Fostering And Understanding Diverse Interpersonal Connections in a Massive Online CS1 Course

Miranda Li
mirandal@stanford.edu
Stanford University
Stanford, CA, USA

Ali Malik
malikali@cs.stanford.edu
Stanford University
Stanford, CA, USA

Chris Piech
piech@cs.stanford.edu
Stanford University
Stanford, CA, USA

Abstract

Forming social relationships is critical to student success and well-being, but is one of the first aspects to be neglected in the design of massive online courses. We present our experience deploying an in-course networking tool that enabled 1,600+ learners and teachers in a massive online CS1 course to form 2,000+ connections with other individuals. We discuss how social preferences and networking goals vary by demographics, economic factors, course goals, and course role. Contrary to usual online social behavior, users in our network sent more out-group requests than a random baseline by role ($2.04x$), gender ($1.1x$), and developing vs. developed country ($1.07x$). We highlight differences between developing vs. developed country users: developing country users send $2.5x$ requests and make, on average, $1.78x$ as many connections as those from developed countries. From a randomized control trial we find that random recommendations increase the volume of sent requests by 44.48% and promote cross-group requests across developing vs. developed countries (+28.9%), age (+15.1%), and gender (+8.6%). Ultimately we show that integrating socialization as a core feature of online CS1 classrooms can help support people from all backgrounds in achieving their diverse educational goals, which often extend well beyond improving coding proficiency.

CCS Concepts

• **Human-centered computing** → **Collaborative and social computing**; • **Social and professional topics** → **Computing education**; **User characteristics**.

Keywords

social presence, online learning, MOOC, social network analysis

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1 Introduction

Social presence is crucial for academic engagement and motivation, particularly in massive online courses (MOOCs) [3, 4, 8, 18, 22, 23, 33, 35]. In an era where large language models (LLMs) are enabling more accessible personalized learning [7], the true value of MOOCs may be to increase accessibility to human co-learners and teachers. Our objective is to empower diverse online learners and teachers to cultivate interpersonal relationships in order to promote academic success and community formation.

We introduce a novel in-course networking tool called Connections that integrates interpersonal relationship-forming as a core part of the online course experience. On the course platform, all users have profiles and can send connection requests to other users. If a request is accepted, the two users are connected and exchange contact information. We deploy it in Code in Place, a free, global online CS1 course with 9,000+ adult participants [21, 31].

We discuss the differences in social engagement, preferences, and intentions between user demographics. We highlight the experiences of CS1 students from developing countries, who are traditionally disadvantaged in MOOCs [13, 20], under-studied by MOOC researchers [2], and under-served by CS education [30]. Finally, we conduct a randomized control trial to evaluate the effects of encouraging users to form interpersonal relationships by "recommending" a random subset of other users.

Our main contributions are as follows:

(1) We describe our experience deploying, to the best of our knowledge, the first course-embedded social networking system for a CS1 MOOC, enabling 1,600+ users to safely form and strengthen 2,000+ connections. We outline how to reproduce our tool.
(2) We reveal interesting global patterns in social interaction across demographics. Compared to those from developed countries, students from developing countries $2.5x$ as many requests and have around $1.78x$ as many connections. Teachers are more socially engaged than learners, and there are differences by age and gender. We observe more out-group requests than would occur by chance across role, gender, and developing vs. developed country. However, developed country users exhibit strong in-group preference.
(3) From topic modeling of 6,700+ messages we find that users more often seek professional (19.59%) or co-learning (15.07%) over cultural (5.95%) or personal (4.63%) connections. We also find that developing country users send $1.36x$ requests seeking co-learning and $1.29x$ professional networking requests compared to developed country users.
(4) We find that having at least one organic connection is correlated with significantly higher course completion.

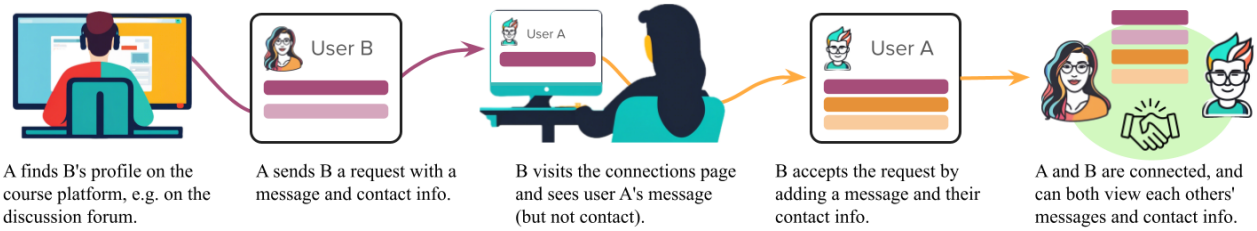

Figure 1: An overview of the process for user A and user B to become connected, using our tool.

(5) We run a large scale randomized control trial and find that showing users uniformly random "recommendations" significantly increases the volume of sent requests as well as the proportion of out-group requests across age, gender, geography, and economic development.

2 Related Work

Social presence & social network analysis in MOOCs. Social presence – the ability to perceive others in an online environment [33] – impacts student retention, grades, and satisfaction [18, 23] in online courses. [28] adds that the social context of online courses differs meaningfully from in-person learning: small decisions can powerfully influence relationships and communication patterns. Further, teacher isolation in online education [6, 36] causes teacher burnout and low motivation. We combat the "facelessness" of virtual space by providing each course participant a customizable profile. We also enable a new interaction mode previously impossible on our course platform – 1-on-1 relationship formation – and assess the relationships and discourse that result.

Previous work has used social network analysis to understand the social dynamics of MOOCs, primarily on discussion forum data [5, 29, 37, 38]. We extend this body of work with new signal: sending a connection request conveys what kind of bond a learner seeks to form more clearly than responding to a forum thread. Homophily, the tendency of individuals to connect with those similar to themselves [14, 15, 24], has been shown in MOOCs based on role, geographic location, and language [11, 12]. We investigate the homophily of users in our network to understand how the dynamics of our tool differ from other MOOCs.

Impact of demographic factors on student success. Literature has shown variation in MOOC outcomes and learning process based on demographics, intentions, and socioeconomic background [9, 13, 16, 19, 20, 32, 40]. However, there is less literature on how *social dynamics* of MOOCs vary by background. [34] compared populations of learners in regional versus global MOOCs and suggested that the importance of social dynamics may vary by sub-population. We discuss the social dynamics of a global MOOC in finer detail, e.g. by learner background, role, interests. [13] closed the achievement gap among MOOC participants from less vs. more developed countries by prompting them to reflect on valuable relationships and write advice to future learners, suggesting that interpersonal dynamics may particularly motivate under-represented groups. Our course is a CS1 course; CS also has known achievement gaps by, e.g., gender and socioeconomic status [10, 17, 27, 30]. Thus we hope that a better understanding of MOOC social behaviors and preferences by demographic will aid the development of future interventions to foster achievement and motivation of under-represented groups.

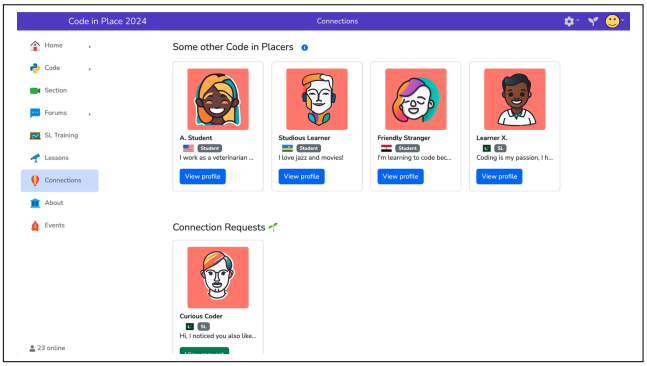

Figure 2: The Connections page. At the top are randomly selected recommendations which are only shown to users in the treatment group of our RCT. Successful connections are shown on this page below Connection Requests.

3 The Connections tool

Connections is a networking tool which enables a "friend request" ability within a CS1 MOOC's course platform.

3.1 Components

Connections page. The Connections page, shown in Figure 2, is a sub-page of our course website where users can view their connections and connection requests. For the treatment group of our RCT we also display 4 user profiles, randomly selected from users who consent to connecting and updated every 6 hours.

User profiles. As part of onboarding, users are asked to complete their course profiles with a non-empty display name (defaults to first name and last initial provided in user's course application) and country, but both can be anonymized – display name can be set to an alias and country can be set to "Somewhere on Earth." Users can optionally populate an "About Me" and "Goals" section. From the profile editing page, users can opt out of the Connections feature so that their profiles do not allow connection requests from others.

Users' view-only profiles are accessible from various places on our course platform, namely the discussion forum, the section page,

and the Connections page. From the view-only profile of another user, users can perform the following actions:

Sending a request: A and B are unconnected. On B's profile, A fills out a message and contact information and sends the request.

Editing a request: A has sent B a request. A can change their provided message or contact information or unsend the request.

Accepting a request: A has sent B a request. On the Connections page, B sees A's profile under "Your Requests". On A's profile, B can see the message A sent (but not their contact information). B sends a message and contact information back in order to accept the request; A and B are connected and will appear on each others' connections pages under "Your Connections." When A and B visit each others' profiles they can see both messages and contact information.

Dismissing a request: A has sent B a request. On the Connections page, B sees A's profile under "Your Requests". On A's profile, B can see the message A sent (but not their contact information). B dismisses the request by clicking a button; B can review A's request at any time, but the request is hidden by default to indicate dismissal. From A's perspective, their request to B is still pending.

Editing a connection: Users A and B are connected. Both can edit the information they have shared with the other or remove the connection, in which case the users return to an unconnected state.

3.2 Design considerations

Formation of lasting ties. We afford users the ability to exchange contact information in order to enable participants to stay in touch after the course ends, and we require users to write a message in order to encourage more intentional requests.

Privacy. To protect user privacy, we do not reveal user contact information until both users have mutually agreed to share their information, i.e. they are connected. We also encourage sharing less-sensitive contact information by including this message above the contact information field in the form for sending a request: "We will only share this with {Recipient Display Name} if they accept your request. For your own privacy, we recommend sharing a Linkedin link or making an email alias." We also enable users to edit or revoke all shared information at any time.

Safety. In order to maintain a professional course atmosphere while also not discouraging friendly, non-academic outreach, we provided the following suggestions above the message field in the request form: "Here are some ideas… Discuss a shared learning goal Share a common subject of interest Ask a question"

Not distracting. We designed our tool to be minimally distracting, restricting on-platform dialogue between two users to one message each. We did not implement notifications for our system in order to minimize the interruptions to the academic experience.

4 Deployment in massive CS1 course

We deployed our tool as a core part of the platform in a free, 6-week CS1 MOOC with 641 volunteer teachers and 8956 adult (18+) learners from 148 countries. The course had weekly synchronous section meetings with one volunteer teacher and a small group of learners. Outside of weekly sections, learners worked asynchronously on lectures and assignments, consulting the discussion forums if they had any issues.

Our analysis is done on a dataset ($n = 6827$) excluding users who did not want to connect ($n = 187$), did not engage at all with the course, or were outliers with more than 8 connections ($n = 87$, 1.26%) , corresponding to those 3+ z-scores from the mean. We look at correlations between connections usage and course completion metrics (assignment and lesson completion, section attendance), and we outline trends in tool usage based on the following demographic factors:

- *Age group*: 18-27, 28-37, 38-47, 48-57, 58-67, and 69+
- *Role → learner / teacher*: Our course had four roles – student, experienced student, mentor, and section leader – which we group into *learners* (experienced students and students) and *teachers* (mentors and section leaders)
- *Region*: Russia, North America, Middle East, Africa, Central America, South America, Asia, Caribbean, Europe, Oceania, Eastern Europe, South Asia, based on user's home country
- *Developing / developed*: The Human Development Index (HDI) quantifies the development level of a country as a score from 0 to 1 based on three key qualities: health (life expectancy at birth), education (average years of schooling), and quality of life (gross national income per capita) [25]. We group users based on the HDI of their home countries according to the cutoff specified in [26] – countries with HDI < 0.694 are developing and countries with HDI ≥ 0.694 are developed. In our dataset 4660 users are from developed countries and 2100 are from developing countries.

5 Randomized control trial design

In order to investigate the effects of encouraging students to send connections requests we ran a randomized control trial (RCT). In our treatment group ($n = 5542$, $\approx 80\%$), users see 4 uniform-randomly sampled "recommended" profiles on their Connections page, updating every 6 hours. Our control group ($n = 1372$, $\approx 20\%$) has full access to the Connections tool except they do not see recommendations.

6 Results

Our tool was largely able to fulfill the desires of those seeking social connectivity – 72% of users who initiated a request made at least one successful connection. Engagement peaked in the first and last weeks of the course (Figure 4). From a survey of 150 randomly selected users (25 responders) who consented to us publishing their feedback, we received some positive qualitative feedback:

> *"I love connections. I have met some people who are generous and very helpful. I met a friend from Pakistan. I love to chat with her and she is so kind. We become friend and we share our thoughts, culture and many more."*

> *"I connected with two people outside the class. It has been very helpful for two reasons. One is that these interactions kept me motivated to attend the sessions and practice assignments. The other is that since they had some prior knowledge around coding, we exchanged ideas on how to move forward with these skills."*

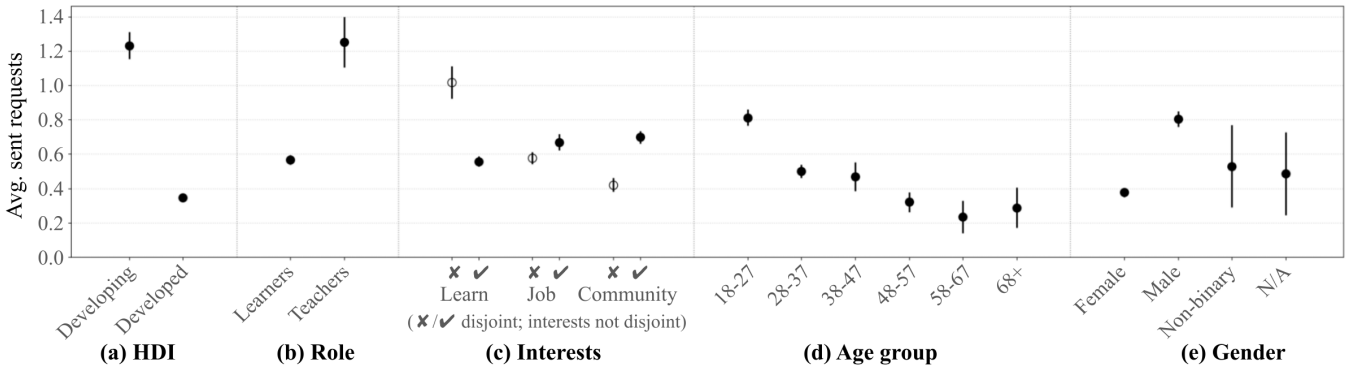

Figure 3: Propensity for social connection varies by user background, role, and interests.

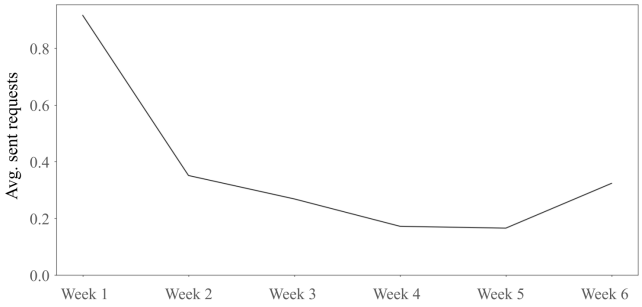

Figure 4: The volume of sent requests peaks at the start and end of the course. We observe a similar trend for the overall engagement with the tool and number of connections.

Statistic	No conn.	Has conn.	Cohen's d	p-value
Assignments done	14.92	16.72	0.20	< 0.001
Lessons done	7.09	7.70	0.16	< 0.001
Sections attended	3.80	4.76	0.44	< 0.001

Table 1: Having one or more connections is significantly correlated with higher course completion.

We find that having made at least one connection is significantly correlated with higher course completion across all metrics – see Table 1 for effect sizes (Cohen's d) and results of one-sided t-tests. Importantly, these results are only correlational and may be confounded by factors that impact both engagement and socialization.

6.1 Patterns in social engagement & preferences

Regional differences by economic development. Users from developing countries ($n = 2100$) engage significantly more with the tool and send significantly more requests than users from developed nations ($n = 4660$; Cohen's $d = 0.39$, $p < 0.001$) – see Figure 3a. Developing country users also make $1.78x$ as many connections as those from developed countries on average (0.64 vs. 0.36).

Teachers seek connection more than learners. In Figure 3b we show that teachers send significantly more requests than learners (Cohen's $d = 0.29$, $p < 0.001$), suggesting that interpersonal interaction is a major motivation for volunteer teachers.

Varying student interests influence social behavior. Students were required to specify one or more goals for taking the course in their application for the course, including:

- **Learn**: I want to learn how to program in Python
- **Job**: I want to get a job as a programmer
- **Community**: I want to be part of a community of other students who are also learning

Figure 3c shows the differences in average sent requests based on whether or not the student expressed a particular interest in taking the course – ✘ means students who did not express this interest, ✓ means students who did. Users could select multiple interests.

Students who cited community building as a goal engaged more than those who did not (Cohen's $d = 0.11$, $p < 0.001$). Students seeking job opportunities also engaged slightly more, by a statistically significant margin, compared to those who did not (Cohen's $d = 0.07$, $p < 0.001$). On the other hand, students who stated that learning Python was one of their primary goals *did not show significant differences* in average sent requests compared to those who did not state this as a goal ($p = 0.15 \not< 0.05$). Thus while some CS1 students may not seek social interaction from their course experience, others may consider it an integral part of their educational objectives.

Engagement trends with age & gender. We also observe a generally negative trend between social proclivity and age, as well as discrepancies by gender, shown in Figure 3d and Figure 3e. The trend with age may be due to lower technical fluency in older individuals, or alternatively, reduced incentive to network due to having more established careers.

Some birds of a feather flock together, but opposites attract. While prior work shows demographic homophily in social preferences of MOOC participants [12], we observe significant cross-group preferences by gender, role, and developing / developed country, as shown in Table 2. However we do observe homophily in age group, country, and region.

The baseline shown in Table 2 assumes requests are sent uniformly at random. Let N be the total users. The total number of

Category	Out-group %	Baseline %	Cohen's h	p-value
Age group	50.93	**68.01**	0.35	< 0.001
Gender	**55.92**	51.05	0.10	< 0.001
Learner / teacher	**28.93**	14.15	0.36	< 0.001
Country	79.40	**88.32**	0.24	< 0.001
Region	66.31	**79.39**	0.30	< 0.001
Developing / developed	**45.79**	42.84	0.30	< 0.001

Table 2: Users prefer out-group requests by gender, role, and developing / developed country, compared to a uniform random baseline. Bolded values are significantly greater.

Statistic	Control	Treatment	Cohen's d	p-value
Sent requests	0.46	**0.66**	0.09	< 0.001
Connections	0.38	**0.46**	0.07	0.01
Assignments done	15.60	15.24	-0.04	0.71
Lessons done	7.33	7.20	-0.03	0.87
Sections attended	4.01	4.00	-0.03	0.82

Table 3: Seeing recommendations increases volume of sent requests and connections but does not impact course completion. Bolded values are significant ($p < 0.05$).

possible requests is $N \times (N-1)$ since self-requests are prohibited. For each category (e.g. gender) with k groups (e.g. non-binary, male, female) and N_i users in group i, the number of possible in-group requests is $\sum_{i=1}^{k} N_i \times (N_i - 1)$. So, the number of possible out-group requests is $N \times (N-1) - \sum_{i=1}^{k} N_i \times (N_i - 1)$. We divide this by the number of possible requests, $N \times (N-1)$, to get the expected out-group percentage if requests were sent randomly.

Users from developed nations prefer to flock together. Users from developed countries sent 90.30 ± 2.30% of their requests to developed country peers, indicating a clear in-group preference. By contrast, users from developed countries sent requests at a rate about proportional to the number of users from each category – 31.28% to 2,100 fellow developing country users and 68% to the 4,660 developed country users.

The acceptance rates of viewed requests (those which we validate that the receiving user saw) further highlight this disparity. Users from developed countries were significantly more likely to accept requests from developed countries (44.17%) compared to developing countries (26.32%, $p < 0.001$ from a two-proportion z-test), while users from developing countries demonstrated no significant preference, with acceptance rates of 54.90% for developing and 54.55% for developed country requests ($p = 0.98$).

6.2 Trends in intentions for networking

We employed an LLM pipeline to understand the intentions of 6,737 request messages. First we repeatedly prompted OpenAI's GPT-4o [1] to identify the main topics from a random sample of 100 request messages. After manual evaluation and refinement we settled on the list of topics below. We then classified messages by providing GPT-4o the list of topics + descriptions and one user message at a time. While we validated the reasonableness of clusters and labels to the best of our ability, the findings of this analysis should be interpreted with caution – the task is inherently difficult and model output may not fully align with human judgement. Here are the topics from most to least frequent:

- *Introductions and Greetings* (2,301, 31.46%): Users introducing themselves, saying hello, and making initial connections.
- *Professional Networking* (1,433, 19.59%): Users emphasizing the importance of professional networking, career development, and connecting with like-minded individuals.
- *Learning Together* (1,102, 15.07%): Messages about forming study groups, collaboration on projects, and sharing resources or experiences for mutual learning.
- *Section Interactions* (739, 10.10%): Users interacting with their section leaders or other students in their section or weekly session.
- *Feedback and Help Requests* (609, 8.33%): Requests for assistance with coding problems, feedback on assignments, and queries about the course progress or materials.
- *Cultural Connections* (435, 5.95%): Users expressing interest in connecting, sharing knowledge, and learning about each other's cultures.
- *Gratitude and Appreciation* (356, 4.87%): Users expressing gratitude and appreciation for guidance, support, or feedback received.
- *Personal Interests and Hobbies* (339, 4.63%): Mentions of personal hobbies and interests outside of coding, such as cooking, hiking, reading, and playing music.

Distribution of message topics varies by demographic group and course progression. Compared to users from developed countries, users from developing countries more often wrote seeking to learn together (16.87% vs. 12.37%, $h = 0.13$, $p < 0.001$) or for professional networking (16.87% vs. 13.06%, $h = 0.11$, $p < 0.001$). Users from developed countries sent proportionally more requests expressing gratitude (8.75% vs. 2.55%, Cohen's $h = 0.28$, $p < 0.001$) or following up on section interactions (16.74% vs. 8.76%, $h = 0.24$, $p < 0.001$).

Women more often discussed section interactions (17.01% vs. 9.68%, $h = 0.22$, $p < 0.001$) or sought feedback and assistance (15.02% vs. 10.51%, $h = 0.14$, $p < 0.001$) compared to men. Men more often reached out to learn together (17.00% vs. 10.54%, $h = 0.19$, $p < 0.001$) and sent proportionally more generic introductions and greetings (31.84% vs. 24.07%, $h = 0.17$, $p < 0.001$).

We also found that message topics varied depending on when during the course the requests were sent. During the first week of the course users tended to send more introductions and greetings compared to during the last week of the course (33.61% vs. 18.27%, $h = 0.35$, $p < 0.001$) and more often reached out to learn together (18.69% vs. 10.33%, $h = 0.24$, $p < 0.001$). During the final week of the course users sent proportionally more messages expressing gratitude and appreciation (10.7% vs. 2.24%, $h = 0.37$, $p < 0.001$) and in order to network professionally (24.54% vs. 12.55%, $h = 0.31$, $p < 0.001$) compared to during the first week of the course.

6.3 RCT results: effect of recommendations

Engagement with the tool slightly, but not significantly, increases under the treatment, with 28.48% of control users and 30.63% of

Category	Control out-group %	Treatment out-group %	Cohen's h	p-value
Age group	45.08	**51.88**	0.14	< 0.001
Gender	52.06	**56.55**	0.09	0.04
Learner / teacher	**35.78**	27.81	0.17	< 0.001
Country	75.67	**80.01**	0.10	0.01
Region	61.71	**67.06**	0.11	0.01
Developing / developed	36.67	**47.27**	0.22	< 0.001

Table 4: Recommendations increase proportion of requests to users dissimilar to the sender across age, gender, and geographical categories but decrease proportion of requests from learners to teachers or vice versa.

treatment users having sent, accepted or dismissed a request (p = 0.11, from a two-proportion z-test). We believe this is because users are not notified of new recommendations, so users who do not actively use the tool are not made aware of recommendations.

The treatment boosts the number of sent requests and connections by a small margin. We observe no effect of the treatment on course completion outcomes from a one-sided t-test – see Table 3.

Presenting random recommendations can counteract homophily across certain demographic divides. As Table 4 shows, recommendations significantly increase the proportion of out-group requests across age, gender, and geography.

Notably, recommendations decrease the proportion of learner-teacher and teacher-learner requests. This is due to a substantial increase in teacher-teacher requests, which represent 0.88% of requests sent by users in the control group and 4.68% of requests sent by users in the treatment group(two-proportion z-test $p < 0.001$).

Compared to control, treatment users sent more messages about personal interests (5.54% vs. 1.92%, Cohen's h = -0.20, p < 0.001), cultural connections (6.54% vs. 3.68%, Cohen's h = -0.13, p < 0.01), and introductions / greetings (30.23% vs. 24.96%, Cohen's h = -0.12, p < 0.01). Conversely, messages requesting help (11.18% vs. 16.96%, Cohen's h = 0.17, p < 0.001), expressing gratitude (4.61% vs. 7.04%, Cohen's h = 0.10, p < 0.01), and concerning section (11.10% vs. 16.48%, Cohen's h = 0.16, p < 0.001) were less frequent in the treatment group. There was no significant difference in professional networking (15.25% vs. 16.00%, Cohen's h = 0.02, p = 0.63) nor learning together (15.55% vs. 12.96%, Cohen's h = -0.07, p = 0.09). We note that two topics which decreased in frequency under treatment (gratitude and section interactions) imply that the users have met before (receiving help or sharing a section). Though we were unable to properly classify requests into "users who have met before" vs. "users who are meeting for the first time", it is possible that the treatment increases the proportion of the latter.

6.4 Safety

There were no reports regarding unwanted or inappropriate behavior from connections on the course's reporting forum. We also manually examined all 151 dismissed requests and 21 removed connections and found no inappropriate behavior or language.

7 Discussion

While some claim MOOCs can fix global educational inequality [39], differences in enrollment and completion between developing and developed countries suggest this goal remains unmet [13]. Our results show that learners from developing countries seek social engagement more actively than those from developed countries, especially for co-learning and professional networking. We postulate that, in alignment with [13], social presence in MOOCs may alleviate social identity threat for students in developing regions, making the online classroom more equitable and inclusive.

Given the prevalence of homophily in other MOOCs [11, 12], we are pleasantly surprised that users in our network both already prefer and can be encouraged to form out-group connections across demographic categories. As MOOC enrollment grows and course populations become more diverse, we hope positive in-course social dynamics can contribute to positive cross-cultural, inter-group online dynamics more broadly [41].

7.1 Future work

Several users requested in-course direct messaging, as the one-message limit made it hard to start a conversation and some prefer to chat before sharing external contact information. A handful of users wanted notifications about connections requests or accepted connections. Both these features are worth exploring but must be weighed against potentially greater distraction and cognitive load. Also, our random recommendation system begs the question of a more intelligent recommendation system. Networking tools focused on the organic formation of groups rather than one-to-one relationships could also be explored.

Though we received a few reports of lasting connections stemming from our tool, many claim their connections progress no further than a Linkedin connection. Future investigation into what kinds of relationships persist, based on user demographics or cultural values, would be informative.

8 Conclusion

In this report we presented an in-course networking tool, Connections. We described its design and successful, safe deployment in a diverse CS1 MOOC. We outlined trends in willingness to form social ties and intentions in networking by user background. We also showed strong quantitative evidence that users can be encouraged, via random recommendations, to send out-group requests.

People of all backgrounds seek and benefit from interpersonal connection in online courses. As LLMs enable personalized but antisocial learning, our study underscores the essential role of socialization in MOOCs. We believe it is both possible and necessary to explore futures of equitable, pro-social online education.

References

[1] OpenAI . 2024. Hello GPT-4o. https://openai.com/index/hello-gpt-4o/

[2] Corlane Barclay and Derrick Logan. 2013. Towards an Understanding of the Implementation & Adoption of Massive Online Open Courses (MOOCs) in a Developing Economy Context. *GlobDev 2013* (Dec. 2013). https://aisel.aisnet.org/globdev2013/7

[3] David A. Bergin. 2016. Social Influences on Interest. *Educational Psychologist* 51, 1 (Jan. 2016), 7–22. https://doi.org/10.1080/00461520.2015.1133306 Publisher: Routledge _eprint: https://doi.org/10.1080/00461520.2015.1133306.

[4] Abraham Carmeli, Daphna Brueller, and Jane E Dutton. 2009. Learning behaviours in the workplace: The role of high-quality interpersonal relationships and psychological safety. *Systems Research and Behavioral Science* 26, 1 (2009), 81–98. https://doi.org/10.1002/sres.932 _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/sres.932.

[5] Daniela Castellanos-Reyes. 2021. The dynamics of a MOOC's learner-learner interaction over time: A longitudinal network analysis. *Computers in Human Behavior* 123 (Oct. 2021), 106880. https://doi.org/10.1016/j.chb.2021.106880

[6] Véra L. B. Dolan. 2011. The isolation of online adjunct faculty and its impact on their performance. *The International Review of Research in Open and Distributed Learning* 12, 2 (Feb. 2011), 62–77. https://doi.org/10.19173/irrodl.v12i2.793

[7] Mohammadreza Farrokhnia, Seyyed Kazem Banihashem, Omid Noroozi, and Arjen Wals. 2024. A SWOT analysis of ChatGPT: Implications for educational practice and research. *Innovations in Education and Teaching International* 61, 3 (May 2024), 460–474. https://doi.org/10.1080/14703297.2023.2195846 Publisher: Routledge _eprint: https://doi.org/10.1080/14703297.2023.2195846.

[8] Carrie Furrer and Ellen Skinner. 2003. Sense of relatedness as a factor in children's academic engagement and performance. *Journal of Educational Psychology* 95, 1 (2003), 148–162. https://doi.org/10.1037/0022-0663.95.1.148 Place: US Publisher: American Psychological Association.

[9] Bahaa G. Gameel and Karin Gwinn Wilkins. 2019. When it comes to MOOCs, where you are from makes a difference. *Computers & Education* 136 (July 2019), 49–60. https://doi.org/10.1016/j.compedu.2019.02.014

[10] Hai Hong, Jennifer Wang, Jason Ravitz, and Mo-Yun Lei Fong. 2015. Gender differences in high school students' decisions to study computer science and related fields. In *SIGCSE*, Vol. 689. 2676723–2691920. Number: 10.1145.

[11] Anna Kasunic, Jessica Hammer, Robert Kraut, Michael Massimi, and Amy Ogan. 2016. A Preliminary Look at MOOC-associated Facebook Groups: Prevalence, Geographic Representation, and Homophily. In *Proceedings of the Third (2016) ACM Conference on Learning @ Scale (L@S '16)*. Association for Computing Machinery, New York, NY, USA, 205–208. https://doi.org/10.1145/2876034.2893415

[12] Shaun Kellogg, Sherry Booth, and Kevin Oliver. 2014. A social network perspective on peer supported learning in MOOCs for educators. *The International Review of Research in Open and Distributed Learning* 15, 5 (Oct. 2014). https://doi.org/10.19173/irrodl.v15i5.1852

[13] René F. Kizilcec, Andrew J. Saltarelli, Justin Reich, and Geoffrey L. Cohen. 2017. Closing global achievement gaps in MOOCs. *Science* 355, 6322 (Jan. 2017), 251–252. https://doi.org/10.1126/science.aag2063 Publisher: American Association for the Advancement of Science.

[14] Barbara S Lawrence and Neha Parikh Shah. 2020. Homophily: Measures and meaning. *Academy of Management Annals* 14, 2 (2020), 513–597. Publisher: Briarcliff Manor, NY.

[15] Paul F Lazarsfeld, Robert K Merton, and others. 1954. Friendship as a social process: A substantive and methodological analysis. *Freedom and control in modern society* 18, 1 (1954), 18–66. Publisher: New York, Van Nostrand.

[16] Kun Li. 2019. MOOC learners' demographics, self-regulated learning strategy, perceived learning and satisfaction: A structural equation modeling approach. *Computers & Education* 132 (April 2019), 16–30. https://doi.org/10.1016/j.compedu.2019.01.003

[17] Alex Lishinski, Aman Yadav, Jon Good, and Richard Enbody. 2016. Learning to Program: Gender Differences and Interactive Effects of Students' Motivation, Goals, and Self-Efficacy on Performance. In *Proceedings of the 2016 ACM Conference on International Computing Education Research (ICER '16)*. Association for Computing Machinery, New York, NY, USA, 211–220. https://doi.org/10.1145/2960310.2960329

[18] Simon Y Liu, Joel Gomez, and Cherng-Jyh Yen. 2009. Community College Online Course Retention and Final Grade: Predictability of Social Presence. *Journal of Interactive Online Learning* 8, 2 (2009), 19.

[19] Zhongxiu Liu, Rebecca Brown, Collin F. Lynch, Tiffany Barnes, Ryan Baker, Yoav Bergner, and Danielle McNamara. 2016. *MOOC Learner Behaviors by Country and Culture; an Exploratory Analysis.* Technical Report. International Educational Data Mining Society. https://eric.ed.gov/?id=ED592695 ERIC Number: ED592695.

[20] Tharindu R Liyanagunawardena, Shirley Williams, and Andrew Alexander Adams. 2014. The impact and reach of MOOCs: a developing countries' perspective. *eLearning Papers* (2014), 38–46. https://centaur.reading.ac.uk/32452/1/In-depth_33_1.pdf Publisher: eLearningeuropa. info.

[21] Ali Malik, Juliette Woodrow, Brahm Capoor, Thomas Jefferson, Miranda Li, Sierra Wang, Patricia Wei, Dora Demszky, Jennifer Langer-Osuna, Julie Zelenski, Mehran Sahami, and Chris Piech. 2023. Code in Place 2023: Understanding learning and teaching at scale through a massive global classroom. (2023), 2.

[22] Andrew J. Martin and Martin Dowson. 2009. Interpersonal Relationships, Motivation, Engagement, and Achievement: Yields for Theory, Current Issues, and Educational Practice. *Review of Educational Research* 79, 1 (March 2009), 327–365. https://doi.org/10.3102/0034654308325583 Publisher: American Educational Research Association.

[23] Joanne M McInnerney and Tim S Roberts. 2004. Online Learning: Social Interaction and the Creation of a Sense of Community. *Journal of Educational Technology & Society* 7, 3 (2004), 73–81. https://www.jstor.org/stable/jeductechsoci.7.3.73 Publisher: International Forum of Educational Technology & Society.

[24] Miller McPherson, Lynn Smith-Lovin, and James M Cook. 2001. Birds of a Feather: Homophily in Social Networks. *Annual Review of Sociology* 27, 1 (Aug. 2001), 415–444. https://doi.org/10.1146/annurev.soc.27.1.415

[25] United Nations. [n. d.]. *Human Development Index (HDI).* Technical Report. United Nations. https://hdr.undp.org/data-center/human-development-index Publication Title: Human Development Reports.

[26] United Nations. 2024. 2023/2024 Human Development Report - Statistical Annex HDI Table. https://docs.google.com/spreadsheets/u/1/d/1GH5Q9bw9yguhyjcYZNHv502MntG3-W0G/edit?usp=drive_web&ouid=112844614192343013521&rtpof=true&usp=embed_facebook

[27] Barbara Martinez Neda, Flor Morales, Kitana Carbajal Juarez, Jennifer Wong-Ma, and Sergio Gago-Masague. 2024. Investigating the Role of Socioeconomic Factors on CS1 Performance. In *2024 IEEE Global Engineering Education Conference (EDUCON)*. 1–8. https://doi.org/10.1109/EDUCON60312.2024.10578863 ISSN: 2165-9567.

[28] David Nicol, Ian Minty, and Christine Sinclair. 2003. The social dimensions of online learning. *Innovations in Education and Teaching International* 40, 3 (Aug. 2003), 270–280. https://doi.org/10.1080/1470329032000103807 Publisher: Routledge _eprint: https://doi.org/10.1080/1470329032000103807.

[29] Poquet Oleksandra and Dawson Shane. 2016. Untangling MOOC learner networks. In *Proceedings of the Sixth International Conference on Learning Analytics & Knowledge (LAK '16)*. Association for Computing Machinery, New York, NY, USA, 208–212. https://doi.org/10.1145/2883851.2883919

[30] Rasha Osman. 2012. Teaching Software Engineering in Developing Countries: A Position Paper. In *2012 IEEE 36th Annual Computer Software and Applications Conference*. 648–653. https://doi.org/10.1109/COMPSAC.2012.91 ISSN: 0730-3157.

[31] Christopher Piech, Ali Malik, Kylie Jue, and Mehran Sahami. 2021. Code in Place: Online Section Leading for Scalable Human-Centered Learning. In *Proceedings of the 52nd ACM Technical Symposium on Computer Science Education (SIGCSE '21)*. Association for Computing Machinery, New York, NY, USA, 973–979. https://doi.org/10.1145/3408877.3432562

[32] Eyal Rabin, Maartje Henderikx, M. Kalman Yoram, and Marco Kalz. 2020. What are the barriers to learners' satisfaction in MOOCs and what predicts them? The role of age, intention, self-regulation, self-efficacy and motivation. *Australasian Journal of Educational Technology* 36, 3 (June 2020), 119–131. https://doi.org/10.14742/ajet.5919 Number: 3.

[33] Jennifer C. Richardson, Yukiko Maeda, Jing Lv, and Secil Caskurlu. 2017. Social presence in relation to students' satisfaction and learning in the online environment: A meta-analysis. *Computers in Human Behavior* 71 (June 2017), 402–417. https://doi.org/10.1016/j.chb.2017.02.001

[34] José A. Ruipérez-Valiente, Thomas Staubitz, Matt Jenner, Sherif Halawa, Jiayin Zhang, Ignacio Despujol, Jorge Maldonado-Mahauad, German Montoro, Melanie Peffer, Tobias Rohloff, Jenny Lane, Carlos Turro, Xitong Li, Mar Pérez-Sanagustín, and Justin Reich. 2022. Large scale analytics of global and regional MOOC providers: Differences in learners' demographics, preferences, and perceptions. *Computers & Education* 180 (April 2022), 104426. https://doi.org/10.1016/j.compedu.2021.104426

[35] Yanhong Shao, Shumin Kang, Quan Lu, Chao Zhang, and Ruoxi Li. 2024. How peer relationships affect academic achievement among junior high school students: The chain mediating roles of learning motivation and learning engagement. *BMC Psychology* 12, 1 (May 2024), 278. https://doi.org/10.1186/s40359-024-01780-z

[36] Natasha Singer. 2020. Teaching in the Pandemic: 'This Is Not Sustainable'. *The New York Times* (Nov. 2020). https://www.nytimes.com/2020/11/30/us/teachers-remote-learning-burnout.html

[37] Alyssa Friend Wise and Yi Cui. 2018. Learning communities in the crowd: Characteristics of content related interactions and social relationships in MOOC discussion forums. *Computers & Education* 122 (July 2018), 221–242. https://doi.org/10.1016/j.compedu.2018.03.021

[38] Tongshuang Wu, Yuan Yao, Yuqing Duan, Xinzhi Fan, and Huamin Qu. 2016. NetworkSeer: Visual analysis for social network in MOOCs. In *2016 IEEE Pacific Visualization Symposium (PacificVis)*. 194–198. https://doi.org/10.1109/PACIFICVIS.2016.7465269 ISSN: 2165-8773.

[39] Ke Zhang, Curtis Bonk, Thomas Reeves, and Thomas Reynolds. 2019. *MOOCs and open education in the Global South: Challenges, successes, and opportunities.* Routledge.

[40] Qing Zhang, Fernanda Cesar Bonafini, Barbara B. Lockee, Kathryn W. Jablokow, and Xiaoyong Hu. 2019. Exploring Demographics and Students' Motivation as Predictors of Completion of a Massive Open Online Course. *International Review of Research in Open and Distributed Learning* 20, 2 (2019). https://doi.org/10.19173/irrodl.v20i2.3730 Publisher: Athabasca University Press (AU Press).

[41] Linda Zhao. 2023. Networks in the making: Friendship segregation and ethnic homophily. *Social Science Research* 110 (Feb. 2023), 102813. https://doi.org/10.1016/j.ssresearch.2022.102813