways in the standard class structure and the extra credits students earned through participation in our study was less than 1% of total grade. This work was in collaboration with the class instructor and proper measures were taken to avoid coercion. We clarified to the students that their participation in our studies would not be shared with the instructor and would not have any impact on their grades.

2 RELATED WORK

In this section, we review existing work on the design of functionalities and social characteristics of AI agents that can provide social support to people in need. We then discuss the social and ethical concerns that have been raised regarding the use of AI technology in online learning contexts.

2.1 AI Agents for Social Support: Functionalities and Social Characteristics

Prior research has investigated the design of AI agent functionalities to provide social support to people in need across a variety of settings. For instance, AI agents can provide everyday companionship, emotional, and informational support to users during crisis and stressful events [57, 65], give health advice and well-being counseling to mental health patients and older adults [18, 33, 68], deliver self-help programs to young adults with depression and anxiety [20], and facilitate positive messages within social groups [45].

With the advancement of AI techniques, AI agents are now capable of inferring people's social needs and initiate interactions with users accordingly through emotion recognition [51, 64] and social media posts analysis [43, 70].

Besides the variety of functionalities AI agents could adopt to deliver social support, AI agents' social characteristics is also a crucial factor that determines the effectiveness of care and the quality of user experience [9]. Prior work has shown that when AI agents are designed with social characteristics such as empathy [14, 18, 65, 68], reciprocal self-disclosure [37, 44], proactiveness in initiating conversations with the users [33, 69], positive personalities [19, 33], the agents are more effective at reducing people's stress and mitigate negative mood [14, 65]. However, when social characteristics [9] are incorrectly implemented, AI agents could unintentionally lay emotional burden and elicit negative feelings in users who are already emotionally vulnerable [12, 47]. For example, prior research has suggested that AI agents' biased or judgemental language could discourage self-disclosure from sexual assault survivors [47]; when AI agents display highly human-like characteristics such as animated avatar [12], or emotion and context awareness [65, 76], they can elicit strong negative feelings or eeriness on users (also known as the "uncanny valley" effect) [12, 65].

Designing AI agents that interact with emotionally vulnerable populations could have huge consequences on users' wellbeing—AI agents could display functionalities and social characteristics that either mitigate users' negative emotional states [20, 45] or add on to users' emotional burden [9, 41, 81]. It is thus critical to understand the desired functionalities and social characteristics of the AI agents from target user populations. Current study thus seeks to understand online learners' preferences on the functionalities and social characteristics of AI agents that could help online learners feel socially connected.

2.2 Social and Ethical Concerns of AI Technology in Online Learning

The use of AI technology is no stranger to online learning— prominent fields such as Learning Analytics and Educational Data Mining have successfully collected and analyzed online learners' digital footprints with the purpose of understanding and enhancing students' learning outcomes and environments [16, 56]. With all the learning activities happening on digital platforms, much of online students' data are readily available— researchers have been able to collect online learners' clickstream data [23, 38, 82], educational records [27, 71], demographics [25, 34], online discussion posts [7, 30, 75, 80], even facial expressions and physiological data [74, 82] in order to analyze and enhance students' learning process. Based on these data, researchers were able to predict online students' learning performance [16], provide decision support for teachers and learners [2, 16, 74], detect students' behavioral patterns [16, 71], and predicting dropouts [7, 16].

While there are many benefits in using AI to advance online students' learning, ethical concerns have been raised regarding the large-scale of data collection, monitoring, and analytics on students' data through AI [58, 61, 74]. Privacy is among the top ethical concerns given that most online students are probably not aware of the extent their data is being collected and analyzed [58]. Since most of the student data are automatically recorded by the online learning platforms, students have limited freedom in controlling what data gets collected [58, 59]. Even if students were given control over data sharing, prior research suggests that for students, the perceived benefit of improving their learning outcomes often outweigh the cost of sacrificing their data [58]. Combining this cost-benefit analysis with students' high levels of trust in giving their data to schools [61, 74], researchers have cast doubt on commonly proposed solutions to protect students' privacy such as informed consent and terms and conditions [58].

Besides privacy concerns, scholars have also brought up issues with the interpretation and validity of learning analytics results [58]. Learning analytics researchers have admitted the difficulty in providing valid interpretation of students' learning behaviors due to incomprehensive data [58, 77]. The transient nature of students' identities also frequently renders the AI inferences outdated and invalid [58]. Misinterpretation of students' learning analytics data often results in misdirected learning intervention which counters the goal of enhancing students' learning experiences [58].

We note that almost all of these concerns regarding the use of AI in online learning center around data collection and analysis with the purpose of improving students' learning. When students' data are being collected and analyzed by AI for social purposes, a different set of ethical and social concerns could surface. For example, prior social media research has shown that people carefully manage their social images online [29, 66] and more scrutiny is required when making social and emotional inferences based on people's online footprints [8]. Additional concerns could also be raised when AI-powered agents are used to collect and analyze student data for social purposes given that AI agents, comparing to humans, are more effective in eliciting private and sensitive personal information (e.g., credit card information [63]) from the users during interactions [47, 63, 79]. The present study thus seeks to understand the potential social and ethical challenges of using AI agents to help online learners feel socially connected.

3 STUDY OVERVIEW

To explore the design requirements and potential challenges of using AI agents to help online learners feel socially connected, we conducted two virtual co-design workshop studies using the visual collaboration tool *MURAL* and the virtual meeting platform *BlueJeans*. We adopted the virtual workshop format due to the geographical spread of online learners all over the world as well as the ongoing COVID-19 global pandemic during data collection.

Each co-design workshop study consisted of three workshop sessions with three different sets of participants. We first conducted co-design workshop study 1 to understand the functionalities of the AI agent desired by the students (RQ1). In particular, we conducted two design activities in study 1: persona creation and storyboarding. We then analyzed the data collected from study 1 to identify desired functionalities of the AI agent, which acted as the basis of the AI agent mockup that we created to probe for potential ethical challenges of agent-mediated social interaction in study 2.

We created the AI agent mockup to showcase one possible version of an AI agent that could help online learners feel socially connected. The AI agent was named SAMI (stands for Social Agent

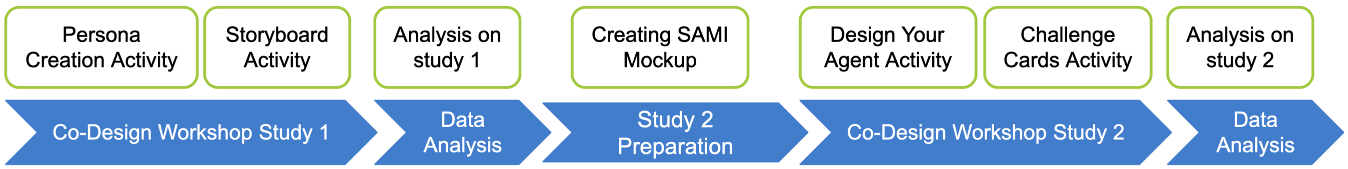


Figure 1: Study flow diagram that shows the different stages of our study and the components of each stage.

Mediated Interaction) and the mockup was created in a storyboard format for easier comprehension of SAMI's functionalities. We emphasized on agent functionalities in the mockup because we want to make the mockup simple enough for participants to envision future agent-mediated social interaction creatively in order to come up with a wide variety of ethical and social concerns in study 2.

We then conducted study 2 to understand the desired social characteristics of the AI agent (RQ2) and the potential social and ethical challenges of agent-mediated social interaction in online learning (RQ3). In study 2, we explored the desired social characteristics of the AI agent through the design activity "Design Your Agent." We then introduced the SAMI mockup and used it as a probe to elicit students' perceived social and ethical challenges of using AI agents to facilitate online learners' social interaction process through the second design activity "Challenge Cards". During the activity, we emphasized that SAMI only showcased basic functionalities that AI agents could have and that students are encouraged to envision extra functionalities or even social characteristics that SAMI could have when considering possible social and ethical challenges of agent-mediated social interaction. Figure 1 shows the overall flow of our study.

3.1 Study Context

Both studies took place at Georgia Tech's Online Master of Science in Computer Science (OMSCS) program. The program currently has thousands of students enrolled, with around 35% international students coming from 100+ countries all over the world. The size of each class varies from 200-1000 students. The average age of a student starting at this program is 32 and the gender ratio of men to women in the program is roughly 8:2. Many students enrolled in this program are working through their degree part-time while working full-time jobs. Student typically enroll in this program for career shift and career advancement. Thus, a lot of the students in the program (around 70%) do not have a computer science degree but most have some level of programming experience.

3.2 Participant and Recruitment

Our participants were recruited from three classes in the OMSCS program. A screening survey was posted on the discussion forum in each class to collect demographic information about potential participants. We then formed our potential participant pool (313 online students) based on students' willingness to participate in our study through the screening survey. We then reached out to students in the participant pool randomly to confirm their availability and schedule workshop sessions. We formed each set of participants (4-5 people) for each workshop session by balancing their gender and seniority in the program. While our original plan for study 1 was to have four participants per session so that we have two teams for the team activity in each session, there were one no-show in session 1 and session 2 each that resulted in one team of three in those sessions (as seen in Table 1). We thus decided to recruit five participants per session for the rest of our studies, as reflected in session 3 in Study 1 and all sessions in Study 2.

When recruiting participants for study 2, we invited some participants from study 1 back due to their familiarity with our study. Both P6 and P10 accepted our invite and participated in two separate study 2 sessions.

4 CO-DESIGN WORKSHOP STUDY 1: DESIRED AGENT FUNCTIONALITIES

To understand the desired functionalities of AI agents that can help online learners feel socially connected (RQ1), we conducted the virtual co-design workshop study 1 with three sets of participants. The participant information of study 1 can be found in Table 1.

4.1 Study 1 Procedure

We began each study 1 workshop session with an introduction of the goal of the co-design workshop— to gain design implication of an AI agent that can help online learners feel more socially connected. We then introduced the agenda of the workshop session: self-introduction and ice-breaker, followed by **two design activities persona creation and storyboarding**, and concluded with a debriefing and further discussion. The worksheet used in study 1 can be found here.

The first design activity **persona creation** aimed at helping online learners to communicate and share their current social experiences with us and other workshop participants. We first introduced participants to the concept of persona and offered some examples of persona taken from the web that focused on different design questions than current study (e.g., persona used to design website that can help travelers plan for their business trips). After students were familiar with the concept of persona, we provided a persona template and asked each participant to work on a persona of an online student, detailing the student's basic information, as well as his or her goals, frustration, and motivation in social interactions in online learning program. Participants were encouraged to draw on their own experience as online learners as well as other online learners' experiences that they knew of. Participants then presented their persona to the rest of the group.

The second design activity was **storyboarding**. The goal of storyboarding was to give students the method and tools to map out their desired version of an AI agent that could help online students

Table 1: Co-design workshop study 1 participant information. "M" stands for "Male", "F" stands for "Female". The "# of Classes Completed" column indicates student's seniority in the program. Online students in the program usually take 1 to 2 classes per semester. The storyboard activity is a team activity and thus the "Team" column reflects the team composition at each study 1 session for the storyboard activity.

Study 1 Sessions	Team	ID	Gender	Age	Country (Born)	# of Classes Completed
Session 1	T1	P1	M	24	India	2
		P2	F	25	United States	1
		P3	F	26	Poland	1
Session 2	T2	P4	F	24	South Korea	5
		P5	F	25	United States	1
		P6	M	28	United States	1
Session 3	T3	P7	M	29	India	7
		P9	F	27	United States	2
		P10	M	29	United States	4
	T4	P8	M	31	England	4
		P11	F	27	United States	6

feel socially connected. Similar to the persona creation activity, we first introduced the concept of storyboarding and provided several storyboard examples taken from existing publications on teens' creation of social robot [6] and other creative ideas of robot design [42] to demonstrate the wide range of storyboards of different sophistication, creativity, details, and functionalities. We then divided the participants into teams and put them into breakout rooms on the virtual meeting platform. The team composition can be found in Table 1. To help participants navigate through the storyboarding activity, we first asked each team to create a story outline following the prompt questions that were given. The prompt questions were created by us to help the team think through the interaction process with an emphasis on the AI agent's functionalities. The prompt questions were in the following order: "What makes the agent talk to you?", "How does the agent talk to you", "Where does this interaction happen?", "How does this interaction make you feel?", "Are there any actions that you or the agent need to perform outside of this interaction?", "When is the interaction over?", "What do you do after the interaction?", "How do you feel after the interaction?", "What makes the agent talk to you again?" After each team mapped out a story outline, they then proceeded to create their own storyboard on a storyboarding tool called StoryboardThat.com. We chose this tool due to its wide selection of pre-drawn scenario settings and characters, as well as its flexibility of adjusting characters facial expressions and postures. We asked each team to pay attention to these details and pick a character to represent the AI agent in their storyboard (e.g., agent could be represented as an animal, a stickie figure, or many other available options) for us to get a better understanding of their expectation of the agent. Each team then presented their storyboards to the others at the workshop for further comments and discussions. We illustrate two examples of the storybaords created by Teams T3 and T4 in Fig. 2, and discuss the study 1 findings below.

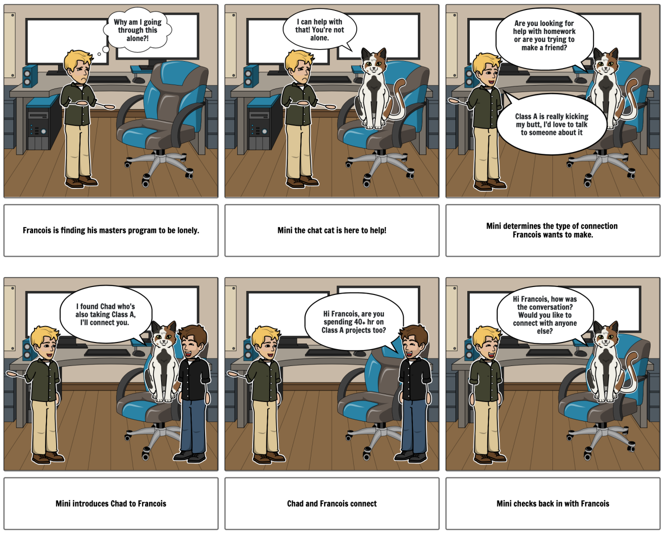
4.2 Study 1 Data Analysis

The data we collected and analyzed included the video recordings of all three co-design workshop sessions from study 1 as well as all the artifacts created by the participants during each workshop session in study 1, i.e., the personas, the storyboard outlines, and the storyboards.

We took an iterative and inductive approach to look at the study 1 data in two rounds of analysis. In the first round, two researchers divided up the three workshop sessions to independently review data from each workshop session. During the independent review, each researcher wrote down detailed notes on what happened during each workshop session as well as important and interesting points students made during each session. After the two researchers finished reviewing the sessions assigned to them, the two researchers together used affinity diagram to map out the detailed insights and distilled patterns and themes on a virtual collaboration whiteboard tool called *Miro*. Affinity diagramming is a bottom-up approach to organize qualitative findings in an iterative and inductive fashion. Affinity diagramming is commonly used to analyze qualitative data generated from co-design studies in prior research [5, 78]. After several iterations and discussions, we ended up with four themes and eight categories. In the second round of analysis, the two researchers switched the workshop sessions to review all data from each workshop session in similar fashion in the first round of analysis. Then the researchers came together again and continued to group and organize new insights into the categories and themes distilled from the first round of analysis. After some iteration and reorganization, we ended up with six categories and three themes.

4.3 Study 1 Findings: Desired AI Agent Functionalities

4.3.1 Online Learners' Social Connection Goals and Frustrations. To explore how AI agents could help online learners feel more socially connected, we first examined online learners' social connection



(a) Storyboard created by Team T3.

(b) Storyboard created by Team T4.

Figure 2: Two examples of the storyboard created by the co-design workshop participants.

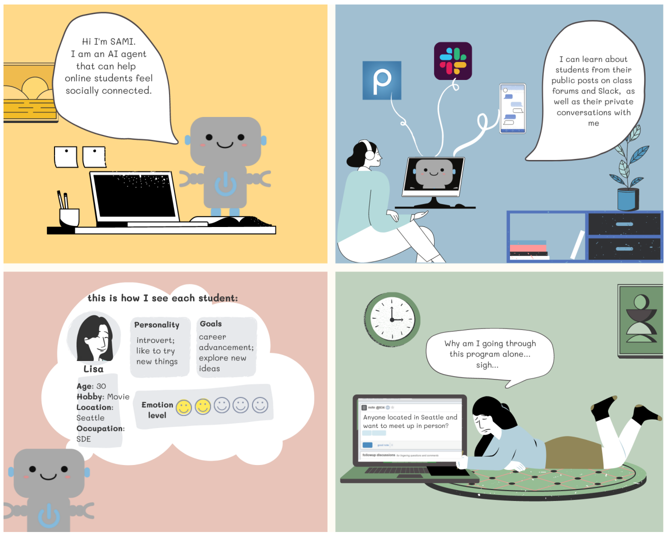
goals and frustrations through the persona artifacts the participants created. We identified two social connection goals that were commonly shared among the workshop participants: to build long-lasting connections beyond classes (P2, P6-P9, P11) and to build connections with like-minded students who share similar interests or in similar situations (P1-P3, P5, P6). Specifically, participants revealed their desire to make friends with other online learners (P6, P7, P9), to build their professional network (P4-P6, P8-P10), and to find people who could share their online learning experiences and struggles (P7, P9-P11). However, online learners encountered a number of obstacles attempting to achieve these goals. They found it difficult and awkward to reach out to other students that they didn't know of (P5, P7, P9-P11). In the online learning program that often had hundreds and even thousands of students per class, online learners found it difficult and time-consuming to identify students that they wanted to connect with (P1-P4, P7, P11).

4.3.2 In-Situ Agent-Mediated Social Support through Continuous Monitoring. Participants suggested that the AI agent should "know when" to connect the student with others— identifying the right time that students would want to talk to someone. For example, in the storyboards participants created, the agent would reach out to the student and try to connect him/her with others when the agent noticed that the student was feeling down (T1) or when the student's discussion forum activity was lower then usual (T2).

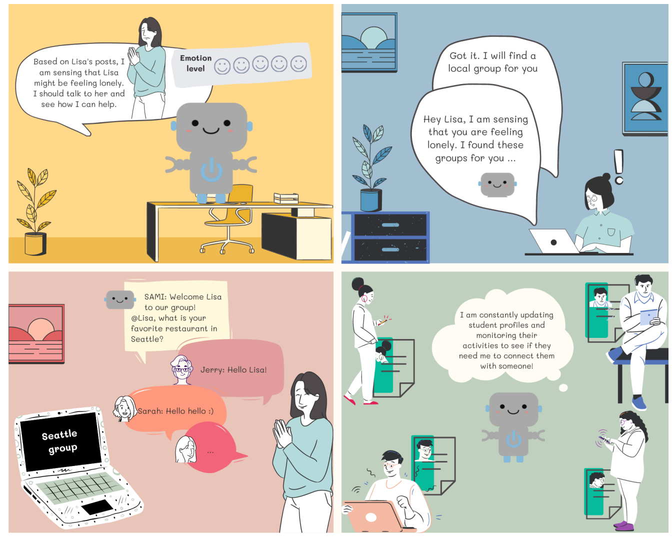
For AI agents to conduct in-situ agent-mediated social support, participants admitted that the agents would need to continuously infer and monitor online students' activities within the program. To reach out to students at the right time, participants suggested that the AI agent could monitor students' learning behaviors to look for signs of frustration (T1), monitor the discussion forum activity (T2), monitor when the student log on to learning modules (T3), or even keep track of other online students' availability so that the agent could connect them with students in need (T4).

Another factor that stood out to us was the long-term and continuous nature of the agent-mediated social support demonstrated by the participants in their storyboards. All the AI agents in the storyboards interacted with the student on a continuous basis instead of a one-time interaction. For instance, both T2 and T3 said that they would want their agents to reach out to the students at the beginning of every semester or every new class. T1 and T3's agents also would check back with the students on their interactions with other students introduced by the agents.

4.3.3 Scaffolding Remote Social Interactions. Based on the storyboards participants created, we found that the AI agents were often used to scaffold online learners' remote social interaction process. As we pointed out in the prior section that online learners encounter several obstacles during remote social interaction: the difficulty to identify like-minded students and the awkwardness to reach out to students that they don't know. To mitigate these obstacles, in their storyboards, online learners often designed the AI agents to scaffold their social interaction process through identifying and introducing online learners together based on certain criteria. For example, the agents in T1, T3, and T4's storyboards all presented the same functionalities: identified other online learners that the student would want to build social connections with (e.g., taking the same class), introduced both students together, then disappear from the conversations to let the students communicate amongst themselves. This scaffolding functionality was explicitly called out in T4's storyboard (Figure 2), in which the AI agent was represented as a security blanket, a comfort and transitional object that a young child might hold on to. In T4's storyboard, the student "holds on" to the AI agent when they felt socially isolated but eventually "grew out of" the AI agent after the agent helped the student feel socially connected by introducing others to the student.



(a) Part 1.



(b) Part 2.

Figure 3: SAMI mockup in storyboard format.

5 DESIGNING SAMI MOCKUP

Based on the study 1 findings, we concluded that the agent should help online students identify other like-minded students to connect, offer continuous support to online students’ changing social needs, initiate interaction with online students at the right time, and scaffold online students’ social interaction process throughout.

Building upon these desired AI agent functionalities, we built an AI agent mockup, shown in Figure 3, that could help online learners feel more socially connected on Canva. In this mockup, we showed an AI agent named SAMI (stands for Social Agent Mediated Interactions) that could mediate the social interaction process among online learners. In our mockup, we demonstrated SAMI’s ability to constantly monitor online learners’ online activities within the program to understand each student’s demographic information, personality, goals, their emotion levels, etc.. SAMI could initiate interaction with the student when SAMI felt a student was feeling lonely or isolated. SAMI could reach out to the student and asked about his/her preferences in getting social matches. SAMI would then introduce the student to a group of like-minded online learners. Throughout the interaction, SAMI was able to understand students’ comments and questions and respond with natural language accordingly. SAMI continuously learned about each student’s preferences and needs and reached out to them when needed.

6 CO-DESIGN WORKSHOP STUDY 2: SOCIAL CHARACTERISTICS AND ETHICAL CONCERNS

The co-design workshop study 2 aims at exploring the desired AI agent social characteristics (RQ2) and understanding students’ perceived ethical concerns of using AI agents to improve their social connectedness (RQ3). We explored these two research questions through two co-design activities: “Design Your Agent” and “Challenge Cards” with three sets of participants (shown in Table 2).

6.1 Study 2 Procedure

Similar to study 1, we began each study 2 session by introducing the goal of the co-design workshop sessions— to understand the design requirements as well as the potential social and ethical challenges of an AI agent that can promote social connectedness among online learners. The agenda of each study 2 session included self-introduction and a short ice breaker activity, followed by **two design activities: “Design Your Agent” and “Challenge Cards”**, and ended with a short debriefing and discussion. The worksheet we used for co-design workshop study 2 can be found here.

The goal of the first design activity **“Design Your Agent”** was to understand online learners’ preferences about the social characteristics of AI agents. In this activity, we presented to the workshop participants with five different AI agent dialogues taken and adapted from the existing literature [15, 32, 37, 46, 60]. These dialogues are shown in Figure 4. We chose these agent dialogues because these AI agents possessed a variety of functionalities and social characteristics that are closely related to our vision of an AI agent that could promote social connectedness. We expected the participants to observe and discuss common social characteristics exhibited by social support AI agents such as personalities, ways of communication, use of emoji, avatar, conversation topics. However, participants might miss some agent social characteristics presented in the dialogues given that no general guidance were provided. In this activity, we asked the participants to discuss together and write down what they liked and disliked about each AI agent’s social characteristics through reading the dialogues. After the participants finished discussion on all five agent dialogues, we asked them to draw on their preferences of these agents and write down characteristics or features that the AI agent should definitely have or not have to help them feel more socially connected.

The second design activity is called **“Challenge Cards”** [24] where participants brainstormed the potential challenges and the

Table 2: Co-design workshop study 2 participant information. "M" stands for "Male", "F" stands for "Female". The "# of Classes Completed" column indicates student's seniority in the program. Online students in the program usually take 1 to 2 classes per semester. The "Challenge Cards" activity is a team activity that consists of challenge teams and solution teams. The "Team" column reflects the team composition at each study 2 session for the "Challenge Cards" activity.

Study 2 Sessions	Team	ID	Gender	Age	Country (Born)	# of Classes Completed
Session 1	T5 (Solution)	P12	F	25	United States	3
		P13	M	23	United States	8
		P6	M	28	United States	1
	T6 (Challenge)	P14	M	24	United States	2
		P15	F	26	United States	3
Session 2	T7 (Solution)	P16	M	40	Republic of Panama	8
		P19	M	31	India	2
	T8 (Challenge)	P17	F	23	United States	1
		P18	F	35	United States	2
Session 3	T9 (Solution)	P20	M	28	Russia	2
		P22	M	52	United States	3
		P23	F	24	United States	1
	T10 (Challenge)	P21	F	26	Bosnia and Herzegovina	2
		P10	M	29	United States	4

corresponding solutions to one possible version of the AI agent that could help them feel more socially connected. In this activity, we used the SAMI mockup as a probe to elicit participants' reactions and thoughts. We first showed the SAMI mockup storyboard to the participants. We emphasized that the examples in the SAMI mockup storyboard only demonstrated SAMI's basic functionalities and that during the activity students could add extra functionalities or even social characteristics to SAMI's existing features. We then divided the participants into two teams, the challenge team and the solution team (see Table 2). This design activity began with a 15-minute private brainstorming session for each team in their own breakout rooms: the challenge team brainstormed all potential concerns and challenges that SAMI might elicit and the solution team brainstormed all the benefits and desired features that SAMI had. After the separate brainstorming sessions, the participants all came back together to the main virtual meeting room and began several rounds of competitions. For each round of competition, the challenge team first posted a challenge card with one potential concerns or challenge of SAMI from their brainstorming session. The solution team then tried to come up with a solution to that challenge card, drawing upon the desired features of SAMI that they came up with in their brainstorming sessions. At the end of each round of competition, the workshop facilitator came up with follow-up questions to dive deeper into the reasoning behind those challenges and solutions that participants came up with.

6.2 Study 2 Data Analysis

The data we collected and analyzed included the video recordings of all three co-design workshop sessions from study 2 as well as all the artifacts created by the participants in study 2, including their notes on the likes and dislikes of the agent dialogues, preferred social characteristics of the AI agent to promote social connectedness, brainstorming notes from the challenge team and the solution team, as well as the challenge cards and solution cards during the challenge cards competition.

Our data analysis process for study 2 data is the same as our study 1 data analysis process. We conducted two rounds of data analysis. In the first round, two researchers divided up the co-design session materials and conducted independent review, then came together and used affinity diagrams to map out insights and distilled patterns. At the end of the first round, we had three categories and eight themes. In the second round, the two researchers swapped the workshop sessions for further independent review, and then came together to group and organize new insights. We ended up with two categories and six themes.

6.3 Study 2 Findings: Desired Agent Social Characteristics

6.3.1 Anthropomorphism. A crucial characteristic for AI agents in general is their level of anthropomorphism, or human-likeness, exhibited through interactions with humans. The famous "uncanny valley" effect describes the feeling of eeriness and discomfort that users experience when dealing with a technology that is way too human-like [12]. In our study, we found that AI agents' human-likeness could sift through many aspects of the agent design and potentially elicit discomfort among users.

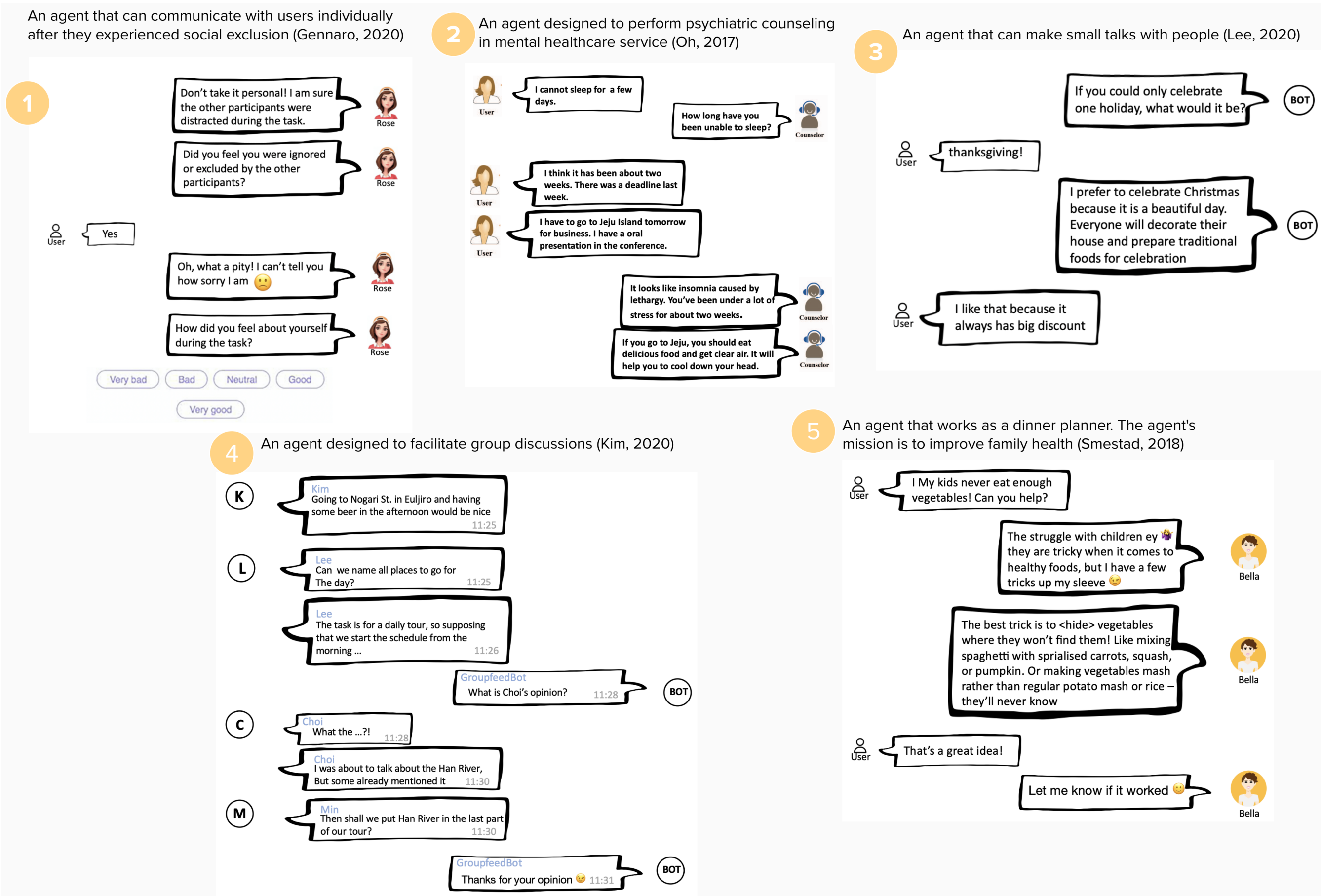


Figure 4: The five AI agent dialogues that were taken and adapted from prior literature [15, 32, 37, 46, 60] used in our co-design activity "Design Your Agent" in study 2. The agents in the dialogues were referred in the paper by the numbering on the upper left corner of each dialogue, e.g., "agent number 1."

During the "Design Your Agent" activity, the biggest complaint among the participants was when some agents "pretend to be human" by expressing the agents' own preferences or feelings. For example, one of the AI agent dialogues involved an agent that could make small talks (Agent number 3 in Fig. 4). During the dialogue the agent expressed its own preferences on the different holidays and said "I prefer to celebrate Christmas because it is a beautiful day." When discussing their likes and dislikes about agent number 3 (as seen in Fig. 4), P23 said, *"It made me uncomfortable when the AI was like 'I have this opinion'. I don't think you do. If it's an AI then they can't feel or have an opinion."*

Other features that triggered online students' discomfort included the use of emoji, human avatars, and human names in the design of AI agents. Many participants explicitly expressed their preferences of agent avatar over agent number 3 and number 4 in Fig. 4 where the agent avatars were just the three letters "BOT" (P6, P12, P14, P15, P21, P20, P23). All participants preferred AI agents to explicitly say that they were agents and not trying to be human by using human photos as avatars or human names as their names.

6.3.2 Social Etiquette. While participants did not want the AI agents to exhibit human-like characteristics, we found that the agents were expected to follow human social etiquette when interacting with the students. Participants pointed out that AI agents should avoid making assumptions about the users. For example, in the "Design Your Agent" activity in study 2, P19 commented on agent number 1 (see Fig. 4) and said, *"I liked that the agent checked in with the user. But I didn't like that the agent kind of had an assumption about the user feeling ignored."* P6 also said agent number 1 made assumptions that the user didn't like being in that situation: *"It sounds a little condescending, what if you didn't want to be involved in that social situation. And you are happy about it."* Other participants also said that *"It felt like a one-sided conversation without much input from the user. "* (P20, 22, 23) P23 suggested that this could be resolved by having the agent asking more questions to gain enough context from the user.

Another instance of AI agents violating social etiquette was when the agent interjected in the middle of a group conversation and called people out. During the discussion on agent number 4 (see Fig. 4), many participants appreciated that the agent was trying to encourage group participation by asking opinions from students who hadn't expressed their thoughts in the group chat. However, some participants also pointed out that the AI agent calling people out by name in the group chat might make them feel uncomfortable (P16-P18). When asked to elaborate on that, P17 compared it to her experience interacting with other students, *"I remember there was one time a student said something a little rude in the group chat. I just privately messaged him to say that was not cool. But some people called him out and it even made me feel uncomfortable."* P18 agreed and suggested that, *"A better way to handle this would be direct message the students instead of calling them out in the group chat."*

Some AI agents were also perceived as "self-centered" or "patronizing" because the agent either ignored the user's message or sounded bossy. For instance, for agent number 3 dialogue (see Fig. 4), P18 said, *"This one seemed to be ignoring what the user said... they are just talking about themselves"* This was further echoed by P20, P22, and P23. P6 also said, *"I wouldn't reply back at all. The agent's response doesn't progress the conversation forward."* When talking about agent number 2 (see Fig. 4), some participants found the agent's suggestion to be patronizing. P21 said, *"I feel like it's almost patronizing at the end saying 'You should...' It's like someone is telling me to do something. It's off-putting for me. Especially it's a bot, like I know you don't care."*

6.3.3 Intelligence. Students' desire for highly intelligent AI agents mostly centered around the agents' conversational intelligence in language comprehension. One example of this was the AI agent's ability to infer implicit information from the interaction. For example, many participants expressed their preferences for agent number 2 (see Fig. 4) in the "Design Your Agent" activity. P14 said, *"I did like that the counselor was able to draw some information that wasn't explicitly given from the user."* P12 also said she liked that the agent was able to infer the user was under a lot of stress because of the deadline. When talking to AI agents, participants want the agents to exhibit human-level conversational intelligence. P13 said, *"I liked it (that the agent was able to infer context) because when you're talking to a real person, that's what they do. If you told your friend that I haven't been able to sleep, and your friends know the context in your life and they say, oh that's because you've been working too hard preparing for the exam ... That's how you talk to a real person. Whereas with a lot of bot they just keep asking you your order number a hundred times and you can't really get anything out of it. "*

Participants also liked that the agent could comprehend free text instead of pre-set answer choices. In the "Design Your Agent" activity in agent number 1 dialogue, the user only answered with "Yes." and that there were pre-set answer choices for the users to choose from. While some participants found this to be convenient and straightforward, other participants also believed that this made the interaction seem "unnatural" and that they would prefer to communicate freely with the AI agent like communicating with other humans.

6.4 Study 2 Findings: Social and Ethical Concerns of SAMI

6.4.1 Privacy. Participants displayed conflicted feelings surrounding the use of student data. On one hand, students were concerned about the continuous and large-scale data collection that SAMI demonstrated— all the challenge teams raised concerns on data privacy that students might not feel comfortable having SAMI reading all their data (T6, T8, T10) and that students might stop asking questions on the discussion forum due to SAMI's continuous monitoring (T8, T10); on the other hand, a highly personalized agent-mediated social interaction experience was also desired by the students— the desired characteristics and functionalities of SAMI that the solution team brainstormed all highlighted SAMI's potential capabilities to know more about the students through large-scale data collection on students' degree progress (T7), students' course schedule (T7), students' preferences and availability for social meet ups (T9), students' postings on the discussion forum (T9), and students' location data for in-person meet ups (T9).

During the challenge cards competition rounds, online learners further discussed their concerns around data privacy and offered some potential solutions to address these concerns. For example, in session 1, both T6 and T8 posted the challenge that students may not feel comfortable with SAMI reading all of students' data within the online program. T5 and T7 both proposed similar solutions to mitigate students' concerns by offering explicit consent, opt-in/out process for students, giving students control over SAMI's data access the entire time, store SAMI's data locally, and implement security measures such as two-factor authentication. However, after some discussion, students also agreed that these measures were not perfect solutions to the data privacy challenge. As P14 accurately put, *"Informed consents are good at establishing legal distance but not good at establishing user trust."* In session 3, T10 posted the challenge that, given SAMI had access to students' private conversations on the discussion forum, it might stop students from reaching out to the instructors. T9 proposed that students could easily opt in and out of what kind of data to share with SAMI. However, when we followed up and asked if the participants thought opting-in and out would be sufficient to protect students' privacy, participants also acknowledged that it might not. P22 said, *"Even something is labeled as 'anonymous', nothing is truly anonymous these days. But proper anonymization for all of students' data and that SAMI could remove students' data according to students' request would help mitigate privacy concerns."*

6.4.2 Emotional Burden. While SAMI's goal was to reduce students' emotional burden and isolation by connecting students with others, some students pointed out that the use of SAMI might counter its goal by adding on to students' emotional burden. For example, during their challenge brainstorming session, T6 pointed out that students might feel embarrassed if they had to use SAMI to make friends. This point was echoed by other participants, saying that students might feel like they were incapable of basic social interaction and that they needed an AI agent to help them to do that. T10 also pointed out that SAMI could also hurt students' feelings unintentionally when trying to initiate interaction (P10). Specifically, in the SAMI mockup storyboard that we created, SAMI reached out to the student Lisa and said "I am sensing that you are feeling lonely..." Participants pointed out that telling students they were lonely might make students feel uncomfortable.

In the challenge cards competition and the debriefing sessions later, participants further discussed the issue of emotional burden, specifically when system transparency could add on to students' emotional burden. We discussed with the students that we felt it was necessary for SAMI to explain why the interaction was initiated and hence SAMI started the conversation by saying "I am sensing that you are feeling lonely... " Participants said that offering transparency into why SAMI initiated the interaction was desired, however, it would be better if SAMI could stick to factual language and avoid using emotional words like "lonely." P14 said, *"When putting it in particular terms it might risk people interpreting it in the wrong way and add to students' emotional burden."* P17 also agreed that wording would be important to avoid adding emotional burden to students: *"If SAMI said 'you haven't checked in with your classmates for a while, would you want to check in?', that would be much better than 'are you lonely?"'* As P23 summarized, the way SAMI communicated messages should be based on facts instead of trying to convey the idea that "the machine understands you."

6.4.3 Misinterpretation by SAMI. Another set of ethical and social challenges was the possibility of SAMI misinterpreting students' social needs or preferences. Part of this concern stemmed from participants' uncertainty about how accurate were SAMI's inferences made from students' online digital footprints. For example, participants were concerned about SAMI misunderstanding a student's social needs (T6), misinterpreting students' "emotional level" (T6, T10), or misconceiving students' level of desire for social connections (T8). Participants further elaborated on their concerns about SAMI misunderstanding their emotional level. T6 pointed out that emotions do not change linearly and could fluctuate frequently. Inferring students' emotion from their online posts on the discussion forum might miss the time that students actually needed help. T10 was also doubtful that SAMI could infer students' emotion level just based on students' discussion posts which were often centered around class assignments.

To resolve this challenge, participants offered several strategies that could improve SAMI's accuracy in making inferences about the students. Both T5 and T7 proposed that SAMI should always check with the student to confirm the accuracy of SAMI's inferences made and that students should have the ability to correct SAMI's inferences if they were inaccurate. T7 also pointed out that students' social needs and preferences tend to change over time. In order to improve the accuracy of SAMI, SAMI could continuously keep track of students and adjust the inferences accordingly.

However, even if SAMI could make highly accurate inferences about the students, other challenges remain such as the malicious usage of SAMI. Both T6 and T10 believed that people's online profile could be completely different than their actual persona. Online persona could also be easily manipulated to achieve individual goals. One example that T6 gave was that if SAMI could provide more academic help when students were frustrated with the course material, some students might intentionally present themselves as frustrated in order to gain more help on their assignments. Another rather extreme example given by T6 was that this could also be leveraged by cyberbullies. A hypothetical example was that a bully would pretend to be the same type of people as their potential victims in order for SAMI to connect them together.

7 DISCUSSION

Our findings offer insights into online learners' desired functionalities and social characteristics of AI agents that can promote social connectedness among online learners. Specifically, we identified online learners' desire for in-situ agent-mediated social support through continuous monitoring as well as the need for AI agents to scaffold their social interaction process. We found that online learners' discomfort about the AI agents could be triggered through agents' expressions of opinions or preferences. Online learners also wanted the AI agent to follow social etiquette and be aware of interaction context. Our findings also shed light on the perceived social and ethical challenges of using AI agents to mediate social interactions among online learners, including concerns about privacy, emotional burden, and misinterpretation.

In this section, we first summarized and distilled several design implications for AI agents' functionalities and social characteristics in Table 3. Based on our findings, we establish the role of AI agents as facilitators to scaffold online learners' social interaction process and highlight the design direction of agent-mediated social interaction. We further identify unique social and ethical challenges in leveraging student data for social purposes and discuss potential strategies to mitigate students' concerns about agent-mediated social interaction.

7.1 Examining the Role of AI Agents in Promoting Social Connectedness Among Online Learners

We found that supporting online learners' social connectedness should be a continuous process that caters to students' changing social needs. Students reported that they want to build social connections that last beyond classes with students who are similar to them or have similar struggles in the program (e.g., difficulties comprehending the same study materials) [62, 73]. We want to point out that while long-term social connections could be fostered by identifying shared identities [62, 73], online learners' feelings of social isolation could often be triggered by encountering difficult course materials, therefore more urgent social needs to connect with "buddies" who can relate to their struggles in the program fluctuate as online learners take different classes each semester. As online students progress through the program, their interests and goals might also change over time. The transient and temporal characteristics of online students' identities and needs are further echoed by prior work [58, 61]. Designing AI agents to be long-term companions for students could be an effective way to support their changing social needs and preferences over time.

While many prior studies have situated AI agents as advisors or empathetic listeners to people who are in need of emotional or social support by offering advice or empathetic messages [15, 33], we found that positioning AI agents in these roles in online learning context could risk eliciting online students' discomfort due to the languages these AI agents tend to use (e.g., "You should do XXX." or "I can't tell you how sorry I am"). Online learners found this type of messages to be "condescending" and attempts of the agents trying to pretend to be humans that have feelings and opinions. This suggests that AI agents should be designed to align with people's machine heuristics (i.e., people's heuristics that comparing to

Table 3: This table summarizes the design implications for AI agents to help online learners feel socially connected based on our findings. We also list examples of how to implement each design implications.

Categories	Design Implications	Examples
Functionalities	Help online students identify other like-minded students to connect.	Identify and connect students who are interested in similar hobbies, or students who are struggling with the same assignment.
	Offer continuous support to online students' changing social needs.	Continuously update online students' social needs and preferences by checking with the students or monitoring their online activities.
	Initiate interaction with online students at the right time.	Incorporate advanced AI techniques to make inferences about students' real-time status (e.g., emotional state, loneliness)
	Scaffold online students' social interaction process throughout.	Introduce online students together with ice-breaker questions or schedule meetups and social events based on student schedule.
Social Characteristics	Having personality is not necessary.	Personality could be neutral without overly expressing humors or emotions.
	Use non-humanlike avatars and names.	A simple "BOT" avatar could convey clearly that the agent is not a human.
	Don't pretend to be humans.	AI agents should avoid saying things like "I prefer to celebrate Christmas." which implies that the agent has opinions or preferences.
	Follow social etiquette during conversations.	AI agents should not ignore users or use seemingly condescending language such as "you should do X."
	High conversational intelligence in language comprehension.	Understand the context of current conversations through cues by free text.

humans, AI agents are machines that are often unbiased and nonjudgemental [63]) when providing support to avoid upsetting users in emotionally vulnerable states [47, 63, 64]. However, students also wanted the agents to follow social etiquette when interacting with them— AI agents should avoid making assumptions about the students or calling students out in group settings. AI agents should therefore be designed to go beyond typical machines and possess a certain degree of social and conversational intelligence [9] to follow human social etiquettes during conversations.

While much of the existing work focused on studying how social support AI agents could be designed as a direct source to make the users feel heard [13, 15], loved [11, 15], and encouraged [68] in order to mitigate users' negative emotions, we found that online students want the AI agents to have less personality and to avoid using emotional languages during interactions. P22 also explicitly expressed that he would be less inclined to gain social support directly from an AI agent: *"I use AI agents to track my packages. Would I go to an agent to figure out my personal feelings? Probably not."* Our work thus echoes with some recent work suggesting that for some users AI agents are not preferred resources to offer adequate social or emotional support [4, 65]. We hypothesize that this could be due to the fact that our study took place in an online community context where better social support resources—other online students—are available. In an online learning program, online students could be less inclined to seek social support from a machine that is incapable of relating to them when there are plenty of other online students who could be struggling and feeling the same emotions as them [4]. Our work thus presents another new research and design opportunity to investigate the different roles AI agents could play in offering social support in community contexts [55, 83] as opposed to individual contexts.

Building upon that, we posit that **the role of AI agents should be more of a facilitator to scaffold online learners' social interactions** instead of attempting to offer social and emotional support directly to the students. In the four storyboards online learners created, none of the teams used a human character to represent the agent, yet using AI agents as facilitators to help students identify, match, and introduce other like-minded students was a common theme across most of the storyboards online students created. Online students further suggested that AI agents could provide icebreakers to trigger the interactions or even help students schedule meetups, which are common responsibilities of a facilitator. Our work thus opens up a new opportunity for future work to study the design and social impact of AI agents as facilitators to provide social and emotional support across different settings.

7.2 Ethical Design of Agent-Mediated Social Interaction

Our work identified three major perceived ethical and social challenges of agent-mediated social interaction: privacy, emotional burden, and misinterpretation. While students' concerns of privacy and misinterpretation of their online learning data have also been suggested by prior work in learning analytics [58, 59], collecting and analyzing online learners' data for social purposes presents new unique challenges on students' perception of privacy and the possibility of AI agents adding emotional burden during agent-mediated social interaction.

The present study raises the concern that when data collection and analysis by AI serves social purposes, students could be more open and inclined to share their data comparing to data collection and analysis for learning purposes. Even though the large-scale data collection and monitoring of SAMI raised online learners' privacy concerns [8] during our study, having a highly personalized agent-mediated social interaction experience was also highly desired by online students. Prior research in social matching [67] has also suggested that users are often more willing to sacrifice their data privacy to gain more accurate and personalized social matches due to humans' inherent social nature [67]. However, what online learners did not show concerns about was the fact that SAMI also collected and analyzed data from private conversations between SAMI and individual students. Existing literature has pointed out that AI agents could elicit more private and sensitive personal information (e.g., credit card information [63]) from the users comparing to humans [47, 63, 79]. This is due to people's "general machine heuristics" which refers to people's rule of thumb that AI agents as machines are perceived as more trustworthy and secure comparing to humans [63]. Combining with the social purposes of agent-mediated social interaction, AI agents' capability of encouraging deep self-disclosure, and students' heightened trust in schools collecting and using their data [74], a concern is that online students could be put in an even more vulnerable position to have their data exploited in agent-mediated social interactions.

While online learners also proposed several mitigation strategies to lessen their privacy concerns such as offering consent forms and giving students the freedom to opt-in and out of SAMI at all times, we posit that these strategies warrant more scrutiny and further investigations to ensure their applicability and effectiveness in real-world online learning contexts. Offering terms and conditions to online students was also suggested by prior work to preserve students' privacy [58, 61, 74]. However, implementing terms and conditions and opt-in/out is extremely difficult given the scale of online learning programs as well as the fact that it is near-impossible for individuals to comprehend the complex processes, scale, and layers of data collection, analysis, and inferences drawn from the data [49]. Our work thus provides empirical evidence for the necessity of further exploring and evaluating different privacy measures in the wild to mitigate students' privacy concerns for agent-mediated social interaction in the online learning context.

Modest concerns regarding the communication of learning analytics results to students have been raised in prior literature. However, the social nature of agent-mediated social interaction posits new social challenges of AI agents adding to online learners' emotional burden when they are socially isolated. In our study, online learners pointed out that SAMI's emotional language to convey system transparency in initiating the conversation with students, "I am sensing that you are feeling lonely..." could add on to students' emotional burden. Our work provides empirical evidence that validates the hypothesized concern in prior literature that AI agents communicating in emotional and judgemental language could cause harm to users [47]. Designers should be mindful of the languages that AI agents use when communicating with students who could be feeling socially isolated to avoid adding further emotional burden on them. While communicating transparency about AI agents' working mechanism is highly desired [17, 39], AI agents should stick to factual, unbiased, and non-judgmental language [33, 47] when communicating with students. For example, if students' emotional states were monitored and used to initiate interactions, AI agents should avoid using emotional labels such as "I am sensing that you are lonely..." but explain the initiation by communicating analytics-based language like, "I noticed you have lower forum activity than normal..."

8 LIMITATIONS AND FUTURE RESEARCH

While our work offers important design and ethical implications on using AI agents to promote online learners' social connectedness, our work has several limitations. First, this study assumed that AI agent, or even technology in general, could help improve online learners' social connectedness. This assumption could have influenced participants' ideas of what is possible to help reduce their feelings of social isolation. Second, the perceived social ethical challenges of agent-mediated social interaction were elicited based on one AI agent mockup that we created. We acknowledge that there could be many ways in which AI agents can facilitate and scaffold online learners' social interaction and we encourage future research to further examine the social and ethical concerns in other types of agent-mediated social interaction. Third, all participants were recruited from a computer science for-degree master program in an U.S. educational institution. Therefore participants in our study could have more, or less, concerns compared to online students in other disciplines that are less technology-centered. Future work should replicate our study with online students in less technology-centered disciplines (e.g., liberal arts) to gather a complete range of concerns that online learners might have about agent-mediated social interaction. Finally, our findings might not be applicable to other forms of online learning environment such as Massive Online Open Classes (MOOC) or online learning programs at undergraduate or K-12 level.

9 CONCLUSION

In this paper, we took a co-design approach to include online learners as active participants to explore the design requirements and potential ethical challenges of using AI agents to help online learners feel socially connected. Through two virtual co-design workshop studies with 23 online learners, we identified the desired functionalities and social characteristics of the AI agent and designed an agent mockup to elicit potential social and ethical challenges of agent-mediated social interaction among online learners. We found that AI agents should help students identify other like-minded individuals and offer continuous support to online learners' changing social needs. Online learners didn't want AI agents to have human-like characteristics yet agents were desired to follow social etiquette during interactions. While prior research has suggested that AI agents could be a direct source of social support for people who are isolated, based on our findings, we established the role of AI agents as facilitators to scaffold online learners' social interaction process to help online learners feel socially connected. We distilled a set of design implications (see Table 3) for AI agents to promote social connectedness among online learners, then posited the design direction of agent-mediated social interaction in online learning, and outlined the unique social and ethical concerns in collecting online learners' data for social purposes, including heightened privacy concerns and emotional burden.

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