**SOCIAL ARCHITECTURES OF UNIVERSITY FORUMS:
GRADE-BASED SIMILARITY IN ONLINE INTERACTIONS**

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Abstract

The COVID-19 pandemic hastened the transition of higher education towards more digital learning practices. While the adoption of online learning provided universities with the ability to continue their service, there were noted impacts on student welfare and learning experiences. Students overwhelmingly reported that the lack of peer connections negatively affected their satisfaction and well-being. This perceived lack of connectivity can be addressed through deliberate design of social architectures for student learning. However, to date, the design of social architectures for learning online has focused on the teaching and learning practices within a single course. To extend our understanding of social learning beyond a single course toward a holistic university experience, this study examined social interactions in online course forums in three universities. Digital interactions of 14,643 students were analyzed across several years in three universities located in the North American, South-East Asian, and the Pacific regions. The results indicate that students interact online with those in similar performance-bands. We used stochastic actor-oriented modelling to understand reasons for the observed similarity. Modelling showed that learners interacting over several semesters were more likely to interact with others similar to them in performance (social selection), rather than be change their performance towards that of the peers they interact with (social influence). The study discusses the implications of these interaction patterns on the design of social architectures for learning online. The study is among the first in its multi-site analysis of university online interactions and poses questions about the design of social architectures in learning environments and the utility of forum interaction data for understanding them.

1. Introduction

The impact of the COVID-19 pandemic has forced significant and lasting changes on how education is designed, delivered, and assessed. Universities globally were forced to rapidly transition to online and remote delivery. As a result of the speed of change, students were confronted with a new set of challenges linked to a loss of structure and routine, as well changes in social connectivity with peers and instructors. Student evaluations during this period provide overwhelming evidence of the importance of peer interactions on the student learning experience. Just under two thirds of 22516 undergraduates and over 7000 graduate students surveyed in the US reported that the lack of interaction and communication with peers was the second largest obstacle to remote learning (SERU, 2020). Besides the lack of peer support, the restrictions to social mobility (lockdowns) triggered by the shift to online education can modify student's formative years (Watermeyer et al., 2020), negatively affect long-term student well-being. The loss in social architectures also raises concerns of the impact on student employability, since student post-college jobs are often associated with the personal networks they build during their course of studies (Pham, 2020). Given the long list of benefits compromised when social interactions are removed from the learning process, there is a clear imperative for educators to pay greater attention to the design and development of social architectures in online learning.

In the theory of ‘designing for learning’ Goodyear and colleagues (Goodyear & Dimitriadis, 2013; Goodyear et al., 2015; Goodyear and Carvalho, 2013) posit that social architecture is among three key elements that enable learning. Together epistemic (i.e. activity-related), physical, and social architectures create conditions for learning to emerge. Conceptually, the ‘design for learning’ approach differentiates that learning takes place at various scales of impact and within varying timeframes, that also extend beyond learning within the parameters of a single course. However, most of recommendations on how to design social architectures for technology-mediated learning focus on understanding social architectures at the level of an individual course (e.g. Strauss & Rummel, 2020, Rapanta, Botturi, Goodyear, Guardia, Koole, 2020). The impact of the pandemic on higher education has exacerbated the need to advance our understanding of how to design more holistic and integrated online social architectures that transcend courses.

Most research relevant for the design of social architecture for student learning comes from studying social relationships in educational spaces. Importantly, social relationships differ from social interactions that comprise online social architectures. Social relationships are the states of relating that are underpinned by social dynamics. Social interactions are the events leading to those states. The effects of social relationships through face-to-face interactions have been researched in education, economics, sociology, student development in higher education, learning sciences, and technology-mediated learning. In a seminal study, Tinto (1975) showed the positive influence of on-campus social engagement on student belonging and social capital. Building on this work later, student development literature presented large-scale evidence of how on-campus interactions and relationships can improve student cognitive and personal growth (Bowman, 2010; Gurin et al., 2002; Hu & Kuh, 2003). There is now strong evidence demonstrating the influence friends and learning partners have on educational attainment (Lomi et al., 2011; Sacerdote, 2011; Wilkinson, 2002; Wilkinson et al., 2000), career choices (Raabe et al., 2019), health habits (Christakis & Fowler, 2007), and hobby preferences (Steglich et al., 2006). As face-to-face interactions become reduced, there is a need to understand if similar effects take place through online student-to-student interactions, that at the university level are less explored.

To understand social architectures online, our study examined the interactions of 14,643 students in online forums of three universities. The data were analyzed across multi-year educational programs in three universities, in the North American, South-East Asian, and the Pacific regions. The study examined if students tended to interact with other students of similar average academic performance. Average performance was used to approximate the behaviors needed to succeed in a given academic program. Using descriptive network analysis, we examined at the level of the dyads, if pairs of students interacting in online university forums were similar in average grades. We then examined performance similarity at the level of the ego networks to observe if peers a student interacted with were similar in performance. Finally, we looked at the relationships sustained across semesters in online forums and modelled social influence and social selection statistically. Through stochastic actor-oriented modelling (SAOM), we discerned if observed similarity in peer interactions was a result of: (1) students communicating with those of similar performance; or (2) students changing their performance over time in ways that matched performance of students they interacted with. We found that observed similarity patterns were consistent across three diverse geographic and cultural contexts. The limitations in using digital communication data were also consistent

despite the use of different learning management systems in three universities. In addition to the study results, we discuss implications of the observed patterns for the design and research of social architectures for learning online.

2. Review of Literature on Peer Influences in Educational Settings

This study focuses on examining the patterns observed in university online forum interactions. We review research about the effects of peers in educational environments to demonstrate that despite the great strides made in what we know about peer influences in educational settings, online education research has paid little attention to the mechanisms of interactions beyond those occurring in individual courses.

2.1. Peer Effects Studies.

Economists have demonstrated the role that socio-economic composition of school environments can play on the development and support of student outcomes (Dannemann, 2020; Sacerdote, 2011). The term ‘peer effects’ refers to capture the conditions when individual behavior changes in response to being surrounded by peers with particular characteristics. In education, peer gender, race, and performance have been shown to impact academic choices and educational attainment (Winston & Zimmerman, 2004, p.396; Hoxby, 2000; Sacerdote, 2011; Wilkinson et al., 2000; Winston & Zimmerman, 2004). This peer influence on achievement has been found as modest in effect size and statistically significant (Sacerdote, 2011). Peer effects research commonly uses linear models to estimate social interactions (Blume et al., 2011), where the means of group characteristics are used to describe peer effects (Angrist, 2014; Dannemann, 2020). Such an approach overlooks pair-level effects that can take place through interactions, such as those observed through pair-level interactions that commonly occur in online settings.

2.2. Selection and Influence in Social Network Studies.

Social network analysis (SNA) is often used to examine online interactions. SNA affords an opportunity to consider one-to-one and one-to-many student interactions at the network-level. In sociology, network-based analysis of peer relations often centers around homophily, i.e. a natural tendency to interact with similar others that is widely observed in nature (Fu et al., 2017) and in social life (McPherson et al., 2001). Homophily occurs as a result of two distinct mechanisms: social selection and social influence (Robins, 2015). Social selection is a process of preferential behavior, where individuals form relationships or interact with similar others due to preference (McPherson et al., 2001). Social selection also can occur due to the mechanism of induced structural concerns (Kossinets & Watts, 2009) when individuals have a shared foci of activity (Feld & Grofman, 2009) because of their similar status (e.g. parents) or interest (e.g. sports). Social selection can occur due to a limitation of choices. For instance, low-status individuals could have a higher frequency of interaction as a result of a lack reciprocation from other higher-status groups (Schaefer, 2012). Social influence, on the other hand, is a process of behavior change within existing interactions. Social influence takes place when people change their behaviors, attitudes, and preferences to align with that of their peers’.

Network-based approaches, i.e. where peer relationships are represented and analyzed as networks, show that both homophily and influence can be used to describe student relationships. For example, in education settings close ties or “friends” in peer networks often have similar performance levels (Kossinets &

Watts, 2009; Lomi et al., 2011; Smirnov & Thurner, 2017; Weber et al., 2020). Peers with similar grades tend to take the same classes, suggesting that homophily is, to some extent, induced by the program structure (Gasevic et al., 2013). Even when program structure is accounted for, undergraduate students have been shown to form friendships with those of a similar academic performance level and gender (Weber, Schwenzer, and Hillmert, 2020).

It has been well-documented that choosing “friends” of a similar performance and aligning performance standards to match that of peers is a common occurrence in social networks within educational settings. However, it has been under-explored if such peer selection and influence also describes the social architectures occurring in online programs comprised of social interactions.

2.3. Similarity in Online Peer Interactions.

More recently, digital traces of learner online interactions have offered an alternative data source for the analysis of social architectures in online learning. Prior studies in the fields of learning analytics and educational data mining, have investigated peer interactions in online course forums and have demonstrated that students tend to interact with those of a similar academic level or performance (Casquero et al., 2015; Dawson, 2010). In accord with other studies, Vaquero and Cebrian (2013) found that students with higher performance tend to interact with one another, forming interconnected sub-groups. Such patterns were also observed in massive open online courses, where more frequent and interconnected interactions are found among learners of similar grades (Brown, Lynch, Eagle, et al., 2015; Brown, Lynch, Wang, et al., 2015). The tendency for learners to form online communication sub-groups as noted by Vaquero and Cebrian (2019), is potentially explained by their ability to engage with more meaningful and sustained conversations. Chen and Huang (2019) also observe that similar peers were interacting with one another online. The authors found that pairs of interacting students were similar in their prestige, i.e. the degree of interest shown to them by other learners. The authors suggested that participation rate and frequency of interaction appeared to explain the group dynamics and similarity in grades.

Across the studies, online education researchers have examined patterns of grade-based similarity in single courses. These patterns suggest that processes, such as selection or influence, that explain similarity observed in student relationships may also be present in online interactions, especially those lasting over longer time periods. Yet, these assumptions have not been previously investigated at the level of university, nor have been focused on the mechanisms at play. Understanding whether these performance similarities are limited to individual courses or are more prevalent across the undergraduate student experience has an impact on the interventions to adopt to leverage their potential benefits.

3. This Study and Research Questions

To better understand patterns in social architectures that form through student online interactions in university programs, the study was framed through the following research questions (RQs):

1. How similar, on average, is the performance within a pair of learners interacting in online forums throughout the university study?
2. Do social selection or social influence explain the observed similarity in pairs of students who sustain their online interactions throughout the university study?

4. Methods

4.1. Methods Overview

The data used for analysis contained digital interactions of 14,643 students in three universities located in the North American, South-East Asian, and the Pacific regions. To describe the similarity of learner interactions in online course forums, the study took a network-based approach. We constructed networks for three separate student cohorts, based on the enrolment year. If student A posted a message into a discussion thread, and student B posted a message into the same discussion, both within a particular time frame, then these two students would be linked with a tie and treated as a pair of linked nodes in the *interaction networks*.

To address RQ1, these *interaction networks* were examined descriptively using two different approaches.

First, we analyzed the similarity of performance within each pair of interacting students. To represent performance, student-level grade point average (GPA) was normalized, transformed into standard deviations. The difference between student performance in standard deviations for each pair of students was averaged across the entire network in a given time period, such as a semester or a year.

Second, we grouped student performance into quartiles, i.e. low performing, high performing, etc. We then examined all interactions each student had as her ego-network ties, evaluating if the interactions within each ego-network were with peers whose performance quartile was similar to the performance quartile of this student. Such ego-network perspective offered an aggregate view of who each student interacted with, and how similar they were to this person in their performance.

Both for pair-level analysis and for ego-network analysis, we examined performance similarity in several time periods, throughout the program duration. Information about the size of *interaction networks* and corresponding time periods that they were divided into is presented in Table 1.

To address RQ2, we analyzed if student interactions were explained by social selection or social influence. Social selection and social influence processes presume that ties represent social relations, not social interaction. Not all ties in interaction networks coincide with social ties. In light of this assumption, to model social selection and influence we filtered interaction networks to contain only those student interactions that repeated over a minimum of three time periods (*repeated interaction networks*). Conceptually, the ties in these filtered networks were more aligned with the notion of having a social relationship (for descriptive statistics, see Table 1). Such a transformation resulted in networks of a small size. For instance, as shown in Table 1, only 69 students out of 4619 students interacting online in U2, sustained online interaction ties across a minimum of 3 years. In U1, where the time periods were shorter – semester-length – 258 students sustained ties across a minimum of any three semesters. This demonstrates the overall tendency within the data – students were unlikely to carry interactions over more than one semester or one year.

The *repeated interaction networks* were analyzed with stochastic actor-oriented models (SAOM/Siena models), i.e. statistical network models for longitudinal data. Siena models estimate change for both network ties and node characteristics across several time periods. In Siena models, observations in t_n predict observations in t_{n+1} , presuming temporal dependencies. Therefore, we could explain if social ties underpinning some of the interactions examined in RQ1 were formed through the process of social selection or of social influence (RQ2). A choice of 3

time periods for repeated interaction networks was due to empirical examination – networks with ties sustained in fewer than 2 time periods did not have enough overlap in students between them, required to fit a Siena model.

Table 1. Description of interaction networks and repeated interaction networks

<u>Universities</u>	<u>Number of students in</u>		<u>Change</u>	<u>Data</u>
	<u>Interaction</u>	<u>Repeated</u>	<u>examined across</u>	<u>available for</u>
	<u>Networks</u>	<u>Interaction</u>		
		<u>Networks</u>		
U1	3067	258	Semesters	3 years
U2	4619	69	Years	4 years
U3	6957	168	Years	4 years

Note: Interaction data from 3 and 4 years was split into time periods for temporal modelling (time periods specified per university); but also, were analyzed as one entire network – with unique number of students in such a network reported above. U1 contained only 3 years of data because most students were finished with their studies by then.

4.2 Academic Performance.

Academic performance was operationalized as course grades averaged across a time period and ranked within that period. Academic performance distribution in U1 (N=3,067, students admitted in 2014) was normal. Performance distributions in cohorts in U2 (N=4,619, cohort admitted in 2012) and U3, N=6,957, cohort admitted in 2014) were right skewed. That is, U2 and U3 had more students with higher performance. In both U2 and U3 students overall improved their performance in four years, skewing the distribution even further. Supplementary material includes GPA rank distributions for all universities in every examined time period (Tables S1, S2).

Table 2. Mean and standard deviation of average performance in a given year (semester) for each university (grade distributions included in the appendix).

<u>Case/</u> <u>Length of time</u> <u>period</u>	<u>Performance, Mean (SD) in subsequent time periods</u>					
	<u>1</u>	<u>2</u>	<u>3</u>	<u>4</u>	<u>5</u>	<u>6</u>
U1 (Semester)	3.1 (0.8)	3.1 (0.8)	3.0 (0.8)	3.0 (0.9)	2.9 (0.9)	2.9 (1.1)
U2 (Year)	3.7 (0.6)	3.7 (0.6)	3.8 (0.6)	3.9 (0.5)	--	--
U3 (Year)	3.4(0.4)	3.4(0.4)	3.5(0.4)	3.6(0.4)	--	--

4.3 Network Construction: Tie Definitions and Temporal Boundaries

Analysis was conducted separately for each university. U1 had shorter programs and high flexibility pathways for students. These flexible pathways implied that there was too much change in the composition of the cohort per time period, i.e. as relative to the total number of possible interactions between all students. Data exploration suggested that for U1, technical limitations could be overcome by splitting student interactions throughout 3 years into semester-length periods (total of 6 periods). In contrast, flexible pathways and intermittent participation were uncommon in U2 and U3, where undergraduate several year pathways were more fixed. Data exploration suggested that for both universities year-long time periods were more appropriate to

enable temporal change analysis. Therefore, U2 and U3 interactions were divided into years for the program of study (total of 4 time periods per each university).

Network ties within constructed networks captured temporal co-occurrence of students within a discussion thread, i.e. students posting into the same thread within a time period average for discussion threads within that time period (Poquet & Jovanovic, 2020). The process of network construction can be described as follows. First, post networks were constructed, where forum posts were linked if occurring in the same discussion thread. Then, differences between timestamps of each posts (at the level of each discussion thread) were calculated. Differences were averaged within a time period, with the geometric mean serving as the threshold for temporal co-occurrence (Table 3). If the time difference between the posts in the same discussion was higher than the threshold, these posts were segmented based on temporal proximity. For instance, if a student posted a message about an assignment and was rapidly responded to by two peers, then three days later closer to the assignment deadline another three peers responded, this would be modelled as two conversation. The post-to-post networks were projected into learner interaction networks, if two posts were determined to be linked, then so were the two posters (students) in the network projection. For more information, please see the Supplement (Figure S3).

Table 3. Average time difference between posting into the same thread which was used as threshold for tie construction

Cases/ Length of time period	Average difference between posting in a thread within a time period					
	<u>1</u>	<u>2</u>	<u>3</u>	<u>4</u>	<u>5</u>	<u>6</u>
U1 (Semester)	60 hrs	58 hrs	53 hrs	31 hrs	26 hrs	58 hrs
U2 (Year)	66 hrs	144 hrs	303 hrs	82 hrs	NA	NA
U3 (Year)	25 hrs	24 hrs	15 hrs	14 hrs	NA	NA

4.4 Analysis of Selection and Influence in Repeated Interaction Networks

Stochastic actor-oriented models (SAOMs) (Snijders et al., 2010) were used to estimate if performance-based similarity of learners in interactions was a result of social selection (students with similar ranked GPA in t_n form ties in t_{n+1}) or social influence (students who have a tie in t_n change their ranked performance to that of peers in t_{n+1}). SAOMs are temporal models that estimate the change in ties (online interactions), change in actor attributes (modeled as ranked GPA), and estimate the role of mechanisms that could explain tie formation and attribute change.

For all three full interaction networks, students rarely interacted with the same people longer than one time period. Jaccard similarity coefficient signifying overlap between network ties across different periods ranged 0.0–0.1. This implies high instability in ties across the time slices and is difficult to model, generally a 0.25 Jaccard similarity is recommended. Constructing repeated interaction networks with ties sustained over fewer than three semesters resulted in a low Jaccard similarity, i.e. low overlap of ties across two subsequent time periods. This low overlap between students interacting with one another across time created technical complications for modelling change and required more stability across the time slices. Therefore, SOAM models were fitted only on the *repeated interaction networks*, where ties were present in more than half of the time slices.

SOAMs are well developed models that are well suited to estimate the change in variables describing the network nodes, when those variables are captured in discrete Likert-scale like values. Therefore, student GPA was transformed into 4 quartiles, that is performance for each student was averaged across all courses in one time slice, then ranked within that time slice, and assigned 1–4 value ('1' if student's performance ranked lowest and was in the first quartile, '4' if it was highest performance in the top quartile).

One large SOAM model was fitted for each university, containing a range of features and controlling for the interdependencies between them. After fitting the models, we observed that all three models had convergence ratio 0.25, which is considered acceptable by SAOMs (as per RSiena Manual), with moderate goodness of fit for structural features (measured by triadic census, geodesic distance) and a good fit for predicted behavior (performance).

4.5 Features Modelled in Stochastic Actor Oriented Models

Each model for a university contained around 20 features, briefly described below (see Supplement for technical specification).

4.4.1. Features controlling for network structure.

Model estimation process requires to specify network related features within the model, that help reproduce the network structure and control for artefacts within the network structure when estimating other effects. The model controlled for network structure, such as degree and density. The models were fitted separately per university but included identical hypotheses about student relations and change of their performance. If a hypothesized feature resulted in a model with poor fit (AIC higher than before feature was included into the model), it was substituted with a similar feature.

4.4.2 Change of ties across time periods.

Each model estimated if a number of network ties changed across time periods.

4.4.3 Features representing social selection hypotheses (e.g. two or three students who do not have ties in $time_n$ will have ties in $time_{n+1}$).

Social selection hypotheses were:

- Students whose performance is of the same rank will form a tie;
- Students with GPA ranked within a top quartile (e.g. 4) will form a tie;
- Students with GPA ranked within the bottom quartile (e.g. 1) will form a tie;
- Students with GPA ranked within a top quartile (e.g. 4) will form triads.

The above hypothesis related to the similarity in triads was motivated by the empirical finding that higher performance students interacting online engage in turn-taking, which in a network structure would be represented as a triad.

4.4.5 Change of student performance across time periods.

Each model estimated if overall performance increases or decreases across time periods.

4.4.6 Features representing social influence hypotheses (in a pair of two students who have a tie in $time_n$ one of them will change her performance closer to the rank of the second person in a pair in $time_{n+1}$). Peer influence was estimated through the model specifications derived from the following social selection hypothesis:

- Students who have ties to those with higher GPA ranks will increase their GPA rank towards that of their interaction partners.

4.4.7 Feature controlling for the number of ties that each student did not sustain over a minimum of three weeks.

Each model also included a covariate that controlled for learner interactions that were filtered out from *repeated interaction networks*. To remind, here we statistically examine a (temporally) causal effect of a sustained tie in time 1 on the change of performance in time 2. To model selection and influence, *repeated interaction networks* filtered out other ties that students did not sustain over the minimum of three time periods. Although excluded from modelling, the observed selection and influence effects could potentially result from non-sustained interactions removed from the network. Since we could not model these intermittent interactions explicitly within the networks, we constructed a variable capturing the ratio between non-repeated interactions to repeated interactions. This variable was included in the model to control for the potential effects of social influence that occurs through non-sustained interactions.

5. Results

5.1 Similarity in Performance within Online Interactions

Descriptive analysis shows online forum interactions predominantly take place between learners with similar average performance, within the same grade band or a neighbouring grade band. Figure 1 summarizes the similarity in performance averaged for all interacting learner pairs (dyads). Using the edge weight distribution, we categorized their dyadic ties into categories of low intensity, moderate intensity, and high intensity. Intensity of a tie indicated how often two students interacted. Low intensity interactions were those when a dyad interacted 1–3 times (50% of the distribution); moderate intensity interactions represent dyads with interaction of 4–10 times (25% of the distribution); and high intensity interactions represented dyads that interacted more than 10 times (25% of the distribution).

The x-axis of Figure 1 reports the average difference between learner performance in standard deviations. It shows that interactions occurred between students whose GPA's difference on average ranged 0.5–1 standard deviation of the cohort's GPA distribution. We remind that the value of standard deviations varied across institutions (see Table 2), ranging from 0.4–1.1 of the grade percentile rank. For instance, in U2 student pairs interacting 1–3 times (lowest intensity group) in Year 1 were on average different in performance by 1.1 standard deviations, and standard deviation equalled 0.6 of an average grade (Table 2).

Figure 1. Online Interactions: GPA Similarity and Interaction Frequency. Number of student pairs (dyads) whose performance difference was averaged in the time period is noted on each bar; error bars represent standard errors; the y-axis represents the absolute difference in average GPA normalized within that time period; frequency of interactions counted within each time period. We differentiate between interactions of different frequency, coloring the bars darker with the increase of intensity (low (under 3 times), moderate (4 to 10 times), high (more than 10 times)).

Figure 1 suggests the lack of clear relationship between the intensity of interactions, study progressions, and student performance similarity when looking across the multiple institutions. Despite the diverse of patterns, what is striking about Figure 1 is the overall average similarity between the learners who interact online. The difference of 1 standard deviation or smaller is smaller than 1 point of the grade, which means on average students interact with those whose grades are either the same or very similar to theirs.

Figure 1 also shows that in the first 3 years, performance between learners who interacted more frequently became more and more similar, reaching the lowest difference of 0.7 standard deviation in Year 3. This means, that, on average, U2 and U3 learners interacting with one another over ten times actually had the same grades. Such is because standard deviations in these universities in Year 3 equaled 0.6 of the average grade and 0.4 of the average grade respectively (Table 2). For example, in U3 this would translate into an average interaction between two students with average grades 4 and 3.4, or 2 and 2.4, or 5 and 4.6. This pattern of decreasing similarity in high frequency time over time may be due to increased socialization processes among similarly performing students, although the pattern does differ for the last time period of studies.

In addition to dyadic-level analysis, we examined interactions from the ego-network perspective. Figure 2 provides an overview of this descriptive analysis. Performance here was transformed into four quartiles, and for each student we counted the composition of her interaction network, the percent of high performing peers she interacted with, the percent of peers with the same performance quartile, etc. These were averaged across all students of the same performance. Figure 2 offers a view of selected results (Figure S7 of the Supplement presents all summaries).

The pattern of ego-network composition is stable across the universities. On average, a student interacted the most with peers in the same performance quartile and the least with peers in the opposite performance quartile. For example, at the beginning of their studies, a low performing student would have on average 47% (U1), 48% (U2), and 41% (U3) of their interactions with other low performing peers. The proportion of these interactions would remain highest as students continue in the study program. In contrast, a low performing student would have the least fraction of interactions with students of top performance quartile – 12% (U1, Semester 1), 17% (U2, Year 1); 17% (U3, Year 1). In other words, in all three universities students mostly talk to those who perform at the same level and the least interact with those whose performance is markedly different from theirs.

Numbers reported in Figure 2 are sensitive to the size of the ego-networks. Prior work at the course-level has showed that low-performing students interact with fewer students than higher-performing students did (Casquero et al., 2015; Dawson, 2010). We have qualitatively examined the size of networks of different performance levels in different years (see Supplement, Figure S8). Our analysis is in contrast with previous studies that only looked at the size of ego-networks at the course-level in a few selected courses. We have found that when averaged across the university, the size of ego-networks (number of peers one interacted with) for students with different performance levels was highly variable within and between institutions.

Figure 2. Examining the compositions of online ego-networks**(a) Composition of personal networks for students with GPA rank bottom 25%** **(b) Composition of personal networks for students with GPA rank 50%** **(c) Composition of personal networks for students with GPA rank 75%** **d) Composition of personal networks for students with GPA rank top 25%**

5.2 To what extent is observed similarity explained by social selection and social influence?

Following the analysis of similarity in interactions online between students, we applied statistical network modelling to interactions students had sustained over three years for U2 and U3 and over three semesters for U1. We investigated if similarity in performance within an interaction was the result of *social selection*, whereby students with similarly ranked performance choose to interact, or from *social influence* where students tended to change their performance to that of peers. The results show that social selection is the more likely within repeated online student interactions compared to social influence (Table 3).

Table 4. Selected Results from Stochastic Actor-Oriented Models (full output available in Supplement)

Parameter	U1 (258 learners)			U2 (69 learners)			U3 (168 learners)		
Effects on interaction between students	θ	SE	p	θ	SE	p	θ	SE	p
Network change and structure	Controlled for								
Effect of ranked GPA on number of peers (ie degree)	0.06	0.03	0.03	-0.26	0.083	0.00	-2.73	1.261	0.03
Similarity in ranked GPA	1.48	0.22	0.00	0.588	0.264	0.05	-2.85	0.431	0.00
Top 25% interact in triads	-	-	-	-	-	-	0.216	0.051	0.00
Bottom 25% interact in pairs	-	-	-	-	-	-	1.462	0.311	0.00
Effects on ranked GPA									
Performance change (t_1 to t_2)	2.85	0.39	0.00	2.563	0.671	0.00	1.584	0.308	0.00
Performance change (t_2 to t_3)	2.58	0.37	0.00	2.612	0.648	0.00	1.681	0.409	0.00
Performance change (t_3 to t_4)	2.77	0.4	0.00	4.169	1.429	0.00	-	-	-
Performance change (t_4 to t_5)	2.14	0.35	0.00	-	-	-	-	-	-
Performance change (t_5 to t_6)	1.01	0.14	0.00	-	-	-	-	-	-
Performance, linear shape	0	0.03	0.93	0.043	0.072	0.56	-0.01	0.072	0.92
Performance, quadratic shape	0.23	0.03	0.00	0.323	0.081	0.00	0.169	0.084	0.04
Learners change performance to that of peers	0.56	0.09	0.00	0.415	0.162	0.01	0.013	0.085	0.88
Covariate effect of non-sustained interactions	0	0.01	0.77	-0	0.117	0.98	-0.01	0.006	0.22
Convergence ratio	0.15			0.13			0.21		

Results show that social selection hypothesis was confirmed in all universities. As shown in Table 4, in U1 and U2, students with similarly ranked GPA in t_n interacted with one another in the next time period ($\theta_{U1_similarity_in_ranked_GPA} = 1.48$, $SE = .22$, $p\text{-value} = .001$, $\theta_{U2_similarity_in_ranked_GPA} = .59$, $SE = .26$, $p\text{-value} = .05$). In U3, such social selection across the entire student body was negative and statistically significant ($\theta_{U3_similarity_in_ranked_GPA} = -2.85$, $SE = .43$, $p\text{-value} = .001$). However in U3, we fitted social selection parameters only for highest performing students, and observed social selection for top and bottom 25% of achievers ($\theta_{U3_top_25\%_interact_in_triads} = 2.16$, $SE = .05$, $p\text{-value} = .001$; $\theta_{U3_bottom_25\%_interact_in_pairs} = 1.46$, $SE = 0.3$, $p\text{-value} = .001$). In essence, social selection patterns were significant for both highest and lowest performing students throughout their studies (e.g. low performers formed a tie in the next time period; high performers formed a tie in the next time period).

Social selection should be understood within the context of general activity levels, such as the likelihood of learners of different performance levels to interact with others. The effect of GPA on the number of peers one interacted with (i.e. their network degree) was significant across all institutions. In U1 the higher the student performance, the greater the number of peers they interacted with ($\theta_{U1_effect\ of\ ranked_GPA\ on\ number\ of\ peers(degree)}=.06$, $SE=.03$, $p-value=.03$). In contrast, in U2 and U3 higher performing students were less likely to interact with more peers ($\theta_{U2_ranked_GPA\ on\ number\ of\ peers(degree)}=-0.26$, $SE=.08$, $p-value=.00$; $\theta_{U3_ranked_GPA\ on\ number\ of\ peers(degree)}=-2.73$, $SE=1.26$, $p-value=.03$). Generally, although the effect of GPA on the number of peers is significant, the patterns do differ across the institutions, also in magnitude.

Social influence, modeled to observe if students change their performance to that of their peers was positive and statistically significant in U1 and U2 ($\theta_{U1_total_peer_performance}=.56$, $SE=.09$, $p-value=.00$; $\theta_{U2_total_peer_performance}=.42$, $SE=.16$, $p-value=.01$), but not in U3 ($\theta_{U3_total_peer_performance}=.01$, $SE=.09$, $p-value=.88$). To interpret this effect, one needs to consider the general likelihood of performance to change. Models show that student performance did not change linearly, but quadratically ($\theta_{U1_performance_quadratic}=.23$, $SE=.03$, $p-value=.00$; $\theta_{U2_performance_quadratic}=.32$, $SE=.08$, $p-value=.00$; $\theta_{U3_performance_quadratic}=.16$, $SE=.08$, $p-value=.004$). This means that student's at initially higher ranks of performance tended to increase ranks more than those who were at lower ranks of performance.

Estimating peer effects for each performance level has been conducted through post-hoc analyses where a weighted sum of influence and general tendency of the grade to change were aggregated (see Supplement, S10). The post-hoc analysis of peer influence shows that in U1 and U2, where peer influence was positive and significant, peer interactions of students with top-ranked GPAs were most likely to affect the performance of peers whose GPA was in the 3rd and 4th quartile (their GPA fell between 50–75% of the GPA distribution, or 75%-100%). At the same time, students with GPA under 25% were also most likely to be affected by students with low GPA levels (0-50%). Post-hoc analysis also shows that peer influence was observed for students in neighboring performance levels.

6. Discussion

First, results reveal a high level of similarity between peers interacting online, across all three universities (RQ1). We found that on average, performance within a pair of students interacting online differed within one standard deviation. This ranged from 0.5 to slightly over 1 grade points. From an ego-network perspective, the largest proportion of interactions of a student is with peers whose performance is within the same GPA quartile; with students of the opposite levels of performance least represented

Secondly, we found that interactions sustained over longer periods of time resulted from social selection and social influence (RQ2), with social selection prevalent across all universities, and social influence less so. Peer influence, i.e. propensity to change grades to that of their peers, was most prominent for peers with medium-level performance.

In addition, our work demonstrated the importance of context in performance-based similarity observed in student online interactions. In U2 and U3 performance distributions were more skewed towards higher grades. It is also in these universities that social selection is found specifically in the margins of the

distribution – for students with top and bottom levels of performance. Such patterns may be reflective of different cultures of performance across the three universities.

Across all universities we observe performance-based similarity in interactions. But more granular patterns are diverse. Since very few studies carried out similar analyses beyond a single course and across three different continents, we presume that these differences should be explained by different curriculum pathways, instructional design cultures, as well as performance and behavior cultures within the universities that influence how students interact online. Thus far, studies using learning data derived from online environments rarely reach beyond one institutional context. This is a fundamental aspect of our work, demonstrating that more cross-contextual explorations must be carried out in order to appropriately generalize experimental and analytic findings.

Finally, our study sheds light on the limitations of digital data to understand social architectures online. At the onset we encountered the limitations of digital data for longitudinal network analysis, which were consistent across three universities. Data patterns of intermittent participation were also consistent. The sparsity of repeated interactions was common across all three datasets, i.e. students rarely interacted with the same peers across more than one semester. We made a major methodological decision enabling longitudinal analysis of social relations, as we extracted pairs with repeated interactions to model social processes. This considerably reduced our sample size and generalizability.

The sparsity of sustained interactions is a unique and consistent feature of online discussion forum data, in the pre-pandemic patterns of online interaction. Since online course interactions present only part of what takes place socially, course co-enrolment in smaller courses where personal familiarity can be assumed may help understand patterns of these social architectures. Relational event modelling (REM), where interactions are modelled as a sequence rather than as an aggregated state may be better suited to such data but is not suited to analyzing selection or influence. That is, as a more granular approach to modelling REM would solve data sparsity, but not shed light on relationship formation, as states of relating appear over longer periods of time, and are emergent constructs, not behavior. Constructing complementary datasets of self-reported student relationships are needed to be layered over granular digital data, to better address the research questions we raised in this paper.

7. Implications

There are two important findings derived from the study. Students interact with similar others, and why that happens needs to be further investigated. Also, only few students are prone to influence, as observed through digital interactions.

Understanding what the contexts that help them improve has direct implications for how to design social environments for learning.

To explain, the study findings demonstrate that medium-performing students change performance within the social architecture composed of similar peers and slightly better peers. The analysis shows that peer influence can occur when individuals are exposed to those who are similar or slightly better. This result is akin to Vygotsky's zone of proximal development and is most likely to occur for learners at the second or third quartile of performance. The results are in alignment with work on group effect that found medium-ability students only benefit from heterogeneous groupings when higher-performing students are present (Burke & Sass, 2013). Put simply, those students who reach a certain level of knowledge can improve when partnered with others whose knowledge is slightly better.

However, it should be kept in mind, that these students who experience performance change (i.e. ranked at second or third quartile of performance) are embedded in interactions with peers. In their ego-networks, the highest number of peers they interact with are like them in performance, i.e. have comparative levels of knowledge. So perhaps, their change is caused by this critical mass of similar others. This would be in line with the meta-analysis by Lou and colleagues who found that medium-ability students benefit from being in a homogeneous group ($d=0.51$) (Lou et al., 2001). The students in the third quartile of performance are surrounded by a larger mass of others with good performance and also about 25% of interactions they have with those of higher performance. In other words, they are the only group that can actually improve the grade and is exposed to more than 50% of interactions by students with generally high performance. In that their social context is unique as compared to other groups - it combines their sufficient level of prior knowledge with an optimal amount of similarity and difference. Such a premise can inform the design choices of group formation for medium-performing students.

The results of this study also indicate that low performing students are the least likely to change performance, also suggesting that low performing students are least affected by their peers. More than half the interactions observed among the lower performing group were with those of similarly low performance. The results are consistent with the meta-analysis by Lou et al., (2001) who showed that low-ability students do not benefit from working in groups with other low-ability students ($d=-0.6$). Low-performing students appear to be better off limiting their interactions with peers of similar academic performance. Potentially, these students would benefit from increased instructor presence, rather than in a group that may differ drastically from them in knowledge. Instructor may be better suited to scaffold their learning progress and gradually design for interactions with alternate peers.

The findings from the present study do not elucidate on why selection or influence occurs, and just reveal that selection and influence do arise in sustained peer interactions. In fact, the similarity in performance across the university is rather high, but reasons as to what drives it are not clear. Student agency may play a role in peer influence mechanisms. Future research needs to focus on the student-level perspective to understand what individual characteristics support student agency in adapting to peer influences. Shared foci of activity and similarity of behavior could also impact social selection mechanisms. The timing of when students engaged in a discussion was an essential element of how interactions were conceptualized for this study. Therefore, the propensity of students to interact with similar others can suggest that they simply were interacting at the same time, or that the topic they were interacting with was of shared interest. Future work should experimentally examine students' discussion activity and participation choices, as they are fundamental for the understanding observed performance-based similarity. If timing of interactions is the mechanism, or the way students ask or respond to questions are behind the selection processes, then technologies can be designed to modify how and when students interact, coaching them towards more effective use of language or planning.

To conclude, the study has implication for designing social architectures for learning. It appears that grade-based similarity is prominent in forum interactions and generalizes to different university contexts. Creating feedback loops that reflect this similarity for the instructors is an important step towards diversifying student interactions. Yet, what interactions should be designed for and for whom, remains to be further investigated. Findings suggest that medium-ability students benefit from being situated within social architectures that contain both peers of a similar as and

higher level of performance. In contrast, low performing students appear to be less susceptible to peer influences, and perhaps more scaffolding and instructor presence can help them derive the benefits of interacting with higher performing peers. Future work should seek specific mechanisms for selection and influence, including factors of timing, shared foci of activity within discourse quality, and individual student factors related to student agency.

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