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From Speech Acts to Discussion Dynamics and Course Outcomes

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Comprehensive Analysis of Discussion Forum Participation: From Speech Acts to Discussion Dynamics and Course Outcomes

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***Abstract*—Learning in computer-mediated setting represents a complex, multidimensional process. This complexity calls for a comprehensive analytical approach that would allow for understanding of various dimensions of learner generated discourse and the structure of the underlying social interactions. Current research, however, primarily focuses on manual or, more recently, supervised methods for discourse analysis. Moreover, discourse and social structures are typically analyzed separately without the use of computational methods that can offer a holistic perspective. This paper proposes an approach that addresses these two challenges, first, by using an unsupervised machine learning approach to extract speech acts as representations of knowledge construction processes and finds transition probabilities between speech acts across different messages, and second, by integrating the use of discovered speech acts to explain the formation of social ties and predicting course outcomes. We extracted six categories of speech acts from messages exchanged in discussion forums of two MOOCs and each category corresponded to knowledge construction processes from well-established theoretical models. We further showed how measures derived from discourse analysis explained the ways how social ties were created that framed emerging social networks. Multiple regression models showed that the combined use of measures derived from discourse analysis and social ties predicted learning outcomes.**

***Index Terms*—Discourse analysis, learning outcome, social networks, speech acts, statistical network analysis**

I. Introduction

The sociocultural perspective of learning highlights the importance of social interaction and collaborative learning for creating effective environments that support knowledge construction [1], [2]. Knowledge building and information sharing in digitally connected learning contexts primarily occur through language and discourse [1], [3]. Hence, studying learning in digitally connected computer-mediated setting, as a multidimensional process, needs to account for understanding of a) discourse produced [1], [4], and b) social structures emerging from interactions in digital learning environments [1], [5].

A. Integrating Discourse and Social Networks

In a broader context of computer supported collaborative learning, the literature recognizes various approaches to the study of collaborative discourse. Stahl [6], for example, focuses on analyzing *meaning* as a "shared, collaborative, interactive achievement" [6., p.10] expressed in discourse generated in the process of knowledge construction. Every "artifact, action, word or utterance" [7, p. 71], Stahl contends, obtains a meaning from its position in a sequence of interactions, that is, within a particular context [6]. In that sense, understanding cognitive actions in terms of *intentions*, *purpose* or *effect* expressed in communication, is perhaps of utmost importance when studying collaborative discourse in online education settings [1]. Specifically, speech acts theory, provides a comprehensive framework that observes communication utterances as being beyond "mere meaning-bearers, but rather in a very real sense do things, that is, perform actions" [8, p. 1], such as thanking, apologizing, and asking questions. As such, speech acts theory provides insights into the *intended* action of a communication act and the extent of shared understanding between peers participating in a communication [6], [9], [10]. Speech acts (i.e., intended actions of a communication act), we contend, represent a necessary context for interpreting the meaning of collaborative discourse within the given context.

Discourse, however, is not an isolated process but one that emerges from the interaction among actors in a given educational context [5], [11], [12]. Discourse is "constantly being transformed through contact with other discourses" [11, p. 6]. This further implies that the student-generated content should be observed as inherently social, whereas the meaning and intentions of the discourse could be operationalized only through the social adoption [3], [13]–[15]. Observing discourse properties without accounting for the context of the

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underlying social interaction (e.g., who is talking with whom) could be potentially misleading in explaining learning in technology mediated settings [16].

Social network analysis (SNA) has been commonly applied in examining student interactions emerging from learning in digital educational settings [17]. Shifting the focus of analysis from the individual level to the group level, SNA enables accounting for the importance of group dynamics, and provides comprehensive insights into the quantity and quality of social interactions within a given networked context [18], [19]. Besides the use of descriptive methods and analysis of network structural and generative properties (e.g., centrality, density, triad closure) [20], [21], recent research also offers methods to explain the social dynamic processes (e.g., tendency to form reciprocal or homophilic ties) that drive network formation [16], [22], [23]. Although social network indicators allow for revealing emerging roles and structure of interactions in learning networks, SNA alone is not sufficient for deeply understanding patterns of interactions in a given learning environment. For example, to understand dynamics that affect tie formation, one also needs to account for the specificities of the discourse generated through student communication.

To provide a comprehensive understanding of different facets of learning in digital learning environments, we posit that discourse and social network analysis should be applied as complementary approaches, rather than independent analytical models [1], [24], [25]. It is important to note that the literature recognizes similar attempts to make a connection between the two analytical methods [24], [26]. For example, de Laat [24] utilizes SNA to reveal most influential discussion participants in learning activities and to explain overall patterns of connections between peers. de Laat [24] further applies qualitative coding scheme for analyzing negotiation of meaning and social construction of knowledge in computer-mediated interaction. Although beneficial for understanding learning in computer-mediated settings, de Laat's approach is primarily based on examining the association between discourse and descriptive network properties. de Laat's [24] analytical method does not necessarily establish inferential links between the complementary perspectives (discourse and social structures), thus lacking capacity to explain how actions expressed through discourse frame social interactions observed in a given context. Moreover, de Laat [24] does not necessarily account for the sequence of indicators of knowledge construction that, according to Stahl [4], [7] as well as Molenaar and Chiu [27] among others, provides a basis for understanding the process of knowledge construction. Finally, being primarily based in manual analysis methods, it is questionable to what extent the analytical approach proposed by de Laat [24] is scalable.

B. Research Goals and Research Questions

The contemporary research on collaborative learning usually relies on methods that involve manual analysis of online discourse and, more recently, supervised approaches to automated analysis (Section II). In that sense, discourse and social structures that emerge from the collaborative learning activities are typically analyzed separately without the use of computational methods that can offer a holistic perspective. Therefore, this paper proposes an approach that addresses these two challenges i) by using an unsupervised machine learning approach to extract speech acts as representations of knowledge construction processes and finds transition probabilities between speech acts across different messages; and ii) by integrating the use of discovered speech acts to explain the formation of social ties and predicts course outcomes.

Specifically, to understand *actions* employed in collaborative dialog among participants in discussion forums, we examine the intended meaning of student messages expressed through different speech acts. Hence, we define our first research question as follows:

> ***RQ1.*** What kinds of speech acts are typically used by discussion forum participants in online learning settings?

Further, exploring student messages in MOOC discussion forums, Gillani and Eynon [28] as well as Poquet and Dawson [22], among others, suggest the importance of understanding ways students interact in terms of the nature of the content they share or topics they participate in, as means for understanding the structure of the process of knowledge building. In this study, therefore, we aim at further investigating student participation patterns in terms of sequence of posting messages with a particular speech act, as well as the coherency of discussion threads (i.e., to what extent discussion threads transition from one speech act to another). Thus, we define our second research question as follows:

> ***RQ2.*** What are the characteristic sequences of speech acts generated by students during their participation in a discussion forum?

Moreover, student generated discourse also implies certain actions, and points to various activities or attitudes [9]. This research aims at further examining the interrelationship between student messages and processes that frame social interactions in learning networks. Specifically, by complementing a discourse analysis with SNA methods, we aim to examine to what extent different sequences of speech acts employed in communication, reflect latent regularities that drive social network formation. Without an attempt to provide causal inferences, our goal here is to describe potential patterns of association between conversation dynamics (i.e., sequences of actions) and social processes. Hence, we define the following research question:

> ***RQ3.*** How can conversation dynamics, defined through emerging sequences of speech acts, explain social processes evident in social networks that emerge from student interactions in a discussion forum?

Finally, Joksimović and colleagues [16] highlight the importance of considering network characteristics when examining factors that might help with predicting learning outcomes. Specifically, by analyzing social networks emerging from MOOC interactions, Joksimović and colleagues [16] showed how differences in social dynamics that frame social interactions affect the interpretation of variances in the predictive power of social centrality measures (i.e., degree, closeness, and betweenness centrality) on the final course outcome (i.e., obtained certificate). We move this research foreward by examining to what extent the characteristics of social processes that students participate in provide a context for interpreting the association between discussion forum activities (observed through the conversation patterns and social positioning) and final course grade. Therefore, our fourth research question is as follows:

> ***RQ4.*** To what extent can factors that characterize student social interaction in a discussion forum provide a framework for interpreting the association between learning-related social constructs (namely conversation dynamics and social positioning) and learning outcome?

II. Background

A. Speech Acts Theory at a Glance

Student generated discourse represents one of the richest sources of information about student learning [29]. In addition to self-reports, discourse produced in student interactions represents a source for obtaining insights into cognitive, metacognitive, affective, and motivational dimensions of student engagement [29], [30]. However, student discussions should be observed as being "embedded within structured social activities" [9, p. 311], and as such, dependent on previously generated content that influences social interactions in a given context. Each artefact (piece of text, more specifically) generated by a student or a teacher, creates a social fact for all the participants in the interaction [9]. As further posited by Bazerman [9], social facts are usually comprised of speech acts – intended actions, defined through their intention, purpose, or effect [8], [10]. Therefore, discourse analysis, should also investigate the meaning and intended actions (e.g., asking questions, thanking, or apologizing) of any utterance used in a communication [9], [29], [31], [32].

Being rooted in sociolinguistic and philosophy research, speech act theory allows for departing from analyzing the structure of student discourse to account for the particular purpose the exchanged textual content has in a social interaction [9], [31]. Although there have been various attempts to classify speech acts, the most general classifications have been provided in Austin [32] and Shearle's [10] seminal works on speech act categorization based on illocutionary acts. Specifically, both Austin and Searle argue that speech acts operate on three levels: i) locutionary (propositional) act represents the main message, that is, "what is being said" [9, p. 314], ii) illocutionary act expresses the intended act the speaker wanted to accomplish, and iii) perlocutionary act (effect) that explains how specific act was understood by other participants in communication and what are potential consequences of the act [9], [32]. Both categorizations, therefore, observe an illocutionary act, or intended purpose, as a "basic unit of human linguistic communication" [10, p. 1]. Of special interest for this study is Searle's categorization of speech acts, as it is arguably the most general classification of illocutionary acts, as well as a refined conceptualization of Austin's work. Searle's classification includes the following speech act categories: *representatives*, *directives*, *commissives*, *expressives*, and *declarations*.

As originally defined in Searle's work, the purpose of the *representative* category of speech acts is to "commit the speaker (in varying degrees) to something's being the case" [10, p. 10]. That is, utterances that belong to the *representative* class depict the speaker's belief that could be assessed either as true of false. *Directives*, on the other hand, represent speech acts that point to the speaker's expectations that the listener performs a certain action. Directives could be stated in a form of invite, permit, advise, request, command, or question, to name a few [10]. *Commissives* are defined as a category of speech acts that commits the *speaker* to perform certain action, such as promises, or threats. The main intent of *expressive* speech acts is to communicate the speaker's psychological state about the specific "state of affairs specified in the propositional content" [10, p.12]. Examples include expressions of gratitude, apologizes or welcoming [8], [10], [33]. Finally, *declarative* speech acts are characterized by implying certain alteration "in the status or condition of the referred-to object" [10, p. 14].

B. Meaningful Social Actions and Learning

In the context of analyzing student interactions in online learning settings, speech acts have been commonly used in summarizing discussion threads [34] or in investigating student participation patterns and predicting learning outcomes [31], [35]. For example, Merceron [35] relied on the speech act theory to examine what role student messages have in discussion forums and to what extent the message posting patterns (i.e., number of messages belonging to each of the speech act categories) differ between high and low performing students. The focus of the analysis in Merceron's [35] study was on the data obtained from a traditional online (for credit) computer science course. Merceron manually coded student discussion forum posts according to the categories proposed by Kim and colleagues [36], which include *questions*, *issues*, *answers*, *positive acknowledgments*, *negative acknowledgments*, and *references*. Merceron [35], as well as Kim and colleagues [36], among others, relied on more domain specific categories of speech acts, derived from broad categorizations introduced by Austin [32] and Searle [10]. The study revealed that more successful students tend to be more focused on providing help to their peers and answering questions, whereas student who obtained lower grades, were oriented towards help-seeking. However, there was no association between the forum participation and performance for the high performing students.

The most relevant for our research is Arguello and Shaffer's [31] work on automated prediction of speech acts in discussion forums of a massive open online course (MOOC) and examining the association between the course performance and particular acts of speech. Similar to the work of Merceron [35], Arguello and Shaffer [31] also observed *questions*, *answers*, *issues*, *positive* and *negative acknowledgements*. However, Arguello and Shaffer [31] further included the *issue resolution* and *other* speech acts. Arguello and Shaffer [31] revealed that students raising issues were more likely to successfully complete a course and to submit an assignment. However, their models for predicting assignment completion and course performance explained only a very small amount of variance (4.2% and 1.7%, respectively, using Nagelkerke's R^2 [37]).

The existing research provides evidence for the association between different categories of speech acts (i.e., the purpose a message has in a discussion forum) and a learning outcome. However, there seems to be a lack of studies exploring ways in which acts of speech have been employed in learning-related communication [3]. It is not clear whether and to what extent the utilization of specific categories of speech acts (RQ1&2) influences social processes that frame peer interaction such as development of social ties among peers (RQ3) [16]. Finally, the question remains whether patterns of social interactions (derived through the analysis of speech acts) provide a salient context for interpreting the association between students' social activity and final learning outcome (RQ4).

C. Social Network Analysis

Social Network Analysis (SNA) defines methods that allow for examining patterns of human interaction in diverse social settings [38], [39]. SNA has played a prominent role in learning sciences, providing theoretical and methodological tools for understanding activities and social processes that students and teachers engage with [17], [20].

1) Networks Centrality and Learning Outcome: In the context of educational research, SNA has been commonly applied to examine whether and how structural properties of networks are associated with learning, creative potential, sense of community or educational experience in general [38]–[40]. A prevailing understanding emerging from the existing SNA literature, is that a high centrality in a social network implies more benefits – e.g., a higher centrality is often associated with a higher learning outcome. However, certain inconsistencies in the existing results are also evident. For example, while Jiang and colleagues [41] provide evidence for the significant and positive association between social centrality (degree and betweenness in this case) and learning outcome (i.e., course grade), studies by Zho and colleagues [42] and Gašević and colleagues [43] did not support those findings.

Analyzing this issue, Joksimović and colleagues [16] posited that potential reason for the contradictory findings with respect to the importance of the student social centrality might originate in the social dynamic processes that drive network formation. Specifically, in the study conducted in the context of a MOOC, Joksimović and colleagues [16] empirically showed that the networks built primarily on *super strong* ties [44], [45] – i.e., those ties that potentially represent real and intimate relationships, such as friendship – are unlikely to offer benefits to centrally positioned nodes. Rather, those benefits are afforded in networks that are primarily formed on weak ties as consistent with the social network literature [44].

2) Exploring Factors of Network Formation: Statistical network analysis is gaining increasing attention in studying regularities of student participation in MOOCs. For example, Kellogg and colleagues [18] aimed at understanding social processes arising from interactions in a network of educational professionals. Accounting for various network patterns and contextual properties, such as reciprocity, or tendency to form ties based on the professional role, gender, or educational background, Kellogg's [18] study showed a strong and significant tendency for students to reply to a peer when there has been prior evidence of reciprocity. Tendency to form ties based on similar demographic properties, on the other hand differed across the networks analyzed. Likewise, Poquet and Dawson [22] showed that conversation dynamics (e.g., cognitive or socio-emotional) and participation regularity had a significant effect on how social processes unfold at scale.

One of the objectives of our study is to examine whether social network characteristics (e.g., tendency to form reciprocal or homophilic ties) provide a salient context for understanding factors that are associated with learning outcomes (RQ4). Specifically, applying social network analysis using exponential random graph models (ERGMs), we examine if students' discussion contributions tend to frame the underlying network formation. Here, we are particularly interested in tendency to form *super-strong* ties [44], [45]. The existence of this type of connections between forum participants is expected to affect the association between social centrality (i.e., degree, closeness, and betweenness) and learning outcome (i.e., final course grade).

III. Method

A. Data

This primarily correlational study analyzes forum discussions within two MOOCs delivered by Delft University of Technology in 2014, using the edX platform. The courses included video lectures, quizzes, and assignments delivered across several modules, with a new module released every week. In both courses, students were required to score at least 60% to pass the course and obtain a certificate. With respect to discussion participation, neither of the courses counted discussion forum participation towards the final grade. No guidance was provided for forum participation and forums in both courses were chiefly structured as Q&A forums. The role of the teaching staff was focused on moderating the discussion forum and replying to the students' questions. We analyzed on these two courses not only for their considerable difference with respect to the subject domains (i.e., industrial design and software engineering), but also for the significant differences in student completion rates. Table I further shows the total numbers of students enrolled in both courses, numbers of students who engaged with at least one activity throughout the

TABLE I
DESCRIPTIVE STATISTICS FOR THE NUMBER OF ENROLLED STUDENTS, STUDENTS ENGAGED WITH THE COURSE CONTENT AND DISCUSSION FORUM, AS WELL AS THE OBTAINED CERTIFICATES

		Statistics	DDA	FP
Overall	Students	Enrolled	13,503	38,029
		Engaged*	6,604	22,673
		Forum part.	730 (11%)**	1,067 (5%)**
Discussion Participation	Threads	AVG (SD)	1.478 (1.162)	2.094 (3.198)
		Total	643	1,288
	Posts	AVG (SD)	3.921 (11.585)	7.714 (42.156)
		Total	1,886	6,904
	Contrib.	AVG (SD)	3.436 (10.048)	7.678 (39.422)
		Total	2,598	8,192
Obtained Certificates		Total	136 (2%)*	1,968 (9%)*

Note: * Engaged students were those students who performed at least one activity (e.g., viewing a video, posting to discussion forum), in addition to being simply enrolled in a course; ** the number in the parenthesis represents the percentage of engaged students.

respective course, and numbers of students who posted to the discussion forums (our sample) along with the numbers of contributions.

The *Delft Design Approach* (DDA) course aimed at introducing the key elements, tools, and methods of the product and industrial design approach as taught at Delft University of Technology. During the course, students were taken through the complete product design process, starting with the early stages of framing ideas, to implementation and testing phases. The course was delivered over ten weeks with a planned study load approximately six to eight hours per week. Each video lecture was followed by a quiz, where quizzes, in total, accounted for 10% of the final grade. The course also included a peer-reviewed design exercise and a final presentation that counted 70 and 20 percent towards the final course grade, respectively. Through the peer-review process, students were expected to reflect on and discuss their work and the work of their peers within the course discussion forum.

Introduction to Functional Programming (FP) focused on introducing fundamentals of functional programming using the Haskell programming language. Although the course did not assume prior knowledge of functional programming, at least one year of practice in programming languages such as Java or PHP was recommended. The duration of the course was slightly shorter than DDA (i.e., eight weeks) with four to six hours of estimated workload per week. The course included two types of assignments – homework (eleven in total) and lab assignments (seven in total), that counted towards the final grade. None of the assignments was optional and only one attempt was available per assignment.

B. Speech Act Recognition

To address **the first two research questions**, we adopted unsupervised conversation modeling techniques for identification of different speech act categories that students used in their discussion messages. Most approaches for automated speech acts classification require manually coded student messages [31]. Such manual coding is a time-consuming process that requires considerable expertise and usually includes two or more expert coders [46]. The unsupervised method used in this study consists of clustering written utterances based on the similarity of the underlying conversational roles and does not require previously labeled data [47]. Specifically, we relied on the approach proposed and validated by Ritter and colleagues [47] and later implemented and extended by Paul [48]. To identify different speech acts, the approach combines hidden Markov models (HMM) and Latent Dirichlet Allocation (LDA) [49]. Conceptualizing dialog (or speech acts) with state transitions as a model of conversations stems from the work of Winograd and Flores [50]. In so doing, recent research commonly relies on the use of HMMs to "structure a generative process of utterance sequences" [51, p. 2180]. Thus, each of the hidden states is interpreted as a speech act (or dialog act) [47], [51]. However, the approach proposed by Ritter and colleagues, and implemented by Paul [48], relies on LDA to represent a state (i.e., speech act) as a multinomial distribution over words, from which further specific speech act related words are generated.

It should be noted that our approach focuses at message as the unit of analysis, rather than an utterance, and a message could have more than one speech act. In that, our approach is similar to those used by Merceron [35] and Arguello and Shaffer [31] who also analyzed the role that "messages play in building understanding and knowledge" [35, p.12].

The underlying topic modeling algorithm (i.e., LDA), used in Paul's [48] implementation of block HMM, is a probabilistic technique, commonly applied in social sciences and humanities, that allows for the extraction of prominent themes from a collection of text documents. By examining the co-occurrence of words in a document corpus, LDA identifies groups of words that are commonly used together and could represent different themes across the corpus. The LDA algorithm must be provided with the number of topics to be identified. Based on the insights obtained from data-driven methods for identifying optimal number of topics [52], we opted for a model with six topics. Specifically, using metrics proposed by Cao and colleagues [53] as well as Deveaud and colleagues [54], the algorithm resulted in five to eight topics as optimal numbers for both datasets. After the investigation of the proposed solutions (i.e., exploring to what extent different topics represent distinct groups of speech acts), we decided to use six topics (i.e., speech acts) as the optimal number for both datasets.

To improve the estimation of word co-occurrences, LDA is often preceded by several pre-processing steps such as, the removal of "non-informative" tokens (e.g., highly frequent or very short words, punctuation, and numbers); and lemmatization, (i.e., conversion of words to their root form). However, given that in conversational modeling some of the token categories that are typically removed can potentially indicate different speech acts [47], [48], in our analysis we decided to keep all the word categories. That is, in pre-processing discussion posts, we decided to follow the method proposed by Ritter and colleagues [47] and Paul [48]. Specifically, Paul [48] argues that removing simple stop words might not be beneficial for the implemented algorithm as "common function words often play important roles in the latent classes (i.e., speech acts)" [48, p.6].

To address our **second research question**, we examined sequences of specific speech acts, as means of detecting emerging communication patterns and exploring the structure and the process of knowledge construction [3], or discourse coherence [12]. Specifically, the applied discourse analysis method – i.e., block HMMs [47], [48] – allowed us to generate a matrix of transition probabilities between speech acts employed in a conversation. As such, the employed method allowed for moving beyond simply exploring the speech acts that students commonly relied on in the process of knowledge building, and towards examining sequences of interactions and patterns of transitions between different speech acts. We further relied on transition counts – i.e., the numbers of transitions between different speech acts – to examine the association between conversation dynamics and learning outcome (Section 3.3).

C. Social Network and Statistical Analysis

To explore social dynamics (to address RQ3) and investigate association between social positioning and learning outcome (to address RQ4), we extracted two directed weighted graphs that reflect interactions occurring within discussion forums of the two course instances (DDA and FP). We relied on the most commonly applied approach to extracting social networks from discussion forum interactions, which considers each message as being directed to the previous one in the thread [16]. This approach tends to capture post-reply structure within discussion forum threads, by including directed edges between those students who replied to a specific post and the author of the post. In case certain interaction occurred more than once (e.g., author A2 replied to two posts created by author A1), we would reflect the frequency of interaction in the weight of the corresponding edge. Social graphs included all the students who posted to discussion forums.

1) Exploring Social Dynamic Processes: To complement discourse analysis and explore the association between conversation dynamics and social network formation processes (RQ3), we utilized statistical network analysis. We relied on the exponential random graph models (ERGMs) – a family of statistical models for studying social networks [55]. When fitting ERGMs, we accounted for two variables extracted from the online forum participation. Specifically, we included the number of posts submitted by each student and the number of transitions between different speech acts for each student, to account for the overall student activity and to capture the student's communication patterns (as addressed in RQ2), respectively. These two participation-related metrics were included in the statistical model as main effects on the propensity to form ties.

Exploring further to what extent factors that drive network formation are framed by potentially different conversation dynamics, we relied on commonly used network statistics [18], [22], [53]. Observing network statistics at the dyadic level, we aimed to investigate the effects of selective mixing (based on student achievement level), reciprocity, popularity spread, and expansiveness (i.e., activity spread). At the triadic level, we focused on examining effects of transitivity and Simmelian ties formation.

Selective mixing or homophily is a network statistic that reflects the tendency of creating edges between nodes having the same characteristics [55]. Specifically, we examined to what extent students with the same achievement level (i.e., passed or failed the course) were more likely to reply to each other's posts. Further, students' tendency to form mutual *(i.e., reciprocal) ties* and to cluster was captured by the reciprocity network statistics [56]. By including the reciprocity in our models, we aimed at revealing students' tendency to continue interaction with peers by replying to their posts. Finally, *popularity and expansiveness* identify students who receive a significant number of replies to their posts and students who tend to reply more often to their peers' posts, respectively.

The existing research provides evidence that cyclic and transitive triples are common characteristics of social media networks [56]. In directed networks, these two statistics are captured within the triangle term (i.e., a configuration of links that forms a triangle of nodes) [55], [56]. Nevertheless, models with a triangle term are almost always degenerate (i.e., cannot be fitted). Therefore, geometrically weighted edgewise shared partner distribution (gwesp) was used instead [55]. We also modeled Simmelian ties [44] in order to examine the presence of super strong ties; that is, whether the analyzed network(s) exhibited the formation of cliques of students that tended to interact with each other significantly more often than with the rest of their peers. Such a statistic could indicate that those students were primarily focused on their specific field of interest and rarely interacting with other students.

2) Network Properties and Learning Outcomes: Addressing our **fourth research question** assumed a two-step analytical procedure: i) extracting network structural properties, and ii) examining the association between metrics of learning-related social interaction (i.e., discussion participation patterns and social positioning) and learning outcome. To examine **network structural properties,** we relied on the most commonly used SNA measures that capture various aspects of network structural centrality – weighted degree, closeness, and betweenness centrality [39]. Weighted degree centrality determines how central a node is by accounting for the weight of its direct neighbors. Closeness centrality indicates the potential to connect easily with other network actors (nodes), by measuring the distance of a given node to all other nodes in the network. Betweenness centrality shows which nodes might expect benefits due to having the role of brokers in the network [39]. Additionally, we also explored the association between forum participation patterns, operationalized through the number of posted messages and number of transitions between different speech act categories with the final course grade.

Finally, we built two multiple regression models, one for each analyzed course. Each regression model included one

TABLE II
DESCRIPTIVE STATISTICS OF THE FORUM MESSAGES POSTED IN DIFFERENT SPEECH ACT CATEGORIES, SHOWING TOTAL, AVERAGE NUMBER AND STANDARD DEVIATION (BY STUDENTS AND TEACHERS), AS WELL AS NUMBER AND PERCENTAGE OF MESSAGES CONTRIBUTED BY THE TEACHING STAFF

Course	Speech act	Total # Msg.	Average # (SD) per student	Teacher contr.(%)
DDA	Directives Q&A	735	4.02 (12.44)	264 (36%)
	Directives Instructions	54	2.16 (2.39)	19 (35%)
	Directives Elaborate	362	2.18 (2.31)	37 (10%)
	Expressives	508	1.21 (0.78)	12 (2%)
	Representatives	379	2.56 (4.30)	50 (13%)
	Other	460	1.66 (1.89)	2 (0.4%)
FP	Directives Q&A	3243	4.59 (19.87)	611 (19%)
	Directives Instructions	752	3.20 (8.84)	108 (14%)
	Directives Elaborate	1041	3.90 (13.88)	153 (15%)
	Expressives	1361	3.22 (7.42)	149 (11%)
	Representatives	1010	2.77 (6.14)	102 (10%)
	Other	786	3.49 (12.16)	207 (26%)

dependent (i.e., final course grade) and five independent variables (degree, closeness, betweenness centrality, post count, and transition count). Both models indicated a satisfactory fit, having variance inflation factor (VIF) less than 2 for all the variables observed [57]. However, since both models indicated potential issues with heteroscedasticity, we report coefficients calculated using White's [58] heteroscedasticity-corrected covariance matrices to make inference. All the analyses were conducted using the R software language for statistical analysis [59].

IV. RESULTS

A. Conversation Modeling – Speech Acts (RQ1)

Fitting block HMM [47], [48] resulted in six speech act categories in both courses analyzed (Table SI, supplementary material). However, interpreting the extracted categories, we did not find the alignment with all the speech act categories as defined by Searle [10] (*representatives*, *directives*, *commissives*, *expressives*, and *declarations*). Instead, we identified three subcategories of *Directive* speech acts (questions & answers, instruction, and elaboration), *Expressives*, *Representatives*, and a category of messages that could not be characterized as any act of speech, and thus was labeled *Other*. Table II shows descriptive statistics of students' and teachers' contribution to different categories of speech acts. On average, students' contribution across the categories of speech acts was higher and more evenly distributed in the FP course. Similar to the existing research findings [28], [33], the highest number of messages belonged to the *Directive* speech acts. Specifically, in discussion forums of both courses, most messages posted was categorized as *questions & answers*.

The overall contribution (in terms of the number of messages posted to a discussion forum) of the teaching staff in both courses was rather similar: 17% of the total number of messages in the DDA course, and 19% in the FP course. However, when the contribution to different categories of speech acts was considered, we observed different patterns in the two courses (Table II). The teaching staff in the DDA course seemed to be focused on providing support in answering questions and administering instructions related to the course organization, with more than 35% of messages contributed to *Directives instruction* and *Q&A* speech acts (Table II). Participation of the teaching staff in the FP course seemed to have been more balanced, in terms of similar amount and percentage of posts contributed to each of the detected speech acts (Table II).

The highest percentage of students who posted to the DDA discussion forum focused on creating posts categorized as *Expressive* speech acts (58% - Fig. S1, supplementary material). The DDA course also had a high percentage of students with posts in the *Other* category (38% - Fig. S1, supplementary material). Such messages usually contain just a URL, without further discussion. Given that there were five assignments in the DDA course, an average of 1.66 posts per student (Table II) could suggest a very low engagement with the assessment. On the other hand, the highest percentage of students who were engaged with the discussion forum in the FP course tended to ask for help or assist their peers (66% - Fig. S1, supplementary material). A noticeable number of students focused on social interactions (*Expressives* – 40%) and contributions that took the general form of *Representative* speech acts (34% - Fig. S1, supplementary material). Finally, it is noteworthy that in both courses, most of threads started as *Expressives* (40% of threads in DDA and 35% in FP).

B. Conversation Modeling – Dynamics (RQ2)

The second research question focuses on further investigation of conversation patterns that reflect a coherence of the shared discourse as well as a sequence of speech acts used in a discussion. Thus, we examined to what extent students tended to post across different categories of speech acts or whether they rather clustered their contribution within a single category (Fig. 1 and Table II) [22], [28].

Fig. 1 shows the transition probabilities between the categories of speech acts. An arrow is drawn from one speech act to the other if the probability transition was equal or above 0.16, which represents a probability of transition between speech acts in a uniform model (i.e., that each post transitions to all the other categories with the same likelihood). The transition probabilities plot suggests that most discussion threads tended to converge towards the category of posts that include higher student-teacher interaction, with the primary intent to communicate problems students encountered and provide solutions to those, (i.e., *Directives Q&A* in Fig. 1). It is noteworthy that in both courses under the study, discussion threads starting with a post that was categorized as *Directive (Q & A)*, would remain within this category of speech acts with a very high likelihood (0.75 in FP and 0.88 in the DDA course). Finally, none of the threads seems to transition to the post that was categorized as Other, with the probability higher than the threshold (0.16).

Differences in transition patterns (i.e., thread coherence) were identified in the two courses (Fig. 1). While both courses were characterized with high likelihood of either transitioning

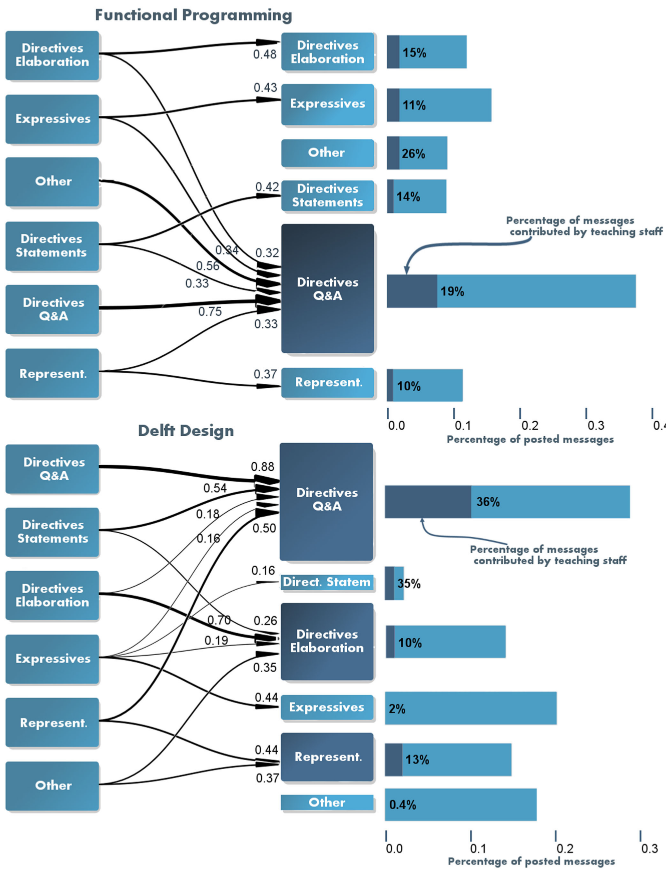

Fig. 1. The likelihood of transitions between different speech act categories where a larger arrow width represents higher likelihood (exact probabilities are represented with numerical values). The right part of the figure represents percentage of messages posted with-in each of the speech act categories, with highlighted values showing the contribution made by the teaching staff.

to the *Directive (Q & A)* category, or remaining within the original category, there were certain differences with respect to the *Directive (elaboration)* and *Representative* speech acts. In case of the DDA course, threads starting with *Directives (elaboration)* would remain within the same category with high probability (0.70, compared to 0.48 in the FP course). However, it was also highly likely that other threads would transition to the *Directives (elaboration)* in the DDA course discussion forum, which was not the case for the FP course (Fig. 1).

Likewise, in the FP course, one-third of the *Representative* posts would most likely remain within the same category, whereas another one-third would transition into *Directives (Q & A)*. This probability was slightly higher in the DDA case where about a half of the posts tended to remain within the *Representatives* category and another half was likely to transition to *Directives (Q & A)*. Another difference between the courses was in the high probability for the *Other* posts to transition into *Representatives* (0.37) in the DDA course.

C. Network Characteristics (RQ3)

Table III presents the two best fitting ERGMs, as indicated by the lowest AICc values. Goodness-of-fit statistics provided a satisfactory fit for the data analyzed. For both networks, indicators of student conversation dynamics yielded a significant

TABLE III
SUMMARY OF ERG MODELS ESTIMATES FOR DDA AND FP COURSES

	DDA		FP	
	Estimate	**SE**	**Estimate**	**SE**
Baseline (Edges)	- 7.459***	0.126	-7.817***	0.075
Selective Mixing				
Achievement (fail)	-0.354^{***}	0.099		
Achievement (pass)	0.646^{***}	0.103		
Achievement			0.403^{***}	0.035
Indicators of Conversation Dynamics				
Post count	0.004^{***}	0.001	0.002^{***}	0.001
Transition count	0.467^{***}	0.024	0.434^{***}	< 0.001
Structural Mechanisms				
Reciprocity	2.271^{***}	0.251	3.608^{***}	0.082
Simmelian ties	-		0.118^{***}	0.047
Transitivity	0.455^{***}	0.092	-	
Popularity	-1.362^{***}	0.146	-0.561^{***}	0.093
Expansiveness	-		-0.824^{***}	0.093

Note: * $p < .05$. ** $p < .01$. *** $p < .001$.

positive effect on tie formation. That is, the number of posts and the diversity of speech acts employed (i.e., transition count) in forum discussions were positively associated with the number of ties students created in social interactions (Table III). Moreover, both networks indicated a significant effect of *homophily based on the final course outcome* (passed or failed the course in this case). Although we modeled selective mixing based on the student achievement in both courses, effects that yielded better fit in the observed networks slightly differed (Table III). Specifically, for the social network extracted from the DDA course, we modeled *differential homophily* (i.e., preference for students who obtained a certificate to create ties with other students who obtained a certificate, and vice versa) [53], [54], whereas in case of the FP course we managed to fit *uniform homophily* for the same attribute (i.e., propensity to form ties based on the achievement in general). Initially, we aimed at investigating differential homophily in both courses. However, in the case of the FP course such configuration yielded worse model fit.

The effect of reciprocity was positive and significant in both networks, indicating that the *two-way interaction* among students or between students and teachers, occurred more frequently than it would be expected by chance [55]. It is further revealing that the network that emerged from the DDA discussion forum was characterized by the significant effect of transitivity. The effect itself suggests a tendency for the forum participants to cluster together, i.e., indicating traces of collaborative or cooperative work. However, our results also showed that connections within such clusters in the DDA course did not evolve to Simmelian (i.e., super-strong) ties [44], as it was the case in the FP course (Table III). Being embedded within relatively small, highly cohesive groups (or cliques), Simmelian ties point to the existence of interactions that are qualitatively and quantitatively different from other connections within a network.

D. Achievement, Discourse, and Networks (RQ4)

Our fourth research question was targeted at examining to what extent the characteristics of social interactions in a

TABLE IV
RESULTS OF THE REGRESSION ANALYSIS OF THE ASSOCIATION BETWEEN STUDENT POSTING BEHAVIOR, SOCIAL CENTRALITY AND FINAL COURSE GRADE

Variable	DDA				FP			
	Est.	β	SE	t	Est.	β	SE	t
Post count	**6.62*****	**0.49**	**1.24**	**5.35**	2.67	0.06	3.12	0.86
Trans. Count	0.15	0.10	0.12	1.29	**0.39*****	**0.28**	**0.08**	**5.17**
W. Degree	**-2.03***	**-0.18**	**0.93**	**-2.17**	0.84	0.04	1.45	0.58
Between.	-0.81	-0.03	1.80	-0.45	-5.99	-0.05	5.56	-1.08
Closeness	**0.10****	**0.17**	**0.03**	**3.14**	0.04	0.04	0.03	1.12

Note: * $p < .05$. ** $p < .01$. *** $p < .001$.

discussion forum provide basis for interpreting the association between learning-related social constructs (namely engagement with peers and social centrality in a discussion forum) and learning outcome (operationalized through the final course grade) (Table IV). Specifically, following the conclusions from the study by Joksimović and colleagues [16], we expected a significant association between the network centrality measures and course outcome, in the case of the DDA course. However, that should not be the case in the FP course, given the significant tendency towards the formation of Simmelian ties in that course. As argued by Krachardt [44], being embedded into super-strong ties, does not necessarily imply benefits and could potentially introduce constraints [44].

In the DDA course, which *was not* characterized with the tendency to form super-strong ties between the course participants, we *were able* to observe significant effect of the number of posted messages ($\chi^2(1) = 5.35$, $p <.001$), weighted degree centrality ($\chi^2(1) = -2.17$, $p = .015$), and closeness centrality ($\chi^2(1) = 3.14$, $p <.001$) (Table IV). The model explained 26% of variance in students' final course grade. As expected [16], there was a significant association between the social positioning and final course outcome. In the FP course, on the other hand, we observed a significant and positive effect only in the case of the transition count (i.e., how many times students transitioned from one speech act to another in their forum contributions): $\chi^2(1) = 5.17$, $p <.001$. None of the centrality measures was significantly associated with the final course grade. The model, however, explained a comparably lower amount of variance (12%) than in the case of the DDA course (Table IV).

V. DISCUSSION

A. Intentions Employed in Collaborative Dialog (RQ1)

Our analysis revealed six categories of speech acts representative of different cognitive actions expressed in communication within the two courses under study. Among those, we identified three broad categories of *directive* speech acts, in both courses analyzed (Table SI, supplementary material). The *Directive* acts, as defined by Searle, represent a speaker's attempt to "get the hearer to do something" [10, p. 11] – e.g., ask a question, invite, or advise. Studying the use of directives or prohibitions in the context of social learning, Ervin-Tripp [60] showed a wide diversity of structural variations that adults rely on in conveying directive speech acts. With respect to the general intention of the posts identified in the directives group and the nature of interactions (e.g., student-student, student-teacher), we further categorized directive speech acts as: *questions & answers*, *instructions*, and *elaborations*. The detected variations of directives could also be found in previous related research. For instance, Merceron [35] or Arguello and Shaffer [31], among others, relied on particular dialog acts, such as answers, questions or issues.

It is interesting to note that in both courses we identified *Directives (questions & answers)* speech acts to be primarily focused on student-teacher interaction (Fig. 1). *Directives (instructions)* speech acts were characterized by posts aimed at providing certain instructions – such as course related information (Table SI, supplementary material). This category might be related to directive statements or hints, as defined by Ervin-Tripp [60]. *Directives (elaboration)* acts were mainly oriented towards a deeper knowledge construction and (primarily student-student) interactions that aimed at more comprehensive elaboration of the topic under discussion. For example, the following post would be categorized as an *elaborative*:

> "This is a very interesting and potentially wide ranging question that you've raised. I don't think that competition necessarily hinders creativity. But sometimes people may act more in their own self interest, perhaps out of a desire to "win" some fortune or status. I think that there is plenty of competitiveness (socially and economically) in Scandinavia and Northern Europe; probably just as much as in the other countries you mentioned. If you haven't watched any movies or read any books by people from those cultures, then I suggest you try some. (I enjoyed, [Borgen] [1], and [The Killing] [2]). These show that competitive behaviour is not beyond the realm of their imagination. A further survey of the daily news from these places will probably confirm less spectacular examples. Although I don't agree with limiting access to food/water, healthcare or education, there are theories that claim competition may actually help people to acheive goals faster and to improve their performance. Maybe even to innovate (I'm thinking of the fabled, Space Race). Having said all that. I'd be interested to hear from the design researchers and economists on this one. *[1]*: *[URL]* *[2]*: *[URL]*".

That is, instead of directly providing a resolution to a problem, this post introduces different views and suggests consideration of additional aspects of the initial investigation. As such, the Directives (elaboration) category of speech acts seems to further capture messages reflective of the integration phase of cognitive presence, as defined in the community of inquiry framework [61].

Expressives as a particular type of social interactions, was mostly characterized by messages that expressed certain psychological states (such as appreciation for provided answer) [10]. However, in an extended meaning and similar to the study by Poquet and Dawson [22], in our study, this category also included messages that reflected specific personal experience (Table SI, supplementary material). This suggests that in the context of online discussions, the category of *Expressive* speech acts captures social interaction that can be qualified as a *socio-emotional conversation*, as defined by Poquet and Dawson [22], or *interpersonal* and *open communication* as defined by Garrison and Akyol [61]. For example, the following message includes indicators of interpersonal and open communication, as defined by Garrison and Akyol [61]:

> "Hi, My name is [NAME], Ím an industrial designer from [CITY, STATE]; I enrolled this course because Ím really into design and I strongly believe that within design my country can progress and improve the industry and economy. Ím [YEAR] years old, and I have been working in fashion industry in [STATE], I have only my Bachelor degree and right now Ím looking for a master overseas in order to complement my education; what would you suggest me? Thanks!!!! Regards [NAME]".

In line with Qadir and Riloff [33], therefore, we observe *Expressives* in discussion forums as a speech act category that conveys appreciation, complimenting, expressing agreement, or bears conventional expression of emotions or student personal details [61].We also observed the *Representative* speech act – an illocutionary point that depicts a student's (originally a speaker's) "belief of something that can be evaluated as true of false" [33, p. 750]. Considering *Representative* acts from a broader perspective (similar to Qadir and Riloff [31]), we recognized as *Representative* those messages that pointed to certain conclusions (or evaluations) that indicated students' understanding of something being the case. For example, providing a solution to a previously posted problem (Table SI, supplementary material). This category (i.e., Representatives) also vaguely relates to the resolution phase of cognitive presence, as defined within the Community of Inquiry framework [61].

Finally, both courses were characterized with a particular group of messages that did not have indicators of an intended action or social activity. Given that they could not be categorized as assertive, commissive, directive, or expressive point [9], [10], we were tempted to label them as *declarative* speech acts. However, those messages also did not imply any kind of "alternation in the status or condition" [10, p. 14], or had the strength of declarations as originally defined. Their primary purpose was to submit an assignment or point to a specific resource (Table SI, supplementary material), without expressed intent to carry out a specific act [9]. Therefore, they were coded as *Other*.

Nevertheless, it is not surprising that *Declaration* speech acts were not identified in the examined discussion forums. This finding is in line with Qadir and Riloff [33], for example, who also did not observe this category in discussion forum posts obtained from a professional learning network. Given the nature of interaction in digital educational settings, it is rather unlikely to expect statements like the ones declaring a war or firing someone [10], [33].

Likewise, we were not able to identify *commissives – illocutionary point that occurs when a speaker commits to a future action* – as a distinct category. A possible explanation might lay in the unit of analysis used in the study. Specifically, we relied on message as the basic level of communication between forum participants. Thus, it does not mean that there were no utterances (e.g., sentences), that could be classified as commissives (Section 2.1). As a matter of fact, our qualitative examination of messages did indeed reveal sentences where students (or teachers) obliged to take some further actions. For example, the following sentence:

"*...What I'll do, I will make a screenshot of the text written and if this text is indeed yours* [NAME]*, than I could assess it after all!...*" could be classified as a *Commissive* speech act. However, this utterance represents a part of a longer message that was ultimately categorized as *Directives (questions & answers)*, which indeed depicts the role this message had in the social interaction.

It should be noted that we intentionally focus on interpreting extracted speech acts according to the general categorization, as provided by Searle [10], instead of relying on more specific and purpose-built classification. As we outlined in Section II, the majority of previous research focuses on domain specific categories of speech acts [35], derived from broad categorizations introduced by Austin [32] and Searle [10]. We contend here that relying on general purpose categorization should allow for making more general inferences and comparisons across different contexts.

B. Exploring Sequences of Intended Cognitive Actions (RQ2)

It is no surprise that most discussion posts in both courses started with *Expressive* speech acts (Section 4.1). Given our understanding of *Expressive* speech acts in discussion forums as means to establish a social connection, this finding aligns with the existing literature in digital educational settings [22], [61]. For example, the original model by Garrison and Akyol [61] posits that this form of communication should indicate the inception of community formation in online settings. Given the wide diversity of learners in MOOCs and challenges related to establishing and sustaining social interactions and development of learning communities at scale [28], [61], it seems reasonable to expect that a considerable amount of conversation begins with *Expressive* speech acts.

The two courses were also similar with respect to the finding that a majority of discussion threads tended to converge towards the category of posts that indicates help-seeking and help-providing. Specifically, our results align with previous research showing that the majority of learners in MOOCs engage with discussion forums to ask a question about an assignment or other course related issues [35], [28]. It is, however, interesting that those groups of speech acts were characterized with considerably high teachers' participation. In the context of more formal context of online learning, the existing research argues for the importance of teaching presence from the perspective of the acquisition of knowledge, students' engagement and achieving higher learning outcomes in general [61]. As Garrison and Akyol posit, it is teaching presence that "provides the structure (design) and leadership (facilitation and direction) required for effective interaction and discourse, which leads to higher-order learning" [61, p. 111]. It can be argued that despite the informal settings and higher independence, it seems that students in context of MOOC still rely on extensive student-teacher interactions in addressing learning and course related issues. Such interpretation also aligns with the existing research that argues for the importance of instructional design, and teaching presence in general, as the critical component for shaping the level of cognitive presence in MOOCs [62].

The difference between the two courses, however, is present in the tendency for the conversations in the DDA course to converge towards those speech acts that might suggest higher presence of knowledge building processes – i.e., *Representative* and *Directive* (*elaboration*) speech acts [8]. This pattern was not present in the FP course. Conversations (i.e., threads) in the FP course tended to be more homogenous – starting and completing with questions and answers or remaining within the same speech act category. It seems that these differences in the sequences of actions employed in communication can be contributed to the nature of the subjects of two courses under study or in the nature of the actual tasks and the type of learning promoted. Specifically, while DDA course focused on the topic of industrial design and most likely promoted inquiry-based learning, FP talks about programming and software development. As posited by Gašević and colleagues [30], among others, this finding further contributes to the understanding that analytics of learning needs to consider contextual factors as well.

C. Factors Framing Social Interactions (RQ3)

Our results showed that students' conversational patterns (i.e., number of posts and count of transitions between speech acts) were positively associated with the number of connections students established with their peers, across both networks analyzed (Table III). A considerably higher estimate for the transition count might further suggest that a simple participation (expressed through the post count) was not enough. What seems to be more important, based on the higher values of the estimates, is the use of different acts of speech when communicating with peers and teachers.

The analysis of selective mixing revealed some notable results. The tendency to form ties based on students' achievement represents one of the defining characteristics of the networks emerging from two MOOC discussion forums. Aligned with the existing literature, homophily based on students' achievement seems to be one of the important factors that frames social interactions in online learning settings in general [16], [18], [21]. Nevertheless, different statistics (i.e., uniform vs. differential homophily) showed that there were certain differences between the two courses analyzed [56]. Our results showed that the students who passed the FP course were equally likely to connect with the students who also passed the course and that the students who failed the FP course were likely to interact with other students who failed the course. This was not the case for DDA course, where students who failed the course were less likely to establish social interactions with other students who also failed the course.

It is no surprise that both networks under study yielded a significant effect of reciprocity. This tendency towards forming mutual ties between peers (i.e., continued interaction) has been recognized as one of the defining characteristics of interactions in online social networks [16], [18], [54]. It contributes to the creation of a comfortable learning environment that supports efficient knowledge sharing [56]. On the other hand, the results of discourse analysis (Section 4.2) suggest that students in the FP course were mainly focused on help seeking (and perhaps answering), i.e., the *Directives Q&A* speech acts. This kind of discourse seems to contribute more to the development of focused discussions in small groups and high "modularity in communicative tendencies" [28, p. 22], as also evident based on the negative effect of popularity spread and expansiveness (Table III) [56].

The tendency to form clusters (i.e., small groups) of students was also reflected in the significant effect of transitivity, as found in both courses [45], [55]. Where the two courses differed, however, was the extent to which those ties evolved into qualitatively and quantitatively stronger social interactions (i.e., Simmelian ties). The existence of Simmelian ties, in the FP course, indicates a tendency towards high fragmentation among forum participants and interactions within small groups of students [28]. The nature of discourse in the FP course further suggests that those super-strong ties could have primarily emerged from students' behavior that was characterized by seeking help and providing solutions to help the inquires of others. It is, however, unclear, to what extent teachers' activity influenced the formation of super-strong ties in the FP course. A possible reason for this could be that a more diverse contribution of the teaching staff in the FP course as compared to that of the teaching staff in the DDA course could have been one of the factors that framed social interactions in this way.

Aiming to deepen our understanding of the formation of super-strong ties in the FP course, we refer to the notion of *common ground*, that is, the presence of shared information in any communication act between two peers, either online or face-to-face [63], [64]. The common ground represents artefacts generated in the communication process that peers employ in "articulating their positions and developing solutions" [64, p. 15]. According to Xin and Freenberg's [64] framework, a successful communication is characterized by constantly growing the common ground that is reflected through a variety of speech acts employed in the interaction. Table III shows that the number of transitions between different speech acts represents one of the defining characteristics of both networks, suggesting that more frequent exchange of different speech acts was positively associated with the number of connections students established with their peers. Fig. 1, on the other hand, shows that most of the FP and DDA discussion threads converged towards questions and answers acts, and it was this category that was necessary for reaching the common ground among the communication participants [65]. However, it seems that the high likelihood of transitions towards the posts labeled as *Directives (elaboration)* and

Representative posts could be explained with the course requirements and topic of the course. However, as these messages seem to be aligned with higher orders of cognitive presence – i.e., being difficult to reach [61], it seems that those types of interactions did not evolve towards establishing qualitatively stronger ties between course participants (characterized as Simmelian ties in Table III). Nevertheless, such claim warrants further research, particularly given that the nature of the two courses considerably differs (computers science vs. design), which will likely influence discourse generated through social interactions.

D. Achievement, Discourse, and Networks (RQ4)

Our fourth research question examined to what extent the characteristics of social interactions in a discussion forum provide basis for interpreting the association between learning-related social constructs (namely engagement with peers and social centrality in a discussion forum) and learning outcome (operationalized through the final course grade). Specifically, following the conclusions from the study by Joksimović and colleagues [16], we expected a significant association between the network centrality measures and course outcome, in the case of the DDA course. However, that should not be the case in the FP course, given the significant tendency towards the formation of Simmelian ties in that course. As argued by Krachardt [44], being embedded into super-strong ties, does not necessarily imply benefits and could potentially introduce constraints [44]. Additionally, we also explored the association between forum participation patterns, operationalized through the number of posted messages and number of transitions between different speech act categories with the final course grade (Table IV).

Overall, our results (Table IV) support findings from the previous research [16]. There was a significant association between the social positioning and final course outcome in the case of the DDA course, whereas this association was not observed in the FP course. However, it is interesting to note that whereas the direction of fit for the student activity in discussion forum was positive, the weighted degree and students' potential for control of communication (i.e., closeness centrality) were negatively associated with the outcome in the DDA course (Table IV). The positive value of the estimate for closeness centrality mean a negative association as small values are indicative of high control of communication. These results might be explained with the forum participation patterns. Specifically, even though most students who contributed to the DDA discussion forum posted messages that were characterized as either *Expressives* or *Other* (Fig. S1, supplementary material), the average number of messages contributed to these two speech act categories was rather low (Table II). These factors suggest rather shallow communication in the DDA course, showing that a high number of students posted only once and did not engage into continuing interaction, that could explain the negative association between centrality measures and final course grade.

In the FP course, we observed a significant and positive effect only in the case of the transition count (Table IV). The highest number of transitions between categories of speech acts could indicate a communication between students with a higher amount of shared information (i.e., common ground), which could have positive effect on students' performance. As for the lack of the association with centrality measures, given Krachardt's [44] interpretation of the super-strong ties, it was rather expected. The model explained a comparably lower amount of variance (12%) than in the case of the DDA course.

VI. Conclusion & Implications

Discourse and social network analyses have a long tradition in educational research and learning analytics. Nevertheless, they have been commonly applied as separate analytical approaches that allow for obtaining insight into the learning process from two different perspectives, rather than as a set of complementary approaches. This study suggests that combining discourse and social network analyses could provide comprehensive insights into the process of learning in networks emerging from interactions in digitally connected, computer mediated settings.

In this study, we grounded the theoretical framework in the speech acts theory [9], [10], as means for investigating intended meaning (i.e., speech act) of the communication in MOOC discussion forums. Relying on unsupervised methods for discourse analysis, namely block HMM [48], we were able to identify, in an automated way, common groups of speech acts emerging from discussion forums of the two MOOCs analyzed. Further, different conversational patterns evident in the students' contributions to the studied discussion forums revealed rather distinct social dynamics that framed emerging social networks. For instance, we showed that a discourse characterized by rather homogenous threads (in terms of speech acts), primarily focused on Q&A sessions, and with a substantial common ground (i.e., shared information), is associated with evolution of super-strong ties.

Complementing discourse analysis with the methods of statistical network analysis, we were further able to interpret the association of social centrality and forum participation with the final course outcome. Specifically, for predicting course grade in a course that is characterized with a close interaction between discussion forum participants (as in the analyzed FP course), it seems that a simple participation and social centrality are not features of great importance. Such findings are in accordance with the results from the previous work [16], which provided an insight into the discourse properties that could be associated with different network configurations.

A. Implications

Our findings suggest several important implications for further research and practice. Whereas the algorithm used in this study (i.e., block HMM – [48]) was previously evaluated using the discussion data from other online communication platforms (i.e., Twitter and CNET), this study showed that the same approach could be successfully applied in more structured educational settings – i.e., to analyze discussion forums. Further, even though the analysis of speech acts at the message level provided useful insights into conversation dynamics, as confirmed in this and previous studies [31], [35], further research should explore approaches that use individual utterances as a unit of analysis. Such approaches would provide more fine-grained insights into emerging conversational patterns.

One of the notable differences with in communication dynamics observed in the two examined discussion forums was related to the patterns of teachers' participation. Although learning at scale in general (e.g., MOOCs) is student-centered and heavily depends on students' motivation to engage and regulate their learning [1], our study suggests that the formation of small, highly cohesive groups, might depend on the presence and the role of the teacher. This could be further related to the instructional design that, in the case of the analyzed courses, did not assume grading of students' discussion contributions [62]. Nevertheless, it is important to further explore how and to what extent teachers' participation could affect students' participation in discussions.

From the practical perspective, the approach presented here, could provide teachers with valuable information about student participation in a discussion forum. For example, relying on the proposed approach, teachers could obtain a comprehensive (automated) summary of discussion threads students are involved with, which could further allow for a more advanced feedback provision than present tools offer [66]. By understanding factors that influence interactions in discussion forums, teachers would be better able to validate certain indicators of learning and make informed decisions about required interventions.

B. Limitations

Several limitations of our study need to be acknowledged. First, the study observed students' interactions within discussion forums of two courses with different subject domains. Still, further research should also consider courses from other disciplines. Further, given that the assessment is recognized as one of the most powerful ways to influence student motivation and achievement [66], it seems rather important to replicate the method presented in this study with courses that include graded discussions. Finally, this study did not account for students' motivation to participate in a course, their level of education, or previous experience with online courses (and MOOCs in particular). Although a majority of students fail to submit survey data [67], this line of research could potentially provide additional insights into the factors that shape social interactions in MOOCs.

From the methodological perspective, our approach also reflects the limitations that stem from the nature of unsupervised methods. Specifically, interpretation of speech acts is subjective, to a certain extent, and requires high contextual knowledge. We also pointed out that our unit of analysis was the entire post (Section 3.2). This means that some of the speech acts could have been omitted due to being nested within a message. Furthermore, the verification of the identified speech acts was done by one coder and reviewed by two experts in the field. To assure more rigorous evaluation of the identified speech acts, in our future research, we intend to verify the results of unsupervised methods by employing at least two coders to independently code a representative sample of the results set. Finally, although we strongly doubt that results would be different, it is important to acknowledge that we did not correct spelling and typing errors when pre-processing the data.

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