Understanding the Design Space of AI-Mediated Social Interaction in Online Learning: Challenges and Opportunities

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Our online interactions are constantly mediated through Artificial Intelligence (AI), especially our social interactions. AI-mediated social interaction is the AI-facilitated process of building and maintaining social connections between individuals through information inferred from people's online posts. With its impending application across a number of contexts, the challenges and opportunities of AI-mediated social interaction remain underexplored. This paper seeks to understand the design space of AI-mediated social interaction in the context of online learning, where students frequently face social isolation. We deployed an AI agent named SAMI in three class discussion forums to help online learners build social connections. Using SAMI as a probe, we conducted semi-structured interviews with 26 students to understand their difficulties in remote social interactions and their experiences with SAMI. Through the lenses of social translucence and social-technical gap, we illustrate online learners' difficulties in remote social interactions and how SAMI resolved some of the difficulties. We also identify potential ethical and social challenges of SAMI such as user agency and privacy. Based on our findings, we outline the design space of AI-mediated social interaction. We discuss the design tension between AI performance and ethical design and pinpoint two design opportunities for AI-mediated social interaction in designing towards human-AI collaborative social matching and artificial serendipity.

CCS Concepts: • **Human-centered computing → Empirical studies in collaborative and social computing**; **Natural language interfaces**.

Additional Key Words and Phrases: computer mediated communication; AI-mediated communication; AI-mediated social interaction; social translucence; social-technical gap; online learning; online social interaction;

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1 INTRODUCTION

As Artificial Intelligence (AI) becomes closely integrated into our daily lives, more and more of our interactions are mediated through AI systems. Our messages are constantly enhanced by AI recommendations through smart replies and auto-complete [26, 27]; we now get in touch with our long-lost childhood friends through Facebook's recommendation algorithms [51]; we even find our life partners and business partners through social matching systems [54, 74, 75]. With the rapid

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advancement in AI technology, especially machine learning applications such as recommendation algorithms, it is not difficult to imagine a future where most human social interactions are mediated through AI systems. We call this *AI-mediated social interaction*.

We define **AI-mediated social interaction** as the *AI-facilitated process of building and maintaining social connections between two or more individuals based on explicit and implicit personal information embedded in people's online posts.* AI-mediated social interaction is at the intersection of two CSCW sub-fields: AI-Mediated Communication (AI-MC) [26] and social matching systems [66]. While recent AI-MC research focuses on the perception and effect of AI-MC in general-purpose textual communication such as smart replies and auto-complete [27, 32], AI-mediated social interaction explores a subset of AI-MC on the design and impact of using AI-augmented messages for socialization purposes. AI-mediated social interaction also expands on the capability of current mainstream social matching systems by extracting all the necessary information for social matching from users' prior digital footprints upon user requests, instead of asking for users' explicit input in the form of a web survey or a user profile.

Existing work has examined the design, ethical and social challenges of AI-MC, social matching systems, and CSCW technology [1, 19, 26, 27, 54, 66], however, the design opportunities and challenges of AI-mediated social interaction remain largely unexplored. For instance, several classical CSCW theoretical frameworks point out the importance of designing technologies to bridge the social-technical gap [1] and bringing social translucence [19] in online interactions, yet whether and how AI-mediated social interaction could fulfill these requirements remain unknown. AI-MC and social matching literature suggest several ethical and social challenges such as privacy [66], agency [26, 27, 54, 63], trust [26, 27], and transparency [26, 63, 66]. Situated at the intersection of AI-MC and social matching, AI-mediated social interaction could raise more challenges by using AI to enhance an already personal process of building social connections. Before AI-mediated social interaction becomes more prevalent, it is critical to examine and consolidate its design space through understanding its challenges and opportunities.

With the rapid advancement of AI, AI-mediated social interaction will soon be utilized not only to help people find social partners but also to create and facilitate social cohesion within online communities. One potential application as such is the use of AI-mediated social interaction in the context of online education, where fostering social connections is not only paramount to learners' success but also urgently needed to improve learners' online learning experience [4, 6]. Strong social ties among online learners are crucial to improving students' satisfaction [28, 58], reducing dropout rates [59], and stimulating intellectual exchange [4, 58]. Conceptual frameworks of online learning such as Community of Inquiry consider students' social presence as an integral part of successful online learning [6, 22, 39]. However, it remains unclear what difficulties online learners actually encounter during their social interactions in online learning, which makes it challenging to design AI-mediated social interaction that could cater to students' difficulties and needs.

The present work seeks to understand the design space of AI-mediated social interaction in the context of online learning. With this goal in mind, we take a human-centered approach to first understand the perceived difficulties online learners face in remote social interaction, then explore the challenges and opportunities in designing human-centered AI-mediated social interaction. Specifically, we explore three research questions:

RQ 1: What difficulties do online learners encounter in remote social interaction?
RQ 2: How can we design AI-mediated social interaction to resolve online learners' difficulties in remote social interaction?
RQ 3: What are the ethical and social challenges in designing AI-mediated social interaction in an online learning environment?

To examine these research questions, we conducted a qualitative study in an online graduate for-degree computer science program. We developed and deployed a preliminary AI system in the form of an AI agent named **SAMI** (stands for **S**ocial **A**gent **M**ediated **I**nteractions) in three online class discussion forums to help match students based on specific commonalities. We used SAMI as a probe to elicit design feedback from students based on their real experience with AI-mediated social interaction. We chose to use an AI agent as the AI system to mediate social interaction among online learners due to AI agents' prior success in providing informational, emotional and social support within online communities [24, 50, 52, 71]. We then conducted semi-structured interviews with 26 online students who had interacted with SAMI to understand their difficulties in remote social interactions as well as their experience and feedback on SAMI.

Through these interviews, we identify online learners' difficulties in building remote social connections, specifically, the lack of social translucence and the existing social-technical gap in current online learning platforms. Our findings reveal how SAMI augmented social translucence in an online learning environment yet did not fully close the social-technical gap. We also identify several ethical and social challenges students had about SAMI, including user privacy and agency. Building upon our findings, we discuss how to design AI-mediated social interaction to resolve online learners' difficulties in remote social interactions. Based on students' perceived concerns about SAMI, we highlight the design tension between AI performance and ethical design in AI-mediated social interaction. We then discuss the design opportunities of AI-mediated social interaction in building human-AI collaborative social matching and creating artificial serendipity to mitigate potential ethical and social challenges.

The contribution of our work is three-fold: *first*, through the lenses of social translucence [19] and social-technical gap [1], we highlight online learners' difficulties in remote social interactions and offer empirically-grounded design implications of technologies that could cater to those difficulties; *second*, we pinpoint the design tension between AI performance and ethical design pertaining to the ethical and social challenges of AI-mediated social interaction; *finally*, taking into consideration the design implications and challenges of AI-mediated social interaction, we outline design opportunities and directions for AI-mediated social interaction in creating serendipitous interactions and in designing human-AI collaborative social matching to mitigate the ethical and social challenges.

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 researcher institution. The interview data and demographic information were collected upon student consent and later anonymized. We offered extra credits to students participated in our interview study. 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 responses during interviews would not be shared with the instructor and would not have any impact on their grades.

2 RELATED WORK

In this section, we first discuss existing research that points out the ethical and social challenges of AI-MC and social matching systems. We then introduce theories on designing technology-mediated remote social interaction, specifically social-technical gap [1] and social translucence [19], and their design implications. We end this section by reviewing related work that examine the importance and necessity of building technology to support online learners' social interaction process.

2.1 AI-Mediated Communication and Social Matching Systems

AI-MC is defined as "mediated communication between people in which a computational agent operates on behalf of a communicator by modifying, augmenting, or generating messages to accomplish communication or interpersonal goals [26]." Existing work in AI-MC has focused on AI-augmented text communication such as smart replies [26, 27, 47] and offered valuable insights into the social and ethical challenges of AI-MC. Several research has found that AI-MC in text communication can influence interpersonal dynamics such as perceived trustworthiness [32] as well as users' perceived agency and responsibility in the communication process [27]. AI-MC could even undermine the social attraction between two human communicators due to positivity bias [47]. The issue of user agency has been frequently brought up in recent literature [26, 63]. Researchers share the concern of AI-MC usurping user agency instead of augmenting it [26, 57, 63] due to the high level of proactivity that current AI-MC systems are designed [57, 63]— sometimes humans are left out of the decision-making progress completely (e.g., auto-correct). To resolve the issue with user agency, anthropomorphic AI systems such as social robots and conversational agents have been suggested to help users gain a sense of agency since the interactions with anthropomorphic AI systems heavily depend on user responses to take further actions [63]. In a recent review of AI-MC research, Hancock et al. also point out the social and ethical implications of AI-MC such as the potential issues of using AI systems to dictate and enforce a certain communication style, as well as concerns surrounding disclosure and transparency of AI-MC [26].

While AI-MC can be incorporated into a variety of technologies across contexts, we envision that one possible scenario is to integrate AI-MC into social matching systems due to the inherent social nature of communications. A social matching system is a particular type of recommender systems that aims at providing recommendations of people that might be of interest for someone to connect with [45, 66]. Social matching systems, while prominently used in the online dating context [75], have also been employed to rediscover old friends on social networks [12, 49], link job-seekers with potential employees [54] and connect academic researchers to local community collaborators [74]. Social matching systems thus offer a new way for individuals to build their social capital [45, 56], satisfy people's needs to socialize [44, 66], offer opportunities for chance encounters [43, 45, 53], and potentially reduce human biases during the matching process [54].

Social matching systems have been traditionally evaluated through accuracy and efficiency [67], however, there have been growing calls for human-in-the-loop evaluation and assessment [54, 66–68]. Terveen and McDonald urge future research in human-centered social matching systems to explore the need for transparency in systems' decision-making process as well as the balance between match accuracy and user privacy. These concerns are also echoed by other relevant literature, calling future research to explore explainability and user privacy in social matching systems from a user-centered perspective [67, 68]. While the basic functionality of social matching system is often to recommend people with commonalities, researchers have pointed out the potential ethical consequences of creating echo chambers and polarization in the community by reinforcing people's similarity-seeking behaviors [54].

With the advancement of natural language processing and recommendation algorithms, one can view future social matching systems as one type of AI-MC, communicating on behalf of individuals by creating or augmenting their profiles to help them achieve social goals. However, we currently don't have a clear understanding of users' perspective on the design and ethical implications of AI-MC in the form of social matching systems— the intimate nature of social matching could raise more ethical concerns than that for AI-augmented text communication. The present study thus seeks to investigate the design and ethical considerations of AI-mediated social interaction.

2.2 Technology-Mediated Remote Social Interaction: Theories and Design

Decades of CSCW research has produced many prominent theoretical frameworks to guide the design of technologies in supporting remote interactions, which is at the core of CSCW research. Among these theoretical frameworks, Ackerman's social-technical gap [1] and Erickson and Kellogg's social translucence [19] both draw inspirations from in-person interactions to design technology that can support remote interactions.

Ackerman defines social-technical gap as "the great divide between what we know we must support socially and what we can support technically [1]." In his seminal work, Ackerman points out that when technology mediates remote interactions, they are often designed to be rigid, reductionist, and do not allow sufficient ambiguity compared to in-person interactions [1]. Much research has since adopted this framework to identify the social-technical gap in a variety of contexts such as health tracking [14], collaboration among telesurgery teams [16], online collaborative consumption [23], and many more. In his original piece, Ackerman proposes first-order approximations to bridge the social-technical gap: solutions that partially solve the problems with known trade-offs. One optimal approximation is to design technical systems in an augmentative manner by offering advice to users without invoking the social-technical gap [1], which can potentially be accomplished through the usage of AI agents [40].

While the notion of social-technical gap typically acts as a general guide and call-to-action for CSCW research to bridge this gap between social and technical requirements, Erickson and Kellogg go a step further and outline detailed principles on designing towards socially translucent systems to support natural online interactions [19]. Specifically, Erickson and Kellogg propose that socially translucent systems should have three characteristics: visibility, awareness, and accountability. *Visibility* refers to system's ability of making social information more visible; *Awareness* refers to people's ability to know each others' existence; *Accountability* refers to system's ability to hold people accountable for their behavior by generating and enforcing social rules. Erickson and Kellogg believe that these three characteristics allow people to observe, imitate, aware, and interact with others socially in in-person context, and thus building socially translucent system is a fundamental requirement for people to carry out normal interactions online [19].

Much research has explored the design and implementation of social translucence in technology-mediated interactions across a variety of contexts. The most common implementations of social translucence is through building social proxy [19] and collective awareness [36]. Building social proxy to implement social translucence was first described in the original Erickson and Kellogg paper, in which they present a design of the "Babble" system that demonstrates user presence and activities through a simple graphical representation. Social proxy is later integrated into system architectures used to support Wikipedia knowledge workers [46]. Collective awareness is also a crucial design factor in socially translucent systems [36, 64]. Prior research has posited methods to support collective awareness through creating common repository to generate mutual understanding for members of globally distributed teams [7] and conducting synchronous coding sessions for learner engagement [9].

However, despite their prominent roles in guiding the design of technology-mediated interactions, to our knowledge, these two theoretical guidelines have not been empirically examined for guiding the design of AI systems that can facilitate social interaction among online learners. It remains unclear of whether and how AI-mediated social interaction could fulfill the requirements of social-technical gap and social translucence in online learning context. The present work thus seeks to explore the role of social-technical gap and social translucence in guiding the design of AI-mediated social interaction among online learners.

2.3 Social Interaction in Online Learning Environment

Building strong social ties among online learners has long been recognized as a crucial factor to improve students' satisfaction [28, 31, 58], reduce dropout rates [59], and stimulate intellectual exchange by providing a safe atmosphere [4, 58]. However, online learners frequently report feeling socially isolated [35, 62, 69]. With the increasing demand of online learning in higher education, much research has offered strategies that could help improve online learners' social presence and sense of social belonging in online learning environments [5, 70]. Most of these strategies center around what the instructors could do (e.g., share personal stories, use humor and emoticons), what the students could do (e.g., contribute to discussion boards), and how the course design should be changed (e.g., limit class size, structure collaborative learning activities) in order to foster social presence for online learners [5, 29, 34]. Despite the increasing call for research on building and designing technologies to address this issue in the online learning environment, we have seen very few technical systems that explicitly focus on helping online learners build social connections.

One of the reasons behind this lack of existing technologies to help online learners build social connections is the tendency to restrict social interactions to academic tasks that are often learning-oriented, in which social interaction is often only in service of obtaining desirable learning outcomes [37]. For example, online learners reported that working on group projects together helped them get to know other students on a more personal level and discover affinities [62]. However, these relationships are often ephemeral and don't usually last beyond group projects—once the common educational goal of completing a group assignment is gone, online learners often go their separate ways [62]. This pitfall is also reflected in the design of CSCW technologies intended for online learners, the majority of which aims at facilitating online learners' cognitive learning processes, such as tools to facilitate peer discussions [73], encourage help-seeking in online discussion forums [65], crowd-edit lecture videos [15], and facilitate student teamwork [3].

For the HCI and CSCW communities, research that aims at examining how technologies can be designed to foster social connections among online learners is only at its nascent stage. A few initial studies have tried to understand how online learners currently build social connections through extensive interviews [62] or short surveys [69]. These studies find that online learners form lightweight social connections through the discovery of shared identity [61, 62, 69], commonalities among online learners such as location in the same city, in either the self-introduction thread or through working on the same group projects [62, 69]. Class-oriented activities such as group projects seem to be one of the few opportunities for online learners to interact closely with each other and identify affinities, with few students building relationships that last beyond the class [62, 69].

We point out the lack of systematic and in-depth investigation into the design of technologies that could cater to online learners' existing difficulties in social interactions and help facilitate their social interaction process. Strong social bonds are often the basis of optimal collaborative learning processes. For students to willingly exchange ideas and make mistakes, students need to have a certain level of trust in each other, feel socially belonged in the learning community, and feel close enough to each other to have that "safety net" for more risk-taking and adventurous learning attitudes [4, 37]. The present research thus takes a human-centered approach to investigate students' perceived difficulties in their existing social interaction process. With this knowledge, we would be able to design technology, especially AI systems, to facilitate online learners' social interaction process that caters to their difficulties and needs.

3 METHOD

To better understand the design of AI-mediated social interaction to facilitate online learners' social interaction process from a human-centered perspective, we conducted a deployment and evaluation

study in an online for-credit graduate computer science program (Online Master of Science in Computer Science, "OMSCS" for short) offered by Georgia Institute of Technology. We deployed an AI agent named SAMI as a probe to understand the design requirements of AI-mediated social interaction in three online classes of this program. We then conducted semi-structured interviews with 26 online learners enrolled in the classes that SAMI was deployed in to understand their experiences and difficulties in connecting with other students in the program as well as their feedback on SAMI. We describe the context of our study, SAMI's versions and functionalities, and the process of our interview study in detail below.

3.1 Study Context

The OMSCS program[1] offered through Georgia Institute of Technology 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 per class. The average age of a student starting at this online program is 32 and the gender ratio of men to women in the program is roughly 4:1. Many students enrolled in this program are working through their degree part-time while working full-time jobs. Students' goal of enrolling in this program usually consists of career shift and career advancement, thus a lot of the students in the program do not have a computer science degree (around 70% of the students do not have an undergraduate degree in computer science) but have some level of programming experience. Students in this program use a variety of communication tools, but mostly through online class discussion forums and the program's informal Slack, organized by students themselves.

At the beginning of each class, the instructor of the three courses in our study will start a self-introduction thread on the class discussion forum and encourage students to introduce themselves on the discussion thread. Information students typically include in their self-introduction posts are: their locations (city, state, country), previous and current jobs, previous and current classes they have taken or are taking, hobbies, etc.

3.2 SAMI Versions and Functionalities

SAMI is an AI agent designed to run on the class discussion forums, where online learners usually conduct class-related discussions and post self-introductions at the beginning of the semester. On the discussion forum, students can post questions and answers freely in an asynchronous format. Instructors can also make announcements and answer students' questions on the forum. The layout of the discussion forum is similar to typical online forums, where all the posts are organized chronologically on the left side of the screen, with pinned posts and the newest posts at the top. People with instructor access can appoint students into private groups in the form of a post thread where students in the group can communicate freely. The private groups and the posts in each group are only visible to group members. The groups appear on the left side of the screen along with all the other class discussion threads. For the purpose of this study, SAMI was granted instructor access to put students into different private social groups.

As with typical systems in AI-mediated social interaction, SAMI is equipped with Natural Language Processing techniques, specifically Named Entity Recognition (NER), to identify and extract different entities such as locations and hobbies from students' posts on the discussion forum.

While we only deployed one version of SAMI (SAMI 2) in our study, we presented three different versions of SAMI to participants in our interviews to better prompt for students' preferences of AI systems that can mediate their social interaction process. Specifically, we presented the previous version of SAMI (SAMI 1), the current version of SAMI (SAMI 2), and a future version

[1]For more details about the OMSCS program see: https://omscs.gatech.edu

Version	Functionalities	Example Interaction
SAMI 1 (Past)	Reads and processes students' self-introduction posts on **the self-introduction thread organized by the instructor**. Students can opt-in by including #ConnectMe in their self-introduction posts. Posts and updates a separate thread that provides a **summary of class demographics** by time-zone, hobby, etc. For example, "23% of the class is in CST timezone...". Generates **individual replies**.	**Student**: "Hi everyone! I'm Sarah. I live in Chicago. I am taking Computer Networks this semester. I enjoy traveling and hiking." #ConnectMe. **SAMI 1**: "Hi Sarah. Welcome to the class! #ConnectMe You may find it helpful to connect with some other students in this course. These students are also taking Computer Networks this semester: • Anthony N. - link to Anthony's self-introduction • Susan L. - link to Susan's self-introduction These students are also interested in hiking: • Mary I. - link to Mary's self-introduction • Tom S. - link to Tom's self-introduction"
SAMI 2 (Current)	Reads and processes students' introduction posts posted on the dedicated **"Introduce Yourself to SAMI" thread**. Generates **individual replies**. **Invites students to private groups** created for students with commonalities. **Posts ice-breakers** in the group to help students start conversations, as shown in Fig. 1.	**Student**: "Hi everyone! I'm Sarah. I live in Chicago. I am taking Computer Networks this semester. I enjoy traveling and hiking." **SAMI 2**: "Hi Sarah. Nice to meet you! Fun fact: This semester, I've already met 7 other students interested in traveling, 12 other students taking computer networks. Are you interested in connecting with any of your fellow classmates? • We have identified potential connections relating to your **region, city, timezone, and hobby**. • Decide whether you like to connect with peers by replying with some, all, or none of the bolded terms above. " **Student**: "city, hobby, timezone" **SAMI 2**: "Based on your reply, I have connected you with the following groups: Chicago, timezone-CST, hiking, traveling. When you get a chance, pop into the 'Welcome' threads to say hi!"
SAMI 3 (Future)	Reads and processes **everything students posted** on the class discussion forum. Generates **individual replies to any posts** student posted that indicated their interest on certain topic and SAMI 3 was able to find students with shared interest.	**Student**: "I just found this article on robotics that looks very interesting. Thought I'd share with all of you. " **SAMI 3**: "Hello! I noticed that you are interested in robotics. Would you like me to connect you with other students who are also interested in robotics?" **Student**: "Sure! That sounds great!" **SAMI 3**: "Awesome! I just added you to the robotics group. You can access the group via this link."

Table 1. The functionalities and example student-SAMI interactions of the three different versions of SAMI we presented to participants during our interviews. Note that SAMI 2 is the current version of SAMI that students interacted with prior to their interviews.

we envisioned (SAMI 3). Table 1 described the functionalities and example interactions of the three versions of SAMI. While all versions of SAMI can extract useful information through the textual data on the class discussion forum to perform matches between students, there are some notable differences that we want to highlight here. SAMI 1 only provides a list of students with commonalities to each individual student while SAMI 2 and SAMI 3 directly put students into

groups. SAMI 2 also posts ice-breakers in the group to help students start the conversations. SAMI 1 posts and updates a running thread that summarizes class demographics while SAMI 2 only provides a short summary that is related to individual student's profile. SAMI 1 and SAMI 2 are restricted to collecting information from students' self-introduction posts while SAMI 3 can collect and infer information from all the posts online students share on the class discussion forum.

In our study, SAMI 2 was deployed in three online classes. After students interacted with SAMI 2 for at least six weeks, we conducted semi-structured interviews when we presented the three versions of SAMI to participants to collect their feedback and understand its design implications.

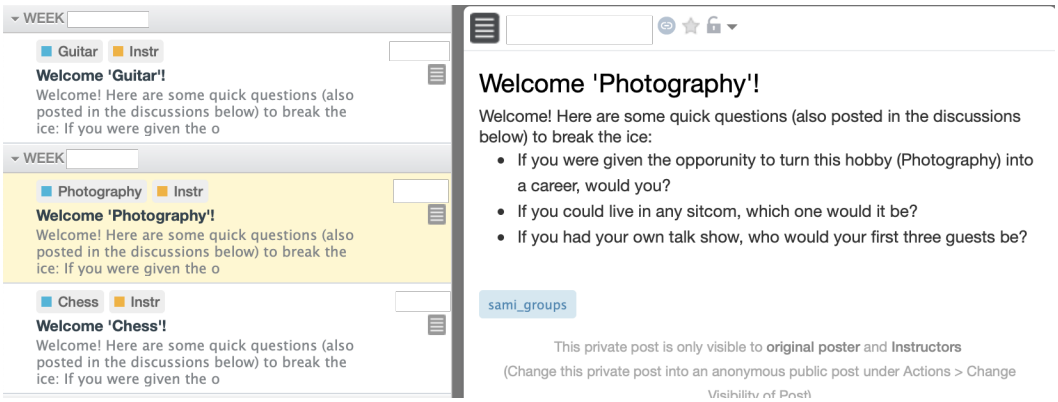

Fig. 1. An example of the groups SAMI 2 created to help connect online students. Note that this screenshot reflects the view from SAMI's account. Students can only see the groups that they are a part of. SAMI 2 also posts ice-breaker questions in the group, as shown in the figure, to help online students start the conversation.

3.3 Semi-structured Interviews with Online Students

To understand online students' difficulties in building social connections with others and understand the design space for AI-mediated social interaction, we conducted 26 semi-structured interviews with online students enrolled in the three online classes where SAMI 2 was deployed. A detailed breakdown of the interview participants' information is shown in Table 2. Participants were recruited through purposeful sampling [55]. We first identified students who indicated their willingness to participate in the interview study through recruitment questions inserted in the standard class survey at the beginning of the semester. During the initial stage of recruitment, we randomly picked a batch of potential participants and sent them email invitations to participate in our study. As we interviewed more students, we then purposefully invited students of certain gender or seniority in the program to ensure we obtain perspectives of a diverse set of students.

The interviews focused on understanding online learners' difficulties in building social connections with other online students in the program [2]. We also discussed students' experiences with SAMI 2 to gain design implications on building AI systems that can help facilitate online learners' social interaction process. During each interview, we started out by understanding online learners' experiences in the online program, which included their goals in enrolling in the online program, their general experiences in the program, and their study routine. Next we asked about online learners' current experience in building connections with other students, specifically what kind of interactions they have had, their preferred types of interactions, and the difficulties they

[2]The full interview protocol can be found here: https://bit.ly/3nnLFye

have encountered in building online social connections. Finally, we asked about online learners' experiences with SAMI and their feedback on the AI agent. To help participants better articulate their preferences, we presented three versions of SAMI (listed in Table 1) and asked about their likes, dislikes, and potential concerns for each version of SAMI.

All the interviews took place virtually after SAMI was active on the discussion forum for at least six weeks. The interviews lasted from 47 minutes to 95 minutes, with an average length of 64 minutes. All the interviews were audio-recorded and later transcribed.

Three researchers analyzed the interview transcripts through open-coding [11]. We conducted three iterations of coding and collaboratively distilled themes emerged throughout the coding process. The first iteration of coding was conducted by the three researchers in a line-by-line fashion and resulted in 74 low-level codes. The codes in first iteration stayed close to the meaning of each sentence, for instance, "don't want to be the first one to reach out" and "timezone differences". During the second iteration, through continuous discussions, we ended up with 20 codes such as "lack of visibility" and "desire SAMI to be more human-like". In the final iteration of coding, we ended up with 10 categories that highlight online learners' current and desired types of interactions, challenges encountered when building connections with others, and design implications for building conversational agent to mediate their connection process. Throughout the entire coding process, the three researchers met and discussed the codes on a regular basis and resolved conflicts that arose in each iteration of the data analysis process.

ID	Gender	Age	Country	# of Classes Completed	ID	Gender	Age	Country	# of Classes Completed
P1	M	18 to 24	United States	0	P14	M	25 to 34	United States	6
P2	F	25 to 34	United States	2	P15	F	18 to 24	United States	5
P3	M	45 to 54	India	7	P16	M	25 to 34	United States	7
P4	M	35 to 44	Uzbekistan	7	P17	F	18 to 24	United States	3
P5	F	25 to 34	India	0	P18	M	25 to 34	Canada	3
P6	M	25 to 34	United States	3	P19	F	35 to 44	China	2
P7	M	25 to 34	United States	7	P20	F	35 to 44	Cuba	3
P8	M	35 to 44	United States	1	P21	F	25 to 34	China	1
P9	M	25 to 34	South Africa	0	P22	M	35 to 44	Iraq	3
P10	M	25 to 34	United States	0	P23	F	25 to 34	Canada	4
P11	M	25 to 34	United States	0	P24	F	18 to 24	Lithuania	5
P12	M	25 to 34	China	4	P25	F	25 to 34	India	2
P13	M	25 to 34	United States	3	P26	M	35 to 44	Argentina	7

Table 2. Interview participant information. "M" stands for "Male", "F" stands for "Female". "Country" column indicates the countries that participants were born in. The "# of Classes Completed" column indicates student's seniority in the program. Online students in the program usually take 1 or 2 classes per semester.

4 FINDINGS

Through our analysis, we found that deep social connections were rare yet highly desired among online learners. However, there were a number of difficulties that online students encountered when trying to establish social connections with each other. We present these difficulties through the lenses of social translucence and social-technical gap. Our interviews also revealed that SAMI was able to augment social translucence to some level yet not able to fully bridge the social-technical gap in online social interactions. We also identified a set of challenges and concerns that students had about SAMI in AI-mediated social interaction. We discuss our findings in detail below.

4.1 Perceived Difficulties in Remote Social Interactions Among Online Learners

Our interviews revealed that online learners had little social interactions with each other, especially private social interactions. About half of the participants reported having only interacted with other students academically (P3, P5-14, P18, P21, P23), through either working on group projects together or discussions on public discussion forum threads. The other half of the participants managed to keep in touch with one or two other students in the program and checked in with each other on a less than frequent basis (usually monthly). These private connections were usually established through the discovery of shared identities or experiences during previous group projects (P1, P16, P17, P19, P22, P26), meetup events organized by the program or students themselves (P4, P15, P24), class communication channels (P20, P25, P26), or common experiences (e.g., working at the same company, attended the same undergraduate institute) outside of the program (P1, P2, P15).

While not all private connections developed into deep friendships, establishing close interpersonal relationships like friendships was highly desired by majority of the participants in our interviews (P1, P2 P5-7, P9, P10, P12, P14-P18, P20-26) to reduce the feelings of social isolation and to offer emotional support and social support. Yet only eight participants reported building friendships through the program (P2, P4, P16, P19-P21, P24, P25). Through our interviews, we further investigated the difficulties online learners encountered while attempting to build social connections with each other. We found that these perceived difficulties were largely due to the lack of social translucence offered by the online learning platforms— the reduced visibility of social information, the diminished awareness of potential social companion, and the decreased accountability in social behaviors. Another set of difficulties stemmed from the existing social-technical gap in online social interactions— the lack of randomness and spontaneity that is inherent in in-person social interactions but difficult to replicate in online learning environments. We describe these difficulties through the lens of social translucence and social-technical gap below.

4.1.1 Reduced Visibility of Social Information. Reaching out and building connections with strangers can be an intimidating process. During in-person interactions, we are able to gain social cues from other people's behaviors, gestures, or facial expressions, however, all of these social cues become invisible in an online environment [19]. This is exactly what happened to online learners when they tried to establish social connections with others.

We found that the reduced visibility of social information, such as others' willingness to connect, often left students hesitant in reaching out or maintaining the connections with others. Many participants mentioned that not knowing whether other students were willing to talk or build connections with them made it difficult to initiate conversations with others (P1-P6, P12-P14, P17, P19, P20, P22, P23). P23 said, *"When I go introduce myself on the introduction thread on the forum, I can also see other people's introductions. But then it's also a little bit vague on the signal on whether they really want to connect with someone."* While online learners were able to meet others through class group projects or the discussion forum, students said they were not sure whether others wanted to maintain the connection with them. P14 mentioned that he really bonded with some of the students in his previous group projects, yet when asked about maintaining the connection after the group project was over, he said *"When I thought about reaching out to some of the folks I've worked with before, my first thought was like 'Oh no, you'd be imposing', 'That was just a group they wouldn't want you reaching out...' That's just my first reaction whenever I thought about it."*

Communicating with other students on public channels such as Slack and the class discussion forum was one of the main methods to get to know other students and to make students themselves known to others in the program. Yet for some students who described their own personalities as more reserved (P1, P3, P5, P7, P11, P13-P15, P17, P19, P20, P22, P23, P25), the reduced visibility of how their messages could be perceived by others added pressure when they wanted to reach out to

other students. This pressure sometimes even prevented them from posting messages on public communication channels. P23 said *"I know some study groups exist but then I don't really have a desire to join them to some extent. I think it might be because I'm doing it online. Sometimes you feel intimidated to join a big group and then posting your view on certain things since you don't know anyone in the group."* For female students who were minorities in the program, the pressure was even higher when posting on public channels. P15 said *"Being a minority in this program, sometimes it makes me feel even more nervous about posting anything because I don't want to represent females badly. I don't want to post something bad or stupid on the class discussion forum and other people would be like 'Oh that's one of the very few women in this program. The woman in this program must be dumb.' I don't want to be a bad representative. I don't necessarily feel intimidated to ask questions or to talk to people because I'm a female student, but it can make it harder to relate to people."*

4.1.2 Diminished Awareness of Potential Social Companion. One of the main goals and advantages of online learning is to help education scale up by giving more students the opportunities to learn [38]. The downside of this is that online classes usually have hundreds or even thousands of students per class. This has resulted in online students' diminished awareness of other students' existence in the program when building social connections. In our study, participants talked about how the diminished awareness of potential social companions posed challenges in their social connection process, specifically, the difficulty of identifying potential social companions and the lack of personal touch in the online learning environment.

The overwhelming number of students and activities within each class made it extremely difficult for online students to identify others that they could potentially build social connections with (P2, P3, P6-P9, P11, P12, P14-P16, P19-P21, P23-P26). P14 said, *"The Slack group and the class discussion forum can get overwhelming depending on what's going on with all the posts. Looking for specific students to connect with is like trying to find that needle in a haystack."* P21 also said, *"There are many many posts in the public forum. I may never find the person or the group I'm interested in if I search it manually. "*

With hundreds of students communicating via the class discussion forum and Slack group, these main communication channels could quickly become walls of text, which made all the interactions there seem impersonal. The lack of awareness of human characteristics in a majority of the communications provide a weak foundation and decreased motivation for students to build social connections. When asked about the students' self-introduction thread for each class, P2 said *"The introductions students gave were really nice. But those discussion threads get so overwhelmed and the content of the introductions are people's names, how many classes they have taken, current classes they are taking, where do they work. So it just becomes a wall of text repeating 'Oh I live in New York', 'I live in San Diego'. That's not super valuable to build a strong relationship. It is just nice to see the reminder that 'Right, there are people here'."* P15 also pointed out the missing personal aspects that were inherent in in-person interactions *"The program is huge and it's so hard to differentiate people unless you meet them in-person. That's part of the reason why I like meeting people in-person. There's not as much of space to talk to people about things other than classes. Even though we all relate to each other since we are in the same class, but it's harder to get to the actual personal aspects where you relate to each other."*

4.1.3 Decreased Accountability in Social Behaviors. Erickson and Kellogg point out that while awareness and accountability often co-occur in physical world, they are not usually coupled in the online spaces. Accountability is often fostered through the creation of social norms in the online environment that hold people accountable for their social behaviors [19]. In our study, we found that both the existence and the lack of social rules could prohibit online learners' social interaction processes in online learning environments.

Some implicit social rules could restrict or deter students' social behaviors in online spaces. In our study, we found that online learners designated different purposes for the communication platform that they commonly used— the class discussion forum was for academic discussions and the Slack group was for casual interactions (P1, P3, P4, P8, P10, P11, P18-P22). While the intention of the class discussion forum was to replicate the physical classroom where students could have interactions and discussions about and beyond academics that could facilitate student learning as well as building social connections, the implicit social rules of only using the online class discussion forum for academic discussions seemed to restrict students' social interactions with each other on the forum— students felt accountable to only have academic discussions on the forum instead of casual conversations. Considering most of students' interactions tend to happen on the discussion forum, this social rule significantly limited online learners' opportunities for building social connections. For example, P19 said, *"I prefer Slack if it's just casual conversation. I don't feel casual conversations are okay on the class discussion forum. The forum is for more serious conversation for the class. So I'm not going to post any unrelated things on the forum."* Other students also felt like the class discussion forum was monitored due to the presence of the teaching staff. P22 said, *"The thing about the class discussion forum is that it's not friendly. You don't feel open to post on the forum or maybe that's me. At least I feel like the discussion forum is official and monitored. If I said something wrong on the forum people would judge me for it. "*

While working in group projects with other online learners provided some social pressure for students to interact with each other in small groups, the pressure was gone once the project was finished. Even though the same thing could also happen in in-person classrooms, online students didn't usually run into each other again after the class was over. The lack of repetitive encounter with each other in the online program thus reduced students' feeling of accountability to talk with each other again (P1, P3, P6-P8, P11-P15, P19, P21-P23). P8 said, *"Last semester we had a group project with five students. We had our own Slack channel to communicate and at the end of the semester we were all very friendly. It would be nice to work with them in the future but there's no more intersection of us. Even if we ended up in the same class, there is no way for me to know that because I can't look through everyone's name in my class. I think most likely we are not ever going to be in the same class again so there is no place for us to interact again. "*

4.1.4 The Social-Technical Gap in Remote Social Interactions. Besides the diminished visibility, awareness, and accountability in building social connections in online learning environments, another set of difficulties that online learners faced was the lack of spontaneity and randomness in online environments. While social interactions are inherently spontaneous and random in in-person interactions, participants reported that in online environments, they had to intentionally make efforts to compensate for this social-technical gap [1] in remote social interactions.

Many participants (P1, P3, P5-P7, P9, P10, P13, P14-P16, P21, P26) reported that online interactions were not as spontaneous and organic as in-person interactions. P15 pointed out the importance of having "in-between" moments during interactions, which proved to be difficult to achieve in online environments: *"Sometimes when you meet people, you have those in-between moments, where you are not necessarily actively working on the project, but you are still thinking about the project. I really valued those moments. So I really wanted to be able to meet up with my teammates in person and have that joy in getting to know someone and then have those in-between moments."* Other participants also pointed out that during in-person interactions, work conversations often organically led to more social activities. P6 said, *"My current interactions with other online students are more academic or professional. It wasn't like my friends in undergrad. I think that's one of the other things that's odd about the social interactions with online program. In undergrad I can make friends, go have dinner, we*

can go out and get a drink or whatever. That kind of very natural social interaction can happen, which I don't see the analogy online."

On top of the lack of spontaneity in online social interaction process, several participants (P1, P5, P8, P10) talked about the random encounters that on-campus students could have that offered starting points for them to build social connections. However, these random encounters were almost completely missing from the online program. P8 described different scenarios where random encounters could happen in in-person campus, *"Let's say you are on an actual college campus and you go to the library to study. You might end up being in a situation where you can talk to someone who is in the same university but in a different class or major... Or the university has some open lawn that sits between the lecture halls and the food court. So people would walk through there everyday and that's a place where you can run into someone. So to translate that into online program, I think it's hard to generate a place that students have to go to."*

The lack of spontaneity and randomness of online social interactions forced students to spend extra effort and time to build those social connections (P1, P3-P9, P11-P15, P17, P20, P23, P26). P5 said, *"So when I was in college, I never went out to form connections like 'Oh let me form five new connections'. It just organically happened in the process of studying."* Many students also had to go out of their way to form those connections, such as driving for 40 minutes to meet up with other online students in the same city, emailing every student in the class to build connections, or manually looking up students with commonalities among thousands of discussion forum posts.

The general consensus among participants was that in online learning programs, the social and learning aspects were often separated compared to the traditional in-person educational programs. Instead of forming social connections organically during the process of taking classes or walking around campus that were inherently built into the on-campus educational experience, online learners had to establish social connections in a more intentional way.

4.2 Augmenting Social Translucence in Online Learning through SAMI

Based on students' experiences in interacting with SAMI, we asked for participants' feedback on SAMI. Through our evaluation of SAMI, we found that SAMI was able to augment social translucence in online learning environment mainly by improving the visibility of social signals and increasing students' feeling of accountability in remote social interactions. While SAMI raised students' awareness of potential social companions to some degree, participants pointed out several ways on how SAMI could further improve their awareness throughout the process.

4.2.1 Enhanced Visibility of Social Signals. We found that SAMI made social signals more visible among online learners, especially in reference to highlighting students' willingness to build social connections (P1, P3, P5, P23). Specifically, participants highlighted the feature in SAMI 1 and SAMI 2 that made it easier for them to infer students' willingness to connect. For SAMI 1, the #ConnectMe tag was intended to allow students to opt-in for SAMI 1 to connect them with other students in the class introduction threads. However, online students interpreted this as a signal of whether students were willing to build social connections. P23 commented on the #ConnectMe function in SAMI 1, *"I like SAMI 1 a lot, especially the #ConnectMe. This is sending the student a signal that there's people who are interested in chatting with other students. So I think this is very helpful."*

Students were also able to infer students' willingness to connect from SAMI 2. For example, P1 said, *"People who introduced themselves to SAMI 2 are more likely to want to connect to other people. So it's a group of people that are likely to be more willing to talk to other people."* P23 also said, *"There are Slack groups that can form similar groups that SAMI 2 did for us so forming a group is not a problem here I feel. Knowing who is available to form a group or engaging people who are interested to do certain things is a challenge. SAMI 2 made this process automatic so this is great."*

4.2.2 Improved Awareness of Potential Social Companions. In online classes with hundreds of students per class, SAMI also raised awareness of potential social companions for online learners by highlighting students' shared identities (P1-P5, P7, P9-P19, P22, P23, P26). P21 commented on the feature of connecting students based on similarities in all three versions of SAMI, *"SAMI's useful because manually, I may never find the person or never find the group I'm interested in. But SAMI can find some related groups or students I might want to connect with for me. "* Participants also said even without SAMI's feature of directly connecting students together, the class demographic summary statistics posted by SAMI 1 was also useful in offering the lost personal aspect to online learning, *"I really appreciate SAMI 1's class demographics summary. I think it's interesting to see how many people are from different places and in different classes. It's cool to see just how broad the classes are and where everyone is from."*

Some students also suggested that the next generation of SAMI should connect students together based on more specific commonalities, instead of the current broad shared identities (P2-P4, P9, P11, P15, P17, P23, P26). For example, P2 commented on SAMI connected her with other students in the San Francisco area, *"That's great but it's not something you can make a strong connection with. Bay Area is huge so even if there is someone else in the Bay Area, they could live literally two hours away from me. So you really have to narrow in the location."* P4 also suggested SAMI to connect students based on multiple shared identities instead of only one, *"Let's say I want to meet people who are also interested in hiking, I wouldn't want to connect with people who are located outside of my city. Because sure we could probably connect on the forum and share some past experiences, but that would probably be it. Hiking is not something you discuss online, it is something you do outside of online environment."*

While SAMI gave students awareness of potential social connections, many students pointed out the necessity of continuing to support that awareness throughout the entire process (P3, P6, P7, P12, P16, P17, P20, P22, P24). Participants expressed their preference to know more about the students recommended in SAMI's reply, instead of just how many students share similar commonalities. For example, P17 commented on SAMI 1, *"I like how SAMI 1 is sort of pointing out, like here's the list of people you might want to connect with. I like how it links to the students' posts in the introduction threads. I think that's useful for quickly seeing 'Oh this is what this person said about themselves'."*. SAMI 2 did not provide information about each student in each SAMI group, which diminished students' awareness of others in the group. P22 suggested, *"Maybe if there is a student join the group, SAMI will say 'hey everyone, we have a new member just joined the group. This is John Doe. Please say hi to him. John Doe please introduce yourself.'"*

4.2.3 Greater Accountability in Social Interactions. SAMI also provided some level of accountability by offering some structure to the social interaction process (P1, P3, P5, P6, P14, P15, P16, P19, P21, P22, P24). By putting students directly in groups, SAMI provided the push for students to start interacting with each other and helped alleviate students' mental barriers on having to reach out to other people. For example, P3 compared SAMI 1 and SAMI 2, *"I think SAMI 2 is a better approach because it actually places you in the group as opposed to SAMI 1. I would probably not going to initiate any communication with the list of people SAMI 1 recommended to me because you typically don't initiate communication with somebody directly for no purpose right? So SAMI 2 creates that sense that you are already in a group and that you can share something more at ease."* P15 also said, *"I like SAMI 1's reply, but I do think it puts a lot of pressure on the students to have to reach out. I feel like it gives you a lot of information but it might not be the push that people need in order to reach out to others. Whereas with SAMI 2, because it makes the group so it at least starts to move in the direction of eliminating barriers that people would have to reach out to other people."*

After putting students in individual groups, SAMI 2 also posted ice-breaker questions that were relevant to the group topic for everyone to start the conversations. P24 believed this provided some kind of accountability for people to start talking since the questions were straightforward, *"I think if SAMI 2 did not post anything, it would be like, what are we supposed to do here? But having the questions that specifically relate to the topic to the group, like Seattle group 'what would you do in Seattle?' is great. Because you obviously all have that shared interest. So being able to talk about it in a structured way is very smart. "*

4.3 Challenges and Concerns about SAMI in Mediating Social Interaction

While SAMI efficiently augmented social translucence during online learners' social interaction process, we also identified several challenges and concerns that students' expressed about SAMI in terms of AI-mediated social interactions. Based on our interviews with the online learners, we found that SAMI was not able to fully bridge the social-technical gap in online social interactions and even exacerbated the gap due to its lack of human-like characteristics and unnatural behaviors. Students also pointed out that SAMI did not offer enough transparency into its working mechanism and decision-making process. When asked about concerns about the potential continuous usage of SAMI in online learning environment, students pointed out that privacy was not a perceived concern, however, there were concerns about SAMI 3 potentially excluding certain students out of the social connection process as well as students losing their agency in building social connections.

4.3.1 Social-Technical Gap Remains: Lack of Human-likeness and Naturalness. One of the difficulties that online learners experienced during social interactions was the lack of spontaneity and randomness compared to in-person interactions. This existing social-technical gap forced online students to intentionally spend more effort, time, and energy to build social connections with each other. SAMI helped reduce this gap slightly by automating the social interaction process and thereby reduced some efforts that students spent in building social connections (P1, P4-P7, P10, P11, P14, P17, P21, P26). P17 believed that by providing social recommendations, SAMI played the similar role to that of a mutual friend. P14 also said that since SAMI recommended social matches automatically, he didn't have the need to intentionally put himself out there to build social connections.

However, throughout our interviews with online students, we noticed that SAMI also contributed to the social-technical gap in online social interactions due to its lack of human-likeness and naturalness (P2, P4, P5-P7, P15, P18, P21-P24). While many technologies are often designed to be artificial, rigid, and reductionist, when introducing an AI agent to operate in human communities to build social connections among community members, the agent was expected to act more human-like and natural. In our interviews, online learners believed that SAMI did not act natural enough. For example, P2 said *"I think SAMI 2 needs to feel more human-like and not as robotic to make people more comfortable interacting with it. SAMI 2's response just seems so numerical with those statistics and normal human don't really talk like that."* P7 also said, *"It would be good if it seems like it's actually interacting with me instead of an automated response. Even though it's an AI I don't want to feel like it is. If SAMI 2 acts more like a human, it would seem like a person responding to me who knows the people that are recommended. So I want it to seem like it is a person."* When asked about why they wanted SAMI to be more natural, P4 said that when SAMI acted unnaturally, it would "break" the natural atmosphere of online forum environment and therefore broadened the social-technical gap in online environment:

> *"So with the class discussion forum is that, when you have a conversation with someone, it sometimes feels like you're in the same room talking to people. Like when answers to the posts come in real time and you have this sort of atmosphere of speaking in a group. Like you are sitting in the room and talking to people and you could see if others are trying to*

answer your question. Maybe they do some research on the side and then they post their responses or maybe they know it right off the top of their head. So sometimes it feels like a real time conversation. So any sort of artificial-looking posts would interrupt this flow. Like if you imagine a group of students in a study group sitting at the same table studying and then there's like some TA announcer speaking some robotic automated message every once in a while, it would interrupt this flow, right? So, this sort of a robotic type of response kind of interrupts this flow on the discussion forum." (P4)

4.3.2 Insufficient Transparency in SAMI's Working Mechanism. On top of SAMI'S lack of naturalness, students also reported that SAMI was not transparent enough about its decision-making process and working mechanism (P3, P5-P10, P13, P14, P16-P18, P21, P23-P25). We found that students wanted to learn more about SAMI's capability for them to better communicate with SAMI using similar vocabularies. For example, when asked about what he wished he had known before using SAMI 2, P7 said, *"I wish I had known that there was a possibility of not getting matched due to my word choices. If I were told to use these key words or some word bank to have better matching results, that would be helpful. Like if I knew to use 'travel' instead of 'traveling'."* Other students took guesses as to why SAMI 2 didn't work as they expected, such as not putting them into certain groups when it was clearly mentioned. P3 put "travel" among several other hobbies but was only assigned to "travel" group, he said, *"I'm just trying to see why I got put in 'travel' but not other hobby groups. That's why I figured maybe SAMI 2 only picked out the first hobby and place people in those groups."* P16 also had similar doubts, *"I guess I am curious as to whether I didn't get assigned to 'Virginia' group. Maybe because I said 'Nothern Virginia', so it got stuck in 'Nothern Virginia' and it thought it was different from 'Virginia'. I guess if SAMI 2 told me what it is thinking that would be great. Because SAMI 2 also didn't pick up on the courses I listed, which might be because I abbreviated the course names."* To improve transparency, P24 suggested, *"I would have appreciated if SAMI 2 had another response after my reply, saying something like 'Sure I will look for other people who are also in Los Angeles.' or 'I will let you know if I find someone else that played Ultimate Frisbee.' Just something that tells me 'I've stored this information and I'm looking for that connection.'"*

4.3.3 Concerns about Excluding Some Students Out. While all participants were generally very positive about SAMI, some students brought up concerns that they had about the continuing use of SAMI in online learning contexts. Since SAMI only operated on one of the many platforms online learners used to engage with each other, there were concerns about SAMI inadvertently excluding some students out of the AI-mediated social interaction process among online students (P11, P12, P15, P19, P23, P26). SAMI 1 and SAMI 2 currently only took information from one specific introduction thread on the class discussion forum and SAMI 3 would also be restricted to the class discussion forum. This design thus naturally left out students who were not active on the class discussion forum and students who did not post their self-introductions. P15 commented on this concern regarding SAMI 3, *"I do think it's kind of hard to have something based off of people posting about themselves on the forum. I think the forum can be sort of self-selecting for students who are most willing to put themselves out there on the forum type of people."*

4.3.4 Concerns about Losing Agency in Building Social Connections Online. While students appreciated SAMI automating some of the most difficult processes in building social connections with other online learners, students also raised concerns about losing agency in making social connections online (P7, P9, P10, P11, P14, P15, P20-P22). SAMI 2's feature of putting students directly into groups was popular among the interview participants for creating accountability to interact with each other as well as alleviating the mental barrier of reaching out to other students. However, this feature, while created adequate amount of social pressure for students to initiate

interactions, was also commented by the participants that it took away their agency in choosing which groups they could join. For example, P9 said, *"I would actually prefer to participate in a class community just so that I can hang around the edges of it first before committing. Because there are some things that I'm interested in doing but I haven't done it yet. "* This concern came up more after we described our vision for SAMI 3 that could more naturally and automatically connect students together based on everything they posted on the discussion forum. After hearing our vision for SAMI 3, P14 said, *"It would be great if students could opt-in to particular topics. Maybe SAMI 3 could provide its observation first then let student decide. Just some kind of mediating steps that let you sign off, like 'Oh no I would prefer not to have other people know that I'm interested in this.'"* P10 also brought up the point of whether to trust SAMI 3 on the connections recommended, *"So if we were to compare this to real life, generally, when you meet someone new, you have a bit of a gatekeeper in your friend who introduces you guys. So you have a mutual person whom you both trust. So then because you trust that person, then you trust that the person they introduce you to is going to be not a murderer or something like that. So, yeah, SAMI 3 may not give you that."*

4.3.5 Privacy was Not a Perceived Concern. However, even though privacy is often a concern for AI systems that leverage public data [20], many participants did not have privacy concerns regarding SAMI (P3, P5, P6, P10, P12, P14, P16, 17, P19-22, P24). Some participants believed that the intention of posting on public forum was for others to see it. For example, P12 said, *"If they already posted their self-introductions that means he/she wants that information to be public. If I don't want others to know where I work, I won't put that information there."* In fact, some students indicated their willingness to post more frequently on the discussion forum if SAMI could offer more accurate matches. After hearing about our vision for SAMI 3, P14 said, *"I think that's a really brilliant idea! I think I'd be more inclined to post too, because I don't need to worry that my posts would be falling on deaf ears. I am more willing to put myself out there more since I will be giving SAMI 3 a chance to find more things and possibly make more connections in the program."*

5 DISCUSSION

Our findings offer insights into the challenges and opportunities of AI-mediated social interaction in an online learning context. Specifically, we pinpoint online learners' perceived difficulties in building social interactions due to the lack of social translucence and the existence of the social-technical gap in their current online learning environment. Our findings reveal the potential and challenges of using AI-mediated social interaction to help facilitate online learners' social interaction process.

Based on these findings, we outline the design space of AI-mediated social interaction in this section. We first discuss how AI-mediated social interaction could be designed to cater to online learners' difficulties in remote social interaction. We then discuss the ethical and social challenges of AI-mediated social interaction in the online learning context, emphasizing how these challenges constitute a design tension when designing AI-mediated social interaction. Taking into consideration the difficulties in building remote social connections and the potential ethical and social challenges of AI-mediated social interaction, we propose and discuss two design opportunities of AI-mediated social interaction: designing towards the human-AI collaborative social matching process and designing towards artificial serendipity.

5.1 Designing AI-Mediated Social Interaction for Online Learners

Through our in-depth investigation of online learners' social interaction process, we identified online learners' pressing needs to build close friendships with other students, yet these needs were largely unfulfilled. Our findings echo prior work in that academic-related interactions are the main

sources for students to build connections with each other [62, 69]. While the discovery of shared identities or common experiences could help foster closer connections and may occasionally lead to long-term relationships [61, 62, 69], close friendships are uncommon among online learners [61, 62] yet highly desired by students seeking emotional support. Many online learners stepped out of their comfort zones to pursue an online degree that is very different from their academic background often with the goal of career shift or career advancement, which makes the online education process even more difficult for them. Therefore, social and emotional support become crucial to help online learners persist through the online program. One example of this is P25, who did not have any programming experience prior to the online CS program, teared up when talking about her experience struggling with the course materials at the beginning. She admitted that without her friend in the program to offer her emotional support she would have dropped out a long time ago. Our work motivates future research to explore how technologies could be designed to directly help online students offer emotional and social support to each other.

We also identified two sets of difficulties that online students encountered during remote social interactions: the lack of social translucence [19] and the existence of the social-technical gap [1] in current online learning platforms. Specifically, current online learning platforms do not offer enough visibility of social information (e.g., others' willingness to connect), provide limited support of students' awareness of potential social connections due to the large number of students, and do not facilitate sufficient accountability that is often necessary to create social pressure for students to connect during in-person interactions. Designing online learning platforms to be more socially translucent could mitigate a large set of difficulties that online students tend to experience during remote social interactions. Some design strategies to achieve socially translucent online learning platforms could be adding icons on students' avatars to indicate their willingness to connect with others, thus improving visibility of social cues [64]; highlighting students' shared identities through social matching features to offer awareness of potential social companions; and providing dedicated socializing sections or instant video chatting features on the discussion forums [35] to improve students' accountability in building social connections.

The second set of difficulties online learners experienced stemmed from the existence of the social-technical gap [1] in the online learning environment, which created a separation between social interactions and education activities in online learning. In in-person educational programs, students often build social interactions or long-term friendships spontaneously through random encounters that happen in between learning activities (e.g., repeatedly taking the same classes, randomly running into each other in the dining hall, spontaneously grabbing coffee together after group project meetings), this kind of randomness and spontaneity is difficult to replicate in the online learning environment— in online environments, all virtual meetings are intentional and every message has a specific purpose. Without randomness and spontaneity embedded into their online education experience, online learners are forced to spend extra effort and time (e.g., driving for an hour to meet others in person or emailing everyone in the class to connect) to intentionally form social connections. This speaks to the lack of nuance, flexibility, and ambiguity in building social interactions on online learning platforms. Our work thus points out the direction for future research to explore how to integrate more social activities into online learners' learning activities to artificially create more random and spontaneous encounters in online learning environments.

5.2 The Design Tension in AI-Mediated Social Interaction

As more and more education programs and workplaces advocate for remote work, it is not difficult to imagine AI-mediated social interaction being widely adopted in a variety of settings. Understanding the potential ethical and social challenges is crucial in order to protect human well-being in remote environments. Our work offers a first glimpse into the ethical and social challenges of AI-mediated

social interaction in the context of online learning. Through our interviews, we identified challenges and concerns such as the possibility of excluding certain students from the the social matching process [25], the lack of transparency in AI-mediated social matching processes [26, 48], and the possibility of strengthening people's similarity-seeking behavior [54].

While some of the challenges we identified align with prior findings in CSCW, AI-MC, and social matching space, AI-mediated social interaction, situated at the intersection of several fields, also presents another challenge that combines concerns from these fields and creates *a unique design tension between AI performance and ethical design.* In our study, this design tension in AI-mediated social interaction is manifested in two areas: *the tension between matching accuracy and user privacy, and the tension between the effectiveness of social introduction outcome and user agency.*

Our work highlights the tension between achieving high social matching accuracy and maintaining user privacy in AI-mediated social interaction. The basis of getting accurate social matches is the deep understanding of user preferences, goals, and needs, which would require the AI system to collect as much user data as possible [48, 54, 66]. In the case of AI-mediated social interaction, such information can not only be gathered through information that users voluntarily offered to the AI system, but also through analyzing prior public postings to make inferences that users don't explicitly consent to sharing [60, 72]. This renders the protective measures suggested by prior literature in social matching system such as restricting data source to public information or obtaining user consent before data collection [66] less applicable. What concerns us more is the fact that no privacy concerns were raised in our interviews with the online CS students even after we showed them SAMI 3, which would have access to all of students' prior forum postings and have the ability to make inferences about their preferences and goals— in fact, participants in our study indicated that they were willing to post more frequently on the discussion forum to improve matching accuracy. Does this suggest that designers of AI-mediated social interaction should always weigh accuracy over privacy? We think not due to the intangibility of people's understanding of privacy harms and people's tendency to trade privacy for potential gains [2]. In fact, we see this as an opportunity to further investigate what types of latent behavioral data would improve social matching results yet raise little privacy concerns for users in different contexts.

Another tension presented in AI-mediated social interaction is the balance between maintaining user agency and ensuring successful social introduction processes. The introduction process between two matches is crucial for an effective social matching process [66]. In our study, SAMI 2 directly put matches into a group on the discussion forum instead of waiting for students to reach out to others. Students found this to be helpful as several of them pointed out that they would have never reached out to their matches to build connections otherwise. However, during our interviews, students also expressed concerns about losing their agency in choosing whom they could connect with, which is inherently a very personal decision-making process. While prior research has suggested that given the convenience and efficiency AI systems facilitate in our daily lives, some level of human agency could be sacrificed as a trade-off [63], in our study we found that students were unwilling to cede control of the decision-making process in choosing whom they should connect with. This differs from prior research in AI-MC and recommender systems where issues regarding user agency have been repeatedly brought up yet could mostly be resolved by giving users as much agency during the decision-making process as possible [26, 27, 48, 63]. Based on our findings, we note that in AI-mediated social interaction, designers should strike a delicate balance between putting enough social pressure on the matches to initiate interactions and maintaining users' agency in choosing whom they could start a conversation with.

5.3 Design Opportunities for AI-Mediated Social Interactions

Building upon the design implications and ethical challenges our work has identified, we highlight two potential design opportunities for AI-mediated social interaction: designing towards human-AI collaborative social matching and creating artificial serendipity.

There are several ethical and social challenges that we outlined in the previous section that could be properly mitigated through a human-AI collaborative social matching approach. In a human-AI collaborative decision-making process, AI systems could constantly negotiate with users on important social matching steps to take next while also creating enough social pressure to prompt users to reach out to their matches. Certain way of maintaining user agency could be achieved through the use of AI agents that display proper anthropomorphic qualities [63]. Human-AI collaboration in social matching process could also resolve the design tension of maintaining user privacy and ensuring matching accuracy. This could be done by building explainability and transparency into the AI system to constantly explain what data was collected and how the data was used [18]. In human-AI collaborative decision-making processes, users' willingness to collaborate is crucial for a desirable collaborative experience and outcome [10]. Luckily, aligned with prior literature [33, 42], participants in our study indicated their willingness to understand the AI agent's vocabulary beforehand to adjust their choice of words during communication in order to improve the accuracy of matching results.

Another design opportunity for AI-mediated social interaction is to artificially create serendipity, i.e., unexpected yet meaningful encounters, to artificially create randomness and spontaneity in online social interactions. Serendipitous encounters in in-person interactions such as elevator chat or water cooler conversations often result in fruitful interactions, new collaborations, new ideas, and may sometimes lead to meaningful long-term relationships [53]. In our study, one set of difficulties that online learners encountered during remote social interactions is the social-technical gap that made the online social interaction process more intentional and less natural. Designing for artificial serendipity in remote social interactions could thus re-introduce randomness and spontaneity into the online environment by helping individuals discover unexpected meaningful relationships and potentially mitigating people's similarity-seeking behaviors in social interactions [54]. Prior research has suggested that serendipity can be created by identifying individual's preferences and social networks through mobile phone sensors [17], social network information [13], and sensing technologies in the workplace [8]. Following this direction that we highlighted based on our work, future research could explore what kinds of information could be leveraged to artificially create serendipity without raising privacy concerns.

While there are many types of technical artifacts that could create serendipity and bridge the social-technical gap in remote social interaction(e.g., inserting synchronous chat or offering explicit social cues as part of the online platforms), many solutions are first-order approximations that only partially address the social requirements but cannot fully mitigate or avoid the social-technical gap [1]. An elegant solution should create technical architectures that do not invoke the social-technical gap by offering advice or other sources of information to augment existing facilities [1]. One possible solution that satisfies this requirement is the use of AI agents to mediate online learners' social interaction process.

Designing for agent-mediated online social interaction has the advantage of having an anthropomorphized technology to deliver suggestions that can augment existing social facilities through natural back-and-forth conversations without invoking the social-technical gap [1, 40]. When AI agents are equipped with the right technique, AI agents have the potential to create serendipity in online learning environments. For example, AI agents can help students recognize and remember others who have taken similar classes before and prompt both students to connect; AI agents can

also recognize the implicit social cues hidden in walls of text to identify and connect students with similar interests. AI agents thus can act as a mutual "friend" to all online learners, leveraging knowledge about learner preferences and information to connect students. However, designers should also caution the potential issue of users oversharing with AI agents as AI agents' human-like characteristics could encourage people's self-disclosure during conversations [21, 30, 41]. This might lead students to unintentionally disclose sensitive information to the AI agents.

6 LIMITATIONS AND FUTURE RESEARCH

While our work has important implications for the design of AI-mediated social interaction, it also has some limitations. First, we used an AI agent with an anthropomorphic form to mediate online social interaction in our study, but we acknowledge that AI-mediated social interaction could be performed by other types of AI systems that do not take an anthropomorphic form. Prior research also suggests that people could act more "courteous" towards AI agents due to their human-like characteristics and thus other non-anthropomorphic AI systems could raise additional concerns than currently investigated in our paper. We encourage future research to replicate our study using other kinds of AI systems. Second, the online class discussion forum was heavily used in the online learning program that our study took place in and was also most frequently brought up by students during the interviews. However, we acknowledge that this could largely be attributed to each online program's preferences and thus other forms of communication tools such as Learning Management Systems could also be leveraged to facilitate online learners' interactions with each other in other online programs. Future research should explore alternative mediums and tools that online learners in other programs used and how they could be designed to support online learners' social interactions. Third, the interview participants in our study were all studying at the computer science for-degree graduate program. Due to their major of study in computer science, these learners might be more open to the use of technology-facilitated interactions (e.g., they did not have many privacy concerns regarding the use of SAMI). Future research should try to replicate the current study at online learning programs in a different subject area to investigate concerns and preferences of AI-mediated social interaction from learners who are less tech-savvy and/or more skeptical of technology. Our findings might also not be applicable to other forms of online learning environment such as Massive Online Open Classes (MOOCs) or online learning programs at the high school or undergraduate levels. Future work should examine the social interaction experiences across different contexts to contribute more knowledge in the design of AI-mediated social interaction in online learning contexts.

7 CONCLUSION

This paper sought to outline the design space of AI-mediated social interaction through understanding the potential challenges and opportunities of AI-mediated social interaction in the context of online learning, where the learners frequently experience social isolation. We deployed an AI agent that could connect online learners based on commonalities identified through their posts on the class discussion forum. Using the AI agent as a probe, we elicited design feedback and identified potential challenges and opportunities of AI-mediated social interaction in online learning, through understanding students' current difficulties in remote social interaction and their experience with the AI agent. We summarized online learners' difficulties in social interaction through the lenses of social translucence and social-technical gap. Online learners in our study believed that the AI agent augmented social translucence yet did not fully bridge the social-technical gap in online social interaction. We also pinpointed potential ethical and social challenges in designing AI-mediated social interaction in online learning environment. Building upon our findings, we outlined the

design space of AI-mediated social interaction. We discussed how AI-mediated social interaction could be designed to cater to students' difficulties and needs, identified the design tension between AI performance and ethical design in AI-mediated social interaction, and proposed two design opportunities for future AI-mediated social interaction on human-AI collaborative social matching and artificial serendipity. We believe our research will inspire future work to understand and design AI-mediated social interaction from a human-centered perspective.

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REFERENCES

[1] Mark S Ackerman. 2000. The intellectual challenge of CSCW: the gap between social requirements and technical feasibility. *Human–Computer Interaction* 15, 2-3 (2000), 179–203.

[2] Alessandro Acquisti, Laura Brandimarte, and George Loewenstein. 2015. Privacy and human behavior in the age of information. *Science* 347, 6221 (2015), 509–514.

[3] Rohan Ahuja, Daniyal Khan, Danilo Symonette, Marie desJardins, Simon Stacey, and Don Engel. 2019. A Digital Dashboard for Supporting Online Student Teamwork. In *Conference Companion Publication of the 2019 on Computer Supported Cooperative Work and Social Computing*. 132–136.

[4] Tahani Ibrahim Aldosemani, Craig Erschel Shepherd, Ibrahim Gashim, and Tonia Dousay. 2016. Developing third places to foster sense of community in online instruction. *British Journal of Educational Technology* 47, 6 (2016), 1020–1031.

[5] Steven R Aragon. 2003. Creating social presence in online environments. *New directions for adult and continuing education* 2003, 100 (2003), 57–68.

[6] J Ben Arbaugh, Martha Cleveland-Innes, Sebastian R Diaz, D Randy Garrison, Philip Ice, Jennifer C Richardson, and Karen P Swan. 2008. Developing a community of inquiry instrument: Testing a measure of the community of inquiry framework using a multi-institutional sample. *The internet and higher education* 11, 3-4 (2008), 133–136.

[7] Pernille Bjørn and Ojelanki Ngwenyama. 2009. Virtual team collaboration: building shared meaning, resolving breakdowns and creating translucence. *Information systems journal* 19, 3 (2009), 227–253.

[8] Chloë Brown, Christos Efstratiou, Ilias Leontiadis, Daniele Quercia, and Cecilia Mascolo. 2014. Tracking serendipitous interactions: How individual cultures shape the office. In *Proceedings of the 17th ACM conference on Computer supported cooperative work & social computing*. 1072–1081.

[9] Jeongmin Byun, Jungkook Park, and Alice Oh. 2020. Cocode: Co-learner Screen Sharing for Social Translucence in Online Programming Courses. In *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems*. 1–4.

[10] Carrie J Cai, Samantha Winter, David Steiner, Lauren Wilcox, and Michael Terry. 2019. " Hello AI": Uncovering the Onboarding Needs of Medical Practitioners for Human-AI Collaborative Decision-Making. *Proceedings of the ACM on Human-computer Interaction* 3, CSCW (2019), 1–24.

[11] Kathy Charmaz. 2014. *Constructing grounded theory*. sage.

[12] Jilin Chen, Werner Geyer, Casey Dugan, Michael Muller, and Ido Guy. 2009. Make new friends, but keep the old: recommending people on social networking sites. In *Proceedings of the SIGCHI conference on human factors in computing systems*. 201–210.

[13] Yu-Shian Chiu, Kuei-Hong Lin, and Jia-Sin Chen. 2011. A social network-based serendipity recommender system. In *2011 International Symposium on Intelligent Signal Processing and Communications Systems (ISPACS)*. IEEE, 1–5.

[14] Chia-Fang Chung, Nanna Gorm, Irina A Shklovski, and Sean Munson. 2017. Finding the right fit: understanding health tracking in workplace wellness programs. In *Proceedings of the 2017 CHI conference on human factors in computing systems*. 4875–4886.

[15] Andrew Cross, Mydhili Bayyapunedi, Dilip Ravindran, Edward Cutrell, and William Thies. 2014. VidWiki: enabling the crowd to improve the legibility of online educational videos. In *Proceedings of the 17th ACM conference on Computer supported cooperative work & social computing*. 1167–1175.

[16] Pieter Duysburgh, Shirley A Elprama, and An Jacobs. 2014. Exploring the social-technological gap in telesurgery: collaboration within distributed or teams. In *Proceedings of the 17th ACM conference on Computer supported cooperative work & social computing*. 1537–1548.

[17] Nathan Eagle and Alex Pentland. 2005. Social serendipity: Mobilizing social software. *IEEE Pervasive computing* 4, 2 (2005), 28–34.
[18] Upol Ehsan, Q Vera Liao, Michael Muller, Mark O Riedl, and Justin D Weisz. 2021. Expanding explainability: Towards social transparency in ai systems. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. 1–19.
[19] Thomas Erickson and Wendy A Kellogg. 2000. Social translucence: an approach to designing systems that support social processes. *ACM transactions on computer-human interaction (TOCHI)* 7, 1 (2000), 59–83.
[20] Casey Fiesler, Cliff Lampe, and Amy S Bruckman. 2016. Reality and perception of copyright terms of service for online content creation. In *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing*. 1450–1461.
[21] Asbjørn Følstad, Cecilie Bertinussen Nordheim, and Cato Alexander Bjørkli. 2018. What makes users trust a chatbot for customer service? An exploratory interview study. In *International Conference on Internet Science*. Springer, 194–208.
[22] D Randy Garrison and J Ben Arbaugh. 2007. Researching the community of inquiry framework: Review, issues, and future directions. *The Internet and higher education* 10, 3 (2007), 157–172.
[23] Ali Gheitasy, José Abdelnour-Nocera, and Bonnie Nardi. 2015. Socio-technical gaps in online collaborative consumption (OCC) an example of the etsy community. In *Proceedings of the 33rd Annual International Conference on the Design of Communication*. 1–9.
[24] Ashok K Goel and Lalith Polepeddi. 2016. *Jill Watson: A virtual teaching assistant for online education*. Technical Report. Georgia Institute of Technology.
[25] Jonathan Grudin. 1994. Groupware and social dynamics: Eight challenges for developers. *Commun. ACM* 37, 1 (1994), 92–105.
[26] Jeffrey T Hancock, Mor Naaman, and Karen Levy. 2020. AI-mediated communication: definition, research agenda, and ethical considerations. *Journal of Computer-Mediated Communication* 25, 1 (2020), 89–100.
[27] Jess Hohenstein and Malte Jung. 2020. AI as a moral crumple zone: The effects of AI-mediated communication on attribution and trust. *Computers in Human Behavior* 106 (2020), 106190.
[28] Carol Hostetter and Monique Busch. 2006. Measuring up online: The relationship between social presence and student learning satisfaction. *Journal of the Scholarship of Teaching and Learning* (2006), 1–12.
[29] Christopher Irwin and Zane Berge. 2006. Socialization in the online classroom. *E-Journal of Instructional Science and Technology* 9, 1 (2006), n1.
[30] Carolin Ischen, Theo Araujo, Hilde Voorveld, Guda van Noort, and Edith Smit. 2019. Privacy concerns in chatbot interactions. In *International Workshop on Chatbot Research and Design*. Springer, 34–48.
[31] Mizuko Ito. 2013. *Hanging out, messing around, and geeking out: Kids living and learning with new media*. The MIT Press.
[32] Maurice Jakesch, Megan French, Xiao Ma, Jeffrey T Hancock, and Mor Naaman. 2019. AI-mediated communication: How the perception that profile text was written by AI affects trustworthiness. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. 1–13.
[33] Shagun Jhaver, Iris Birman, Eric Gilbert, and Amy Bruckman. 2019. Human-machine collaboration for content regulation: The case of Reddit Automoderator. *ACM Transactions on Computer-Human Interaction (TOCHI)* 26, 5 (2019), 1–35.
[34] Christopher M Johnson. 2001. A survey of current research on online communities of practice. *The internet and higher education* 4, 1 (2001), 45–60.
[35] David A Joyner, Qiaosi Wang, Suyash Thakare, Shan Jing, Ashok Goel, and Blair MacIntyre. 2020. The Synchronicity Paradox in Online Education. In *Proceedings of the Seventh ACM Conference on Learning@ Scale*. 15–24.
[36] Wendy A Kellogg and Thomas Erickson. 2002. Social Translucence, Collective Awareness, and the Emergence of Place. *Proceedings of CSCW2002* (2002), 1–6.
[37] Karel Kreijns, Paul A Kirschner, and Wim Jochems. 2003. Identifying the pitfalls for social interaction in computer-supported collaborative learning environments: a review of the research. *Computers in human behavior* 19, 3 (2003), 335–353.
[38] Jorge Larreamendy-Joerns and Gaea Leinhardt. 2006. Going the distance with online education. *Review of educational research* 76, 4 (2006), 567–605.
[39] Jean Lave, Etienne Wenger, et al. 1991. *Situated learning: Legitimate peripheral participation*. Cambridge university press.
[40] Minha Lee, Lily Frank, Femke Beute, Yvonne De Kort, and Wijnand IJsselsteijn. 2017. Bots mind the social-technical gap. In *Proceedings of 15th European conference on computer-supported cooperative work-exploratory papers*. European Society for Socially Embedded Technologies (EUSSET).
[41] Yi-Chieh Lee, Naomi Yamashita, and Yun Huang. 2020. Designing a Chatbot as a Mediator for Promoting Deep Self-Disclosure to a Real Mental Health Professional. *Proceedings of the ACM on Human-Computer Interaction* 4, CSCW1

(2020), 1–27.
[42] Q Vera Liao, Daniel Gruen, and Sarah Miller. 2020. Questioning the AI: Informing Design Practices for Explainable AI User Experiences. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. 1–15.
[43] Julia M Mayer, Starr Roxanne Hiltz, Louise Barkhuus, Kaisa Väänänen, and Quentin Jones. 2016. Supporting opportunities for context-aware social matching: An experience sampling study. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*. 2430–2441.
[44] Julia M Mayer, Starr Roxanne Hiltz, and Quentin Jones. 2015. Making social matching context-aware: Design concepts and open challenges. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*. 545–554.
[45] Julia M Mayer, Quentin Jones, and Starr Roxanne Hiltz. 2015. Identifying opportunities for valuable encounters: Toward context-aware social matching systems. *ACM Transactions on Information Systems (TOIS)* 34, 1 (2015), 1–32.
[46] David W McDonald, Stephanie Gokhman, and Mark Zachry. 2012. Building for social translucence: a domain analysis and prototype system. In *Proceedings of the ACM 2012 conference on computer supported cooperative work*. 637–646.
[47] Hannah Mieczkowski, Jeffrey T Hancock, Mor Naaman, Malte Jung, and Jess Hohenstein. 2021. AI-Mediated Communication: Language Use and Interpersonal Effects in a Referential Communication Task. *Proceedings of the ACM on Human-Computer Interaction* 5, CSCW1 (2021), 1–14.
[48] Silvia Milano, Mariarosaria Taddeo, and Luciano Floridi. 2020. Recommender systems and their ethical challenges. *AI & SOCIETY* 35, 4 (2020), 957–967.
[49] Marti Motoyama and George Varghese. 2009. I seek you: searching and matching individuals in social networks. In *Proceedings of the eleventh international workshop on Web information and data management*. 67–75.
[50] Jaya Narain, Tina Quach, Monique Davey, Hae Won Park, Cynthia Breazeal, and Rosalind Picard. 2020. Promoting Wellbeing with Sunny, a Chatbot that Facilitates Positive Messages within Social Groups. In *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems*. 1–8.
[51] Jeff Naruchitparames, Mehmet Hadi Güneş, and Sushil J Louis. 2011. Friend recommendations in social networks using genetic algorithms and network topology. In *2011 IEEE Congress of Evolutionary Computation (CEC)*. IEEE, 2207–2214.
[52] Oda Elise Nordberg, Jo Dugstad Wake, Emilie Sektnan Nordby, Eivind Flobak, Tine Nordgreen, Suresh Kumar Mukhiya, and Frode Guribye. 2019. Designing Chatbots for Guiding Online Peer Support Conversations for Adults with ADHD. In *International Workshop on Chatbot Research and Design*. Springer, 113–126.
[53] Ekaterina Olshannikova, Thomas Olsson, Jukka Huhtamäki, Susanna Paasovaara, and Hannu Kärkkäinen. 2020. From Chance to Serendipity: Knowledge Workers' Experiences of Serendipitous Social Encounters. *Advances in Human-Computer Interaction* 2020 (2020).
[54] Thomas Olsson, Jukka Huhtamäki, and Hannu Kärkkäinen. 2020. Directions for professional social matching systems. *Commun. ACM* 63, 2 (2020), 60–69.
[55] Lawrence A Palinkas, Sarah M Horwitz, Carla A Green, Jennifer P Wisdom, Naihua Duan, and Kimberly Hoagwood. 2015. Purposeful sampling for qualitative data collection and analysis in mixed method implementation research. *Administration and policy in mental health and mental health services research* 42, 5 (2015), 533–544.
[56] Robert D Putnam et al. 2000. *Bowling alone: The collapse and revival of American community*. Simon and schuster.
[57] Werner Rammert. 2008. *Where the action is. Distributed agency between humans, machines, and programs*. transcript.
[58] Alfred P Rovai. 2001. Building classroom community at a distance: A case study. *Educational technology research and development* 49, 4 (2001), 33.
[59] Alfred P Rovai. 2002. Development of an instrument to measure classroom community. *The Internet and higher education* 5, 3 (2002), 197–211.
[60] Koustuv Saha, Ted Grover, Stephen M Mattingly, Vedant Das Swain, Pranshu Gupta, Gonzalo J Martinez, Pablo Robles-Granda, Gloria Mark, Aaron Striegel, and Munmun De Choudhury. 2021. Person-Centered Predictions of Psychological Constructs with Social Media Contextualized by Multimodal Sensing. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 5, 1 (2021), 1–32.
[61] Na Sun, Mary Beth Rosson, and John M Carroll. 2018. Where is community among online learners? Identity, efficacy and personal ties. In *Proceedings of the 2018 chi conference on human factors in computing systems*. 1–13.
[62] Na Sun, Xiying Wang, and Mary Beth Rosson. 2019. How Do Distance Learners Connect?. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. 1–12.
[63] S Shyam Sundar. 2020. Rise of Machine Agency: A Framework for Studying the Psychology of Human–AI Interaction (HAII). *Journal of Computer-Mediated Communication* 25, 1 (2020), 74–88.
[64] Agnieszka Matysiak Szostek, Evangelos Karapanos, Berry Eggen, and Mike Holenderski. 2008. Understanding the implications of social translucence for systems supporting communication at work. In *Proceedings of the 2008 ACM conference on Computer supported cooperative work*. 649–658.
[65] Hon Jie Teo and Aditya Johri. 2014. Fast, functional, and fitting: expert response dynamics and response quality in an online newcomer help forum. In *Proceedings of the 17th ACM conference on Computer supported cooperative work &*

social computing. 332–341.
[66] Loren Terveen and David W McDonald. 2005. Social matching: A framework and research agenda. *ACM transactions on computer-human interaction (TOCHI)* 12, 3 (2005), 401–434.
[67] Nava Tintarev and Judith Masthoff. 2012. Evaluating the effectiveness of explanations for recommender systems. *User Modeling and User-Adapted Interaction* 22, 4-5 (2012), 399–439.
[68] Chun-Hua Tsai and Peter Brusilovsky. 2017. Providing control and transparency in a social recommender system for academic conferences. In *Proceedings of the 25th Conference on User Modeling, Adaptation and Personalization*. 313–317.
[69] Qiaosi Wang, Shan Jing, Ida Camacho, David Joyner, and Ashok Goel. 2020. Jill Watson SA: Design and Evaluation of a Virtual Agent to Build Communities Among Online Learners. In *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems*. 1–8.
[70] Qiaosi Wang, Shan Jing, David Joyner, Lauren Wilcox, Hong Li, Thomas Plötz, and Betsy Disalvo. 2020. Sensing Affect to Empower Students: Learner Perspectives on Affect-Sensitive Technology in Large Educational Contexts. In *Proceedings of the Seventh ACM Conference on Learning@ Scale*. 63–76.
[71] Qiaosi Wang, Koustuv Saha, Eric Gregori, David Joyner, and Ashok Goel. 2021. Towards Mutual Theory of Mind in Human-AI Interaction: How Language Reflects What Students Perceive About a Virtual Teaching Assistant. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. 1–14.
[72] Dong Whi Yoo and Munmun De Choudhury. 2019. Designing dashboard for campus stakeholders to support college student mental health. In *Proceedings of the 13th EAI International Conference on Pervasive Computing Technologies for Healthcare*. 61–70.
[73] Dongwook Yoon, Nicholas Chen, Bernie Randles, Amy Cheatle, Corinna E Löckenhoff, Steven J Jackson, Abigail Sellen, and François Guimbretière. 2016. RichReview++ Deployment of a Collaborative Multi-modal Annotation System for Instructor Feedback and Peer Discussion. In *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing*. 195–205.
[74] Douglas Zytko and Leanne DeVreugd. 2019. Designing a Social Matching System to Connect Academic Researchers with Local Community Collaborators. *Proceedings of the ACM on Human-Computer Interaction* 3, GROUP (2019), 1–15.
[75] Douglas Zytko, Victor Regalado, Sukeshini A Grandhi, and Quentin Jones. 2018. Supporting Online Dating Decisions with a Prompted Discussion Interface. In *Companion of the 2018 ACM Conference on Computer Supported Cooperative Work and Social Computing*. 353–356.

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