Social Networks 79 (2024) 14–24

Contents lists available at ScienceDirect

Social Networks

journal homepage: www.elsevier.com/locate/socnet

Interaction dynamics in classroom group work

Tomáš Lintner [a,b,c,*], Tomáš Diviák [b,d], Barbora Nekardová [a,e]

[a] Department of Educational Sciences, Masaryk University, Arna Nováka 1/1, Brno 602 00, Czechia
[b] Institute SYRI, Žerotínovo nám. 617/9, Brno 601 77, Czechia
[c] netanlab, Bratislava, Slovakia
[d] Mitchell Centre for Social Network Analysis and Department of Criminology, The University of Manchester, Manchester, UK
[e] Institute for Research and Development in Education, Charles University, Myslíkova 208/7, Prague 110 00, Czechia

A R T I C L E I N F O

Keywords:
Group work
Literacy
Student talk
Classroom interaction
Bursty behavior
Dynamic social network analysis
DyNAM

A B S T R A C T

Group work in classrooms is employed by teachers across all levels of education. For group work to be effective, all students should participate equally. Why some students engage in interaction and how group size and composition influence interaction dynamics is a research gap. We employed dynamic actor-oriented models on a sample of 145 Czech lower-secondary students in 62 small groups and pooled the results from the groups with a meta-analytical procedure. We found bursty behavior resulting from endogenous structural mechanisms of reciprocity, transitivity, cyclicity, and preferential attachment. Students gave preference to initiating interactions with those they initiated interactions with before and off-task interaction contributed to the development of on-task interaction. Students strongly preferred interactions with friends. Those students who talked a lot during regular whole-classroom lessons and students with high levels of literacy tended to both initiate and receive more interactions in group work, and students similar in these attributes preferred to interact with each other. Group size did not affect preferential attachment tendencies in interaction, but smaller groups made the effect of friendship ties on interactions stronger, and communication group norms shifted with changing group composition. Our study shows the suitability of dynamic actor-oriented models for studying interaction in education and small groups.

1. Introduction

Group work in classrooms is widespread and employed by teachers across all education levels. Letting students cooperate, learn from each other, and help each other to achieve a common educational goal is recognized and sometimes even mandated by educators as a desirable part of student-centered learning (Felder and Brent, 1996; Fung, 2022; Webb, 2009). For group work to be successful, all students in the group should actively participate. However, this is not an easy task. Participation in group work is usually unequal and entails free-riding – some students doing everything while others not contributing at all (Le et al., 2018; Slavin et al., 2003). Many student- and group-level factors have been hypothesized to influence student participation during group work (Webb, 2009). Yet, groups are usually arranged by the teacher without any consideration for the group composition and the potential effect the composition may have on group work (Gillies and Boyle, 2010).

Most research on what leads to active and equal student participation during group work is either qualitative or descriptive. Previous research has not considered some important unique characteristics of group work stemming from the fact that group work is wholly based on interactions. Most studies have operationalized interaction as the number of times individual students spoke (see Webb, 1991). Simply counting the number of times a student speaks and relating that number to student characteristics does not capture the nature of interaction, as it ignores their interpersonal structure. Analyses based on such observations may lead to results lacking validity because they have omitted fundamental properties of interactions, which are inherently dynamic, relational, and actor-oriented. They are dynamic because interactions occur over time and each interaction is dependent on a previous interaction; for example, interactions typically occur in a turn-taking manner such as student A addressing student B followed by student B responding to student A. They are relational because interactions necessarily occur between two or more students; each interaction can therefore be understood as a tie between a sender and one or more receivers, and over time the ties form a network of interactions that forms a structure of opportunities for further interaction. Interactions are actor-oriented

* Corresponding author at: Department of Educational Sciences, Masaryk University, Arna Nováka 1/1, Brno 602 00, Czechia.
E-mail address: tomas.lintner@mail.muni.cz (T. Lintner).

https://doi.org/10.1016/j.socnet.2024.05.002
Received 8 October 2023; Received in revised form 24 March 2024; Accepted 26 May 2024

because the individual actors – in our case the students – are agentic and make their own choices regarding how they interact and with whom (Stadtfeld and Block, 2017).

A stream of network models developed in recent years, including stochastic actor-oriented models (Snijders, 2001), relational event models (Butts, 2008), and, most recently, dynamic network actor models (Stadtfeld and Block, 2017), aim to capture the dynamic, relational, and actor-oriented nature of interaction. Dynamic network actor models (DyNAMs) are specifically tailored to fine-grained time-stamped data, such as observations of student interactions during group work, and they make it possible to capture mechanisms driving student choices to interact with other students within a network framework. Despite the availability of network models allowing the study of student interactions, the research employing network analysis on classroom interaction has thus far focused on whole-classroom communication only (e.g., Mameli et al., 2015; Ryu and Lombardi, 2015; Wagner and González-Howard, 2018).

In this study, we aim to provide a new viewpoint on mechanisms driving interactions between students in classroom group work by using fine-grained time-stamped data from videorecorded group works and employing network-based quantitative modelling accounting for the dynamic, relational, and actor-oriented nature of interaction. We differentiate between on-task and off-task interaction allowing us to capture the effect of off-task interaction on-task interaction. We ask two questions: 1.) *What influences interaction dynamics in classroom group work?* and 2.) *How does group composition influence the interaction dynamics in classroom group work?*

2. Theory and hypotheses

2.1. Temporal aspects of interaction

The nature of group work depends on the individual interactions between students, particularly the order and timing of these interactions. Neglecting the temporal dimension of interaction relates to several implicit assumptions – for example, it assumes that interactions between actors do not change over time; that interactions are randomly distributed over time; and that there is no relationship between the individual interaction events (Miritello, 2013). These assumptions are, however, incorrect. Interactions in group work are not static; actors change who they initiate and end interaction with over time, and ties are therefore constantly formed and dissolved. Interactions are also not randomly distributed over time – it was shown that bursty behavior – long periods of activity separated by intense bursts of activity – is a universal feature of human interaction (Karsai et al., 2012; Miritello, 2013; Navarro et al., 2017). Generally, bursty behavior can be described as a tendency to more likely to initiate interaction if an interaction occurred shortly before (Barabasi, 2005). Hence, we expect the following:

- **H1 – general burstiness**: students tend to initiate on-task interaction if another on-task interaction was initiated recently in the group.

Moreover, individual interactions are not independent of each other; rather, the order and relative timing of interactions affect subsequent interactions. It has been established that interactions have a memory that leads to old and repeated interactions being more likely to occur over time than newly established interactions (Miritello, 2013). Just as we expect on-task interaction to stem from previous on-task interactions, we also expect off-task interaction between two students to increase likelihood of on-task communication between them. It was found that activities unrelated to the task function to support the eventual task solution among students and promote the collaborative dynamics (Langer-Osuna et al., 2020). Hence:

- **H2a – repeated interaction**: students tend to initiate on-task interaction with those groupmates that they initiated on-task interaction with before.
- **H2b – cumulative repeated interaction**: students' tendency to initiate on-task interaction with a given groupmate increases with each repeated initiated on-task interactions with that groupmate before.
- **H2c – off-task to on-task interaction**: students' tendency to initiate on-task interaction with a given groupmate increases with each repeated initiated off-task interactions with that groupmate before.

2.2. Relational aspects of interaction

It is also crucial to consider the relational mechanisms in interaction. Each interaction requires a sender and one or more receivers of the message. Each interaction in group work then forms some fundamental pattern – either a dyad when one actor addresses another, or an outgoing star graph when one actor addresses the whole group (Lehmann, 2019). We expect several endogenous relational mechanisms to influence interaction in group work.

Preferential attachment was found to be a frequently occurring phenomenon in all types of networks (Rivera et al., 2010). In the context of interaction networks, preferential attachment denotes the tendency to initiate interaction towards those who either initiated or received many interactions before, or to receive interaction from those who either initiated or received many interactions before. It has been argued that this is the result of a tendency of actors looking for new connections to use other actors' degree as a proxy for their suitability – in the context of group work, we might expect students to be more likely to interact with groupmates who had already initiated or received many interactions, as it shows that the student is open to communication. Hence:

- **H3a – ego type indegree preferential attachment**: students tend to initiate on-task interaction if they received many on-task interactions previously.
- **H3b – ego type outdegree preferential attachment**: students tend to initiate on-task interaction if they initiated many on-task interactions previously.
- **H3c – alter type indegree preferential attachment**: students tend to receive on-task interaction if they received many on-task interactions previously.
- **H3d – alter type outdegree preferential attachment**: students tend to receive on-task interaction if they initiated many on-task interactions previously.

Reciprocity, transitive closure, and cyclic closure also comprise universally occurring mechanisms in communication networks (Kossinets and Watts, 2006; Ten Bosch et al., 2005). In the context of interaction networks, immediate reciprocity is often interpreted as turn-taking behavior (Ten Bosch et al., 2005). Transitive closure is the tendency to initiate interaction with those who have been interacted with before by the receiver of one's previous interaction (student A addressing student C after student A addressed student B and student B addressed student C) – when one student interacts with another, it can lead to subsequent interactions among other students who were indirectly connected through the initial interaction. Finally, cyclic closure denotes the tendency to initiate interaction with those who have interacted with the sender of one's previous interaction (student C addressing student A after student A addressed student B and student B addressed student C). Cyclic closure can be seen as an indirect exchange or generalized reciprocity; once established, it was found to be self-reinforcing (Bearman, 1997). Hence, we expect:

- **H4a – reciprocity**: students tend to receive on-task interaction from a student who was the receiver of their interaction before.
- **H4b – transitive closure**: students tend to form transitive patterns of interaction.
- **H4c – cyclic closure**: students tend to form cyclic patterns of interaction.

In addition to the endogenous relational mechanisms, interaction is potentially influenced by the friendship ties between individual students. On the one hand, friendship may support collaboration and learning among group members; on the other hand, it may also lead to off-task activities (Chiriac and Granström, 2012; Myers, 2012).

Although there is a lack of conclusive evidence of the impact of friendships among group members on group work activity, we anticipate that the presence of a friendship tie between two students will enhance the likelihood of on-task interaction between them. This assumption is based on the notion that the sense of another person's likeability typically increases one's inclination to engage in conversation with them. Hence, we expect:

- **H5 – interaction preference from friendship ties**: students tend to prefer on-task interactions with groupmates they consider friends.

2.3. Attribute-related aspects of interaction

Drawing from expectation states theory, we assume student level of vocality during regular lessons and student level of literacy to play roles in group work interaction. We understand vocality as a usual tendency of a student to speak during regular whole-classroom lessons. Expectation states theory postulates that, when given a collective task to accomplish, individuals bring pre-existing status characteristics into group interactions, which influence the group's power and prestige structure. Some members will be more active than others, exercise more influence than others, and be rewarded more often than others (Berger and Conner, 1969; Correll and Ridgeway, 2003). Vocality and literacy are arguably important characteristics influencing student expectations and status in group work. Vocality and literacy directly impact a student's ability to communicate and articulate ideas effectively, serving as key indicators of competence, leading to higher status within the group and greater influence over group dynamics. Furthermore, students typically have preconceived notions about their peers' vocality and literacy levels well before group work commences, influencing their expectations and the eventual status dynamics within the group. These status characteristics inform members' expectations for each other's performance and contribution to group tasks, affecting how opportunities to participate and lead are distributed among group members. Expectation states theory presumes that student characteristics influence both expectations of themselves – which is also supported by evidence showing that relative student ability within a group is the predictor of their active behavior (Webb, 1991) – as well as expectations from others. Hence, we expect:

- **H6a – vocality promoting interaction activity**:students with higher levels of whole-classroom vocality tend to initiate more on-task interactions.
- **H6b – literacy promoting interaction activity**: students with higher levels of literacy tend to initiate more on-task interactions.
- **H6c – vocality promoting interaction attractiveness**: students with higher levels of whole-classroom vocality tend to receive more on-task interactions.
- **H6b – literacy promoting interaction attractiveness**: students with higher levels of literacy tend to receive more on-task interactions.

Based on the theory of homophily (Byrne, 1971; Turner et al., 1987) and previous research showing that students generally tend to prefer interactions with similar friends (Block and Grund, 2014), it is plausible to assume that students with comparable communication skills and literacy will naturally pair, valuing clear mutual understanding without the need for extended clarifications. Hence:

- **H7a – vocality homophily**: students tend to choose groupmates with similar levels of vocality when initiating on-task interactions.
- **H7b – literacy homophily**: students tend to choose groupmates with similar levels of literacy when initiating on-task interactions.

2.4. Group-level aspects of interaction

We expect group size to influence interaction equality among students. Groups of three have often been criticized by researchers who suggest that these groups lead to a higher probability of one of the students being excluded from active group participation, especially if one of the students does not have good relations with the other two, while the other two are friends (Cullingford, 1988). On the other hand, it was found that smaller groups generally allow a more even participation of all students (Kutnick et al., 2002; Kutnick and Blatchford, 2014). We deem preferential attachment as a proxy for general tendencies for unequal distribution of interactions, because it shows how unequal distribution of interactions stems purely from previous interactions in that group. Hence:

- **H8a – group size influencing preferential attachment**: smaller group size decreases the effect of preferential attachment on interaction.
- **H8b – group size influencing the effect of friendship ties**: smaller group size decreases the effect of preferential attachment on interaction.

We also expect group vocality and literacy composition to shape the dynamics of student interaction patterns within group work. Existing research provides mixed insights on the role of ability composition in group dynamics. For instance, Lou et al. (1996) found that homogeneity in group ability could enhance outcomes, but this does not consistently apply to groups with uniformly low abilities. Conversely, Webb (1991) observed that in groups of high-ability students, communication was often stifled due to a mistaken belief that all members knew how to solve a given problem. These findings suggest that both the average ability of a group and the diversity of abilities within the group may moderate the importance of the individuals' attributes. A higher average level of vocality and literacy within a group suggests that members collectively possess strong communication and comprehension skills, which could lead to more balanced participation based on their vocality and literacy as each member feels competent to contribute. On the other hand, greater heterogeneity may introduce a wider range of perspectives and problem-solving approaches, potentially enriching the group's collaborative process. This diversity also means that the influence of any single student's specific level of vocality or literacy might be diluted, as the group's dynamic becomes less about individual contributions and more about leveraging the collective skill set. Thus, we hypothesize that groups with both higher averages and greater diversity in vocality and literacy will exhibit more equitable interaction patterns, as the variance in individual attributes is balanced by the group's overall composition, reducing the dominance of specific characteristics on group interaction. Hence:

- **H9a – group average vocality and heterogeneity influencing the role of individual students' vocality on interaction**: higher average group vocality level and heterogeneity decrease the effect of individuals' vocality on interaction.
- **H9b – group average literacy and heterogeneity influencing the role of individual students' literacy on interaction**: higher average group literacy level and heterogeneity decrease the effect of individuals' literacy on interaction.

3. Data and methods

3.1. Research context

The data this research is based on were collected for a larger research project called *Collectivity in dialogic learning: An interventional study*. The main aim of the project was to determine whether an intervention led by researchers among comprehensive lower-secondary class teachers could enhance classroom communication. Half of the classrooms in the sample underwent an intervention focused on classroom dialogue. Employing collaborative group work was a part of the intervention, with each interventional classroom experiencing two lessons containing group work – our data came from these lessons. All group work took place during Czech language lessons. The group work all had a similar structure – groups were given a worksheet and everyone in the group was instructed to collaborate with each other to complete the worksheet. Each group work was supposed to take approximately ten minutes, however, the groups greatly differed in how much time they spent interacting – some were interacting for only over a minute, while others were interacting for almost thirty minutes.

3.2. Ethics

Oral consent from school principals and teachers and written consent from the teachers and parents of participating students were obtained. The students were able to withdraw from research at any time. All procedures were performed in compliance with Masaryk University's institutional guidelines on ethics in research.

3.3. Data collection

We collected data during the 2021/2022 school year. We collected data on interactions between students in groups during collaborative group work, relational data on peer friendships, and student-level attributes of talk during regular whole-classroom lessons and reading literacy levels.

For the data on interactions, two members of the research team visited the lessons and videorecorded all group work with one or two recording devices per group work making it possible to identify who was speaking, at what time, and what the content of the communication was. In each classroom, the group work took place twice during the 2021/2022 school year. We worked with a total of 806 minutes of recorded material.

We acquired the relational data denoting friendship ties between the students with a pen-and-paper sociometric questionnaire consisting of a single nomination question (Del Vecchio, 2011; Poulin & Dishion, 2008) worded as "Write the names of the classmates you are friends with. You can write as many names as you want. The order of the names does not make any difference." A trained researcher administered the questionnaire in group settings in the classrooms during school lessons and provided the students with the necessary assistance. We collected relational data at two timepoints – at the beginning and at the end of the school year. For the purposes of this study, we used only the relational data from the beginning of the school year as all group work took place closer to the beginning of the school year and we assumed the interactions among students to be the result of their relationships and not vice-versa.

We acquired the data on whole-classroom talk with video recordings of the lessons. We recorded two consecutive Czech language lessons in each classroom at the beginning and at the end of the 2021/2022 school year, assessed the length of each student's on-task communication in seconds with the help of *EduCoM* – a specialized mobile application designed for bulk collection of educational communication data in classrooms (Švaříček and Chmelík, 2018), and averaged the students' talk in seconds across the two consecutive lessons. Again, for the purposes of this study, we used only the whole-classroom talk data from the beginning of the school year. Finally, we acquired the data on student literacy levels with a standardized computer-based reading literacy test by SCIO (2023) that was administered at schools at the beginning and end of the school year. The test contained 26 items covering five areas of literacy – distinguishing between opinions and judgements, distinguishing between subjective and objective statements, identifying manipulative communication in mass-media, using text as a study resource, and forming new text. Students could score anywhere from −100–100 points – a student would get −100 points if they answered all items incorrectly, 0 points if they did not answer any item, and 100 if they answered all the items correctly. The version with the negative scoring system was validated by SCIO and recommended for use as a measure of literacy. As with the other measures from both the beginning and end of the school year, for the purposes of this study, we used only the reading literacy score from the beginning of the school year.

3.4. Participants

Our sample comprised 145 students in the sixth grade (age 12–13) in six different classrooms mixed into 62 groups. Most of the students were part of both group work sessions during the school year, however, neither of the groups were the same in those two group work sessions. We therefore treated the 62 groups as independent of each other. Our sample was gender-balanced with 78 (53.1 %) girls and 72 (46.9 %) boys. The average vocality level of the participants was 11.9 (SD = 14.6) – in other words, the students spent on average 11.9 seconds talking during whole-classroom lessons. The average literacy level of the participants was 43.5 (SD = 22.9). We had 12.4 % whole-classroom talk data and 10.3 % literacy data missing. We had 14 (22.6 %) groups of three, 41 (66.1 %) groups of four, and 7 (11.3 %) groups of five students. The groups showed a large variance in the average vocality composition (mean = 10.9, SD = 7.9) and the average literacy composition (mean = 42.1, SD = 14.2).

3.5. Coding interactions

We transcribed the recorded classroom group work into a text. Using both the text and the recordings, we coded the interactions into time-ordered and time-stamped relational event data. The basic unit of our analysis was a relational event denoting a directed tie from one student to another – or to the whole group – embedded in time as described by Butts (2008) and by Stadtfeld and Block (2017). Each relational event contained a sender, a receiver, and a time in seconds from the beginning of the group work when the interaction occurred. Since most of the relational events were very brief (~1 sec), we did not separate the beginning and the end of the relational event; instead, we only coded the beginning of the event. We coded both on-task and off-task interaction. On-task communication related to the task the group was working on – it included substantive communication relating to solving the task, but also communication around organizing students' workload. Off-task communication did not relate to the task the group was working on. We did not distinguish between the different types of interaction – e.g., questions, answers, comments. The full codebook used to create the interactional data is available as Supplementary Material S1. The coding was performed by two of the authors of this study with 10 % of the material being double-coded. We calculated the interrater agreement with a Krippendorff's Alpha calculated in *R* (R Core Team, 2021) package *icr* (Staudt and L'Ecuyer, 2020) yielding an agreement of 0.872 (SD = 0.018) for the senders and 0.871 (SD = 0.019) for the receivers denoting high interrater agreement. In total, we worked with 5333 relational events – 4721 on-task and 610 off-task. Fig. 1 shows the number of relational events by type by group. The groups showed a large variance in the number of both on-task and off-task events ($\text{mean}_{\text{total}}$ = 86.0, SD_{total} = 61.1, $\text{mean}_{\text{on-task}}$ = 76.2, $\text{SD}_{\text{on-task}}$ = 59.1, $\text{mean}_{\text{off-task}}$ = 9.8, $\text{SD}_{\text{off-task}}$ = 9.7).

3.6. Handling missing data

We imputed the missing student covariates by a multiple imputation method. We assumed the covariates to be missing at random and applied multiple imputation by chained equations with a predictive mean matching imputation technique (Little, 1988). We imputed the covariates under a fully conditional specification using the default settings of *R* package *mice* (van Buuren and Groothuis-Oudshoorn, 2011). Since multiple imputation requires each model to be calculated multiple times and our models required a significant amount of time for the estimation procedure, calculating many datasets for missing covariate imputation was prohibitive. We therefore decided to rely on the lower side of the recommended number of datasets for imputation (van Buuren, 2018) and made five datasets. We calculated the estimates in each imputed dataset separately and combined them using Rubin's rules (Rubin, 1987).

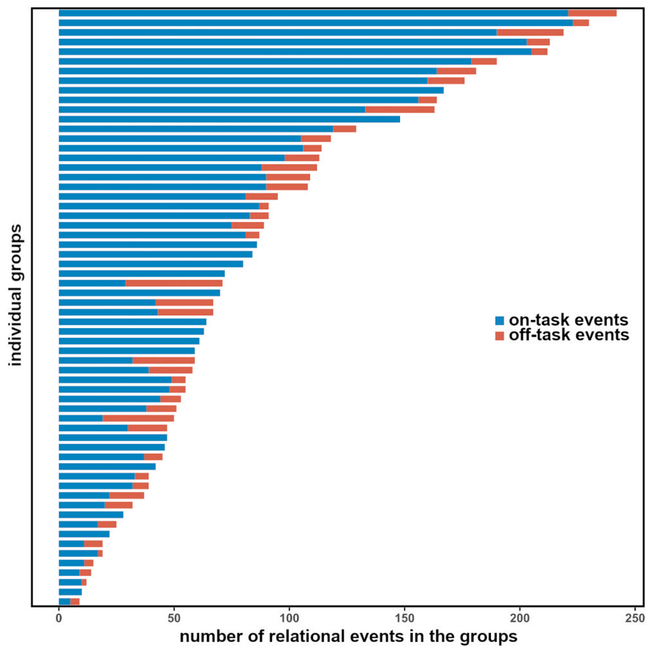

Fig. 1. Number of relational events in the groups.

3.7. Analytical strategy

Network models are usually limited to estimation of parameters of a single network. Two streams of approaches emerged when dealing with multiple networks – a single-step multilevel approach and a two-step meta-analytic approach. There is inconclusive evidence about the accuracy of one approach over another. However, it was argued that the decision to choose between the two should be guided by theoretical assumptions about data-generating process – if it is assumed that the networks come from a single distribution, a single-step approach should be used; on the other hand, if it is assumed that the networks come from different contexts or clusters, a two-step approach should be used (Tolochko and Boomgaarden, 2024). Furthermore, the approach is often guided by practical aspects, such as the degree of implementation of the approaches for different models.

Here, we decided on the two-step meta-analytic approach using dynamic network actor models (DyNAMs; Stadtfeld and Block, 2017). Considering the differences in the numbers of events between the group work sessions and sampling from different classrooms and different schools, we assumed the data to come from different distributions. Also, at the time of our analysis, *goldfish.latent* package built for the single-step multilevel DyNAMs (Uzaheta et al., 2023) was not in a stage of implementation that would allow us to use it as necessary in our research.

3.7.1. Dynamic network actor models

The first step of our analysis consisted of fitting DyNAMs with the same specifications to each individual group work session. DyNAMs aim to capture the network nature of interaction by explicitly modeling emerging network patterns over time as decisions made by the actors about when and with whom they interact. The model aims to explain the emergence of relational events. In our case, the dependent variable of the model is the emergence of an on-task relational event in log odds ratios conditioned on a predefined set of effects based on previous events, network structure, relationships between students, and student attributes. We did not model the emergence of off-task relational events and we used them only as a trigger of the on-task events, because we did not have enough off-task events in our data allowing meaningful off-task interaction models. The DyNAMs consist of two submodels – rate and choice. The rate submodel contains effects relating to the general activity of students. The choice submodel contains effects relating to the tendency of students to choose certain groupmates for interaction (Stadtfeld and Block, 2017).

Since a nonnegligible number of the relational events contained utterances aimed at the whole group ($N_{\text{on-task}} = 523$, 11.1 $\%_{\text{on-task}}$, $N_{\text{off-task}} = 77$, 12.6 $\%_{\text{off-task}}$) and the DyNAMs are not currently built to allow the combination of relational events directed at specific actors along with the relational events directed at the whole group, we had to address the problem of having events directed at the whole group. We did not want to disregard them, as this would result in lower statistics for the activity of many students frequently addressing the whole group. We therefore decided to employ the following permutation method: if a student addressed the whole group, we told the model to randomly select one of the other students in the group as the receiver; we did this with all cases of a student addressing the whole group within that group session; we calculated the model with data containing the relational events addressed at students individually with all cases of events addressed to the whole group substituted; we performed the procedure 100 times; we aggregated the results of the individual models by averaging the log odds ratios and calculating root-mean-square error from the individual models' standard errors. Because of this procedure along with the mice procedure, getting estimates from one model from a single group work session took 30 minutes on average. We calculated DyNAMs in *R* package *goldfish* (Hollway and Stadtfeld, 2022).

3.7.2. Model specification

We fitted two distinct DyNAM model specifications – a baseline model fitted to all 62 groups and a full model fitted to 39 group. The two specifications stem from the fact that the size or composition of some groups prevented fitting the full model specification. For example, we could not include triadic terms on groups of three. We also could not include student attribute effects on groups containing students with very similar levels of vocality or literacy. The subsample of 39 groups used for the full model did not significantly differ from the other groups included in the full sample in the number of events per group ($p = 0.253$), vocality composition ($p = 0.256$), or literacy composition ($p = 0.421$).

Due to the small sizes of our groups, we had to decide on the relevance of the included effects as some effects were highly collinear. We decided not to include any gender and socioeconomic status (SES) effects. The average gender homophily index on friendship ties across the sample classrooms was 0.5 and gender terms were thus highly collinear with the friendship tie effect. Student SES, on the other hand, was correlated with both vocality ($r = 0.2$) and literacy ($r = 0.2$) and in combination with the small groups, including SES in the models along with vocality and literacy resulted in model convergence issues. We gave preference to the inclusion of vocality and literacy effects due to their more direct and observable impact on group dynamics and task-related interactions.

In 22 (35.5 %) groups, there was no off-task interaction and in 7 (11.3 %) groups, there were either friendship ties between all group members or between none of them. Hence, in some groups, it was principally impossible to include effects testing **H2c – off-task to on-task interaction** and **H5 – interaction preference from friendship ties**. We opted not to create separate model specifications for them. Maintaining a unified model approach across groups, despite the lack of off-task interaction and varying friendship ties in some, allowed us to avoid fragmenting the data, which would reduce the overall clarity of the analysis. We conducted sensitivity analyses to test if the effect estimates were significantly different for groups that included off-task interactions and friendship ties compared to those that did not. The sensitivity analysis indicated no substantial effect of the incomplete model specification on our interpretation of the results, thereby reinforcing our decision to treat those groups uniformly within our analytical framework. Results of the sensitivity analysis are available as Supplementary Material S2.

As we worked with small networks which quickly became complete graphs, we had to decide on time windows for some effects. We set a default 20-second window for dyadic effects and a 40-second window for triadic effects as double the window for the dyadic effects as they require one event more. We based our decision on the observation of distribution of reciprocated sequence times. We defined reciprocated sequence time as the difference in times between two events, not necessarily immediately subsequent, where the second one was a reciprocation of the first one. We did not consider the strict AB-BA participation shifts occurring as two immediately following events described in Butts (2008), because our groups would sometimes split into two separate simultaneous conversations in pairs. If we worked with the strict definition of the participation shifts, we would have missed some of the actual reciprocated events as in the time, as two simultaneous conversations would be overlapping in time. Fig. 2 shows the distribution of reciprocated sequence times. The distribution is long-tailed with most reciprocated events occurring within that 20-second window.

The baseline model is the most comprehensive specification that could be fitted to all 62 groups. Apart from *intercept*, the rate submodel contains the following effects:

• $ego_{bursty\ behavior}$ testing **H1 – general burstiness tendency**. It captures the probability of initiating an on-task interaction with any groupmate conditioned on an initiation of on-task event in the window of the previous 20 seconds by any student in the group. *bursty behavior* serves as a dynamic dummy variable, which is same for all students, but which changes in time as a rolling window of 20 seconds. If any on-task event is initiated, all students in that group are "triggered" for 20 seconds assuming that recent activity will trigger future activity and it therefore aims to capture general burstiness tendency independent of any specific connections or attributes.

• $indeg_{weighted}$ and $outdeg_{weighted}$ testing **H3a** and **H3b – ego type in/outdegree preferential attachment**. They capture the tendency to initiate on-task interaction if previously receiving/initiating many on-task interactions. We used weighted specifications for the in and out-degree terms as we wanted to capture the cumulative tendency of those who initiate and receive many interactions to initiate more interaction in future.

The choice submodel contains the following effects:

• *inertia* testing **H2a – repeated interaction**. It captures the tendency to choose a groupmate for on-task interaction if they initiated interaction towards that groupmate before – in other words, the tendency to repeat existing ties rather than create new ones.

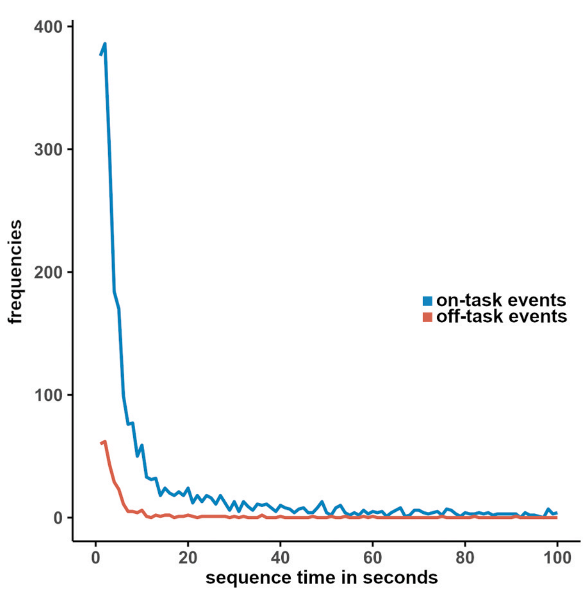

Fig. 2. Distribution of reciprocated sequence times.

• $tie_{on\text{-}task\ interaction\ weighted}$ testing **H2b – cumulative repeated interaction**. It captures the increased tendency to choose a groupmate for on-task interaction with each repeated initiated on-task interactions with that groupmate before.

• $tie_{off\text{-}task\ interaction\ weighted}$ testing **H2c – off-task to on-task interaction**. It captures the increased tendency to choose a groupmate for on-task interaction with each repeated initiated off-task interactions with that groupmate before. It serves as a cross-network term controlling for the effect of off-task interactions on-task interactions.

• $indeg_{weighted}$ and $outdeg_{weighted}$ testing **H3c** and **H3d – alter type in/outdegree preferential attachment**. They capture the tendency to receive on-task interaction if previously receiving/initiating many on-task interactions. As with the rate submodel terms, we used weighted specifications aiming to capture the cumulative tendency of those who initiate and receive many interactions to receive more interaction in future.

• $recip_{window20}$ testing **H4a – reciprocity**. It captures the tendency to reciprocate on-task interactions within the window of 20 seconds of receiving it.

• $tie_{friendship}$ testing **H5 – interaction preference from friendship ties**. It captures the tendency of students to choose those groupmates as receivers of their on-task interaction whom they consider friends.

The full model tests all our hypotheses and could be fitted to 39 groups. It contains all effects included in the baseline model plus triadic and attribute-based effects. The rate submodel contains the following effects:

• $ego_{whole\text{-}class.\ talk}$ testing **H6a – vocality promoting interaction activity**. It captures the tendency of students with higher levels of vocality to initiate more on-task interactions.

• $ego_{literacy}$ testing **H6b – literacy promoting interaction activity.** It captures the tendency of students with higher levels of literacy to initiate more on-task interactions.

The choice submodel contains the following effects:

• $trans_{window40}$ testing **H4b – transitive closure**. It captures the tendency to interact in a way that forms the transitive pattern of an event $i \rightarrow j$ closing more two-paths ($i \rightarrow k \rightarrow j$).

• $cycle_{window40}$ testing **H4c – cyclic closure**. It captures the tendency to interact in a way that forms the cyclic patterns of an event $i \rightarrow j$ closing more two-paths ($j \rightarrow k \rightarrow i$).

• $alter_{whole\text{-}class.\ talk}$ testing **H6c – vocality promoting interaction attractiveness**. It captures the tendency of students with higher levels of vocality to receive more on-task interactions.

• $alter_{literacy}$ testing **H6d – literacy promoting interaction attractiveness.** It captures the tendency of students with higher levels literacy to receive more on-task interactions.

• $sim_{\ whole\text{-}class\ talk}$ testing **H7a – vocality homophily**. It captures the tendency to choose groupmates with similar levels of vocality when initiating on-task interactions.

• $sim_{\ literacy}$ testing **H7b – literacy homophily**. It captures the tendency to choose groupmates with similar levels of literacy when initiating on-task interactions.

3.7.3. Meta-analysis

The second step of our analysis consisted of aggregating the results from the individual DyNAMs. Pooling the estimates across the groups resulted in overall model estimates. We pooled the estimates with a random-effect meta-analysis in *R* package *metafor* (Viechtbauer, 2010), assuming that the observed estimates varied across the groups both because of real differences in the effect sizes in each group and because of the sampling variability.

3.7.4. Meta-regression

The third step of our analysis consisted of fitting meta-regression models with group size and composition as moderator variables. Meta-regression allows for the investigation of the relationships between group-level variables and effect sizes across multiple models fitted to individual groups. It seeks to understand the heterogeneity in effect sizes by examining how they are influenced by external factors. To test **H8a – group size influencing equality of interaction** and explore whether smaller group size is related to weaker preferential attachment tendencies, we used group size as a moderator variable for the *indeg* and *outdeg* effects. A negative coefficient for group size would indicate that in smaller groups, interaction among students is less centralized around a small number of students and the interaction is therefore more equal. To test **H8b – group size influencing the effect of friendship ties** and explore whether smaller group size increases the effect of friendship ties on interaction, we used group size as a moderator variable for the $tie_{friendship}$ effect. We used the baseline model to test the moderating role of the group size as it could be fitted to all 62 groups. To test **H9a – group average vocality and heterogeneity influencing the role of individual students' vocality on interaction**, we used the mean, SD, and the interaction between the two as moderator variables for the $ego_{whole\text{-}class.\ talk}$, $alter_{whole\text{-}class.\ talk}$, and sim $_{whole\text{-}class.\ talk}$ effects. To test **H9b – group average literacy and heterogeneity influencing the role of individual students' literacy on interaction**, we used the mean, SD, and the interaction between the two as moderator variables for the $ego_{literacy}$, $alter_{literacy}$, and sim $_{literacy}$ effects.

4. Results

Fig. 3 shows the event timelines across the groups. Three striking patterns are apparent. First, interaction in all groups exhibit burstiness – the events are not evenly distributed in time, they occur in clusters of high-activity periods split by low-activity periods with no interaction. Second, on-task and off-task interactions do not mix – there are periods of on-task interactions, periods of off-task interactions, but not periods of combined on- and off-task interactions. Third, off-task interaction periods often precede on-task interaction periods. Most group work sessions start with a period of off-task interactions followed by one or more periods of on-task interactions.

4.1. What influences interaction dynamics in classroom group work?

Table 1 shows the pooled DyNAM estimates with their associated standard errors (SE) and p-values. Neither the baseline nor the full model shows a significant $ego_{bursty\ behavior}$ effect, thus providing no evidence for the general tendency of burstiness in a sense of having increased activity due to occurrence of recent previous activity in the group. The observed burstiness seen in Fig. 3 is therefore caused by other mechanisms. Both models show positive and significant *inertia* and $tie_{on\text{-}task\ interaction\ weighted}$ effects, suggesting that students tend to prefer repeated on-task interactions with the same groupmates, and that tendency increases with each repeated initiated on-task interactions with that groupmate before. Both models also show a positive and significant $tie_{off\text{-}task\ interaction\ weighted}$ effect – although borderline significant in the full model – suggesting that off-task interaction leads to on-task interaction. Except for the $indeg_{weighted}$ effect in the choice submodel and $outdeg_{weighted}$ effect in the rate submodel in the full specification, the *indeg* and *outdeg* effects are positive and significant, suggesting that those who initiate and receive many on-task interactions are more likely to initiate future on-task interactions, and those who initiate many on-task interactions are more likely to receive future on-task interactions. This results in interaction-wise active and/or popular students being engaged in interactions disproportionately more than others. The models further show positive and significant $recip_{window20}$, $trans_{window40}$, and $cycle_{window40}$ effects, suggesting that students tend to reciprocate on-task interaction and form both transitive and cyclic patterns of on-task interaction. Both models show a positive and significant $tie_{friendship}$ effect, suggesting that students prefer initiating on-task interactions with groupmates they consider friends. In the full model, all *ego* and *alter* effects are positive and significant, suggesting that students who are vocal in whole-classroom lessons and students with higher levels of literacy are more likely to initiate and receive on-task interaction in group work. Both *sim* effects are also positive and significant, suggesting that students tend to choose groupmates with similar levels of vocality and literacy when initiating on-task interactions.

4.2. How does group composition influence interaction dynamics in classroom group work?

Table 2 shows the results of the meta-regression models. The models do not support the hypothesis that the size of the group would have any effect on the preferential attachment in interaction, with group size not being a significant moderator for any of the *indeg* and *outdeg* effects. The models also do not support the hypothesis that the group average literacy or heterogeneity would have any moderating effect on $ego_{literacy}$, $alter_{literacy}$, or sim $_{literacy}$ effects. On the other hand, the models suggest that larger group size is related to a lower $tie_{friendship}$ effect. It supports

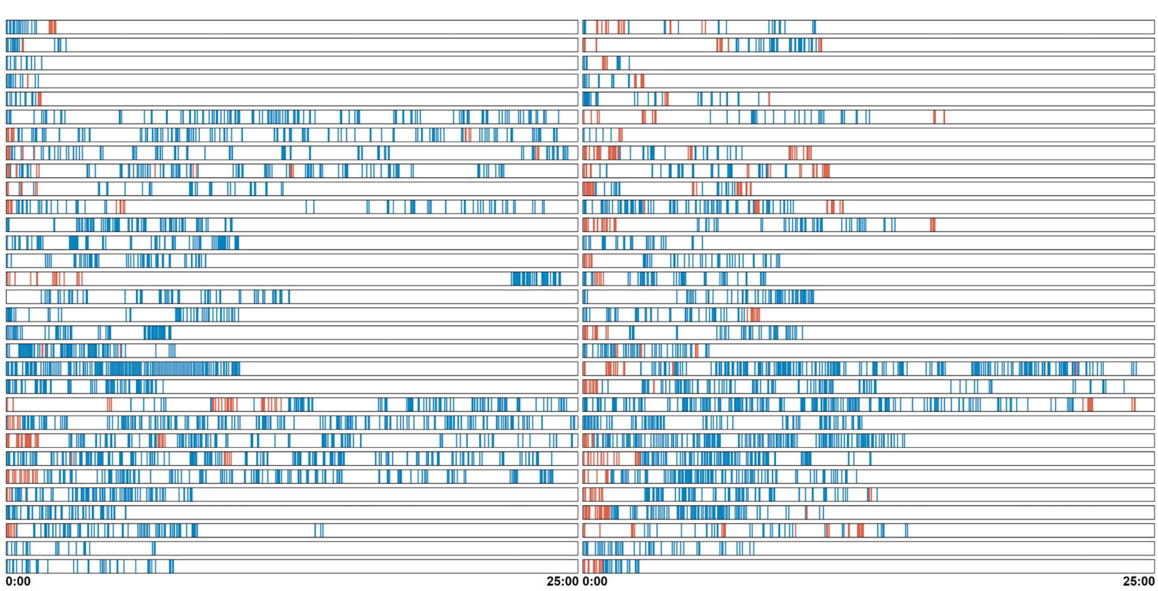

Fig. 3. Event timelines across the groups. Each tick denotes a single relational event in time.

Table 1
Pooled DyNAM estimates.

	baseline model (62 groups)			full model (39 groups)		
	log (OR)	SE	p	log (OR)	SE	p
rate submodel						
intercept	-2.245	0.371	<0.001	-1.309	0.550	0.017
$ego_{bursty\ behavior}$ (H1 – general burstiness tendency)	0.106	0.079	0.177	0.134	0.091	0.138
$indeg_{weighted}$ (H3a – ego type indeg. pref. attach.)	0.039	0.007	<0.001	0.068	0.013	<0.001
$outdeg_{weighted}$ (H3b – ego type outdeg. pref. attach.)	0.029	0.004	<0.001	-0.005	0.013	0.732
$ego_{whole\text{-}class.\ talk}$ (H6a – vocality promoting interact. activity)				0.020	0.006	<0.001
$ego_{literacy}$ (H6b – literacy promoting interact. activity)				0.005	0.001	<0.001
choice submodel						
inertia (H2a – repeated interact.)	0.596	0.079	<0.001	0.502	0.031	<0.001
$tie_{on\text{-}task\ interaction\ weighted}$ (H2b – cumulative repeated interact.)	0.079	0.015	<0.001	0.079	0.031	0.012
$tie_{off\text{-}task\ interaction\ weighted}$ (H2c – off-task to on-task interact.)	0.213	0.081	0.009	0.447	0.265	0.092
$indeg_{weighted}$ (H3c – alter type indeg. pref. attach.)	0.031	0.030	0.301	-0.032	0.088	0.714
$outdeg_{weighted}$ (H3d – alter type outdeg. pref. attach.)	0.118	0.015	<0.001	0.166	0.027	<0.001
$recip_{window20}$ (H4a – reciprocity)	1.038	0.104	<0.001	1.140	0.150	<0.001
$trans_{window40}$ (H4b – transitive closure)				0.342	0.110	0.002
$cycle_{window40}$ (H4c – cyclic closure)				0.616	0.074	<0.001
$tie_{friendship}$ (H5 – interact. preference from friendship ties)	0.448	0.068	<0.001	0.912	0.244	<0.001
$alter_{whole\text{-}class.\ talk}$ (H6c – vocality promoting interact. attract.)				0.068	0.011	<0.001
$alter_{literacy}$ (H6d – literacy promoting interact. attract.)				0.018	0.008	0.021
$sim_{whole\text{-}class\ talk}$ (H7a – vocality homophily)				0.153	0.080	0.055
$sim_{literacy}$ (H7b – literacy homophily)				0.045	0.010	<0.001

our hypothesis that in groups of three, the effect of friendships on preference for initiating interactions is higher than in larger groups and that a student without any friend is more likely to be excluded from interaction in groups of three. The models further provide tentative evidence that a higher average student vocality level in group is related to a lower $ego_{whole\text{-}class.\ talk}$ effect, hence, lower tendency of vocal students to be more active in initiating on-task interactions. The models also provide tentative evidence that a higher heterogeneity of student vocality in group is related to a lower $sim_{whole\text{-}class.\ talk}$ effect, hence, lower tendency of students to choose groupmates with similar levels of vocality when initiating on-task interactions.

Table 2
Meta-regression results.

	log (OR)	SE	p
rate $indeg_{weighted}$ (H8a – group size and equality)			
intercept	0.073	0.051	0.147
group size	-0.009	0.013	0.491
rate $outdeg_{weighted}$ (H8a – group size and equality)			
intercept	0.052	0.038	0.175
group size	-0.006	0.010	0.552
choice $indeg_{weighted}$ (H8a – group size and equality)			
intercept	0.138	0.215	0.522
group size	-0.027	0.053	0.613
choice $outdeg_{weighted}$ (H8a – group size and equality)			
intercept	0.236	0.104	0.023
group size	-0.030	0.026	0.254
choice $tie_{friendship}$ (H8b – group size and effects of friendships)			
intercept	1.455	0.541	0.007
group size	-0.241	0.129	0.061
rate $ego_{whole\text{-}class.\ talk}$ (H9a – group av. vocality and heterogeneity)			
intercept	0.061	0.019	0.001
group average vocality	-0.002	0.001	0.098
vocality heterogeneity	-0.003	0.003	0.246
group average vocality*heterogeneity	0.000	0.000	0.245
choice $alter_{whole\text{-}class.\ talk}$ (H9a – group av. vocality and heterogeneity)			
intercept	0.280	0.169	0.097
group average vocality	-0.010	0.008	0.214
vocality heterogeneity	-0.013	0.027	0.614
group average vocality*heterogeneity	0.001	0.001	0.666
choice $sim_{whole\text{-}class.\ talk}$ (H9a – group av. vocality and heterogeneity)			
intercept	0.545	0.300	0.070
group average vocality	-0.004	0.022	0.847
vocality heterogeneity	-0.081	0.047	0.087
group average vocality*heterogeneity	0.003	0.002	0.138
rate $ego_{literacy}$ (H9b – group av. literacy and heterogeneity)			
intercept	0.030	0.030	0.310
group average literacy	-0.001	0.001	0.485
literacy heterogeneity	-0.001	0.002	0.744
group average literacy*heterogeneity	0.000	0.000	0.794
choice $alter_{literacy}$ (H9b – group av. literacy and heterogeneity)			
intercept	-0.067	0.123	0.585
group average literacy	0.003	0.003	0.396
literacy heterogeneity	0.010	0.011	0.358
group average literacy*heterogeneity	-0.000	0.000	0.313
choice $sim_{literacy}$ (H9b – group av. literacy and heterogeneity)			
intercept	0.060	0.116	0.605
group average literacy	0.000	0.003	0.885
literacy heterogeneity	0.001	0.015	0.941
group average literacy*heterogeneity	-0.000	0.000	0.799

5. Discussion and conclusion

In this study, we explored the interaction dynamics of lower-secondary students in collaborative group work sessions. We addressed the gap in the literature stemming from the fact that interaction in group work has never been considered in its realistic nature: dynamic, relational, and actor-oriented. We employed a recent addition to the actor-based network model family – DyNAMs – suited for the study of fine-grained time-stamped interactional data.

We found that interaction in group work is largely influenced by an array of endogenous structural mechanisms. These include reciprocity, transitivity, cyclicity, and preferential attachment. We also found interaction in group work to be influenced by the interaction repetition, with students giving preference to initiating interactions with those they initiated interactions with before, including both on- and off-task interactions. Hence, off-task interaction also contributed to development of on-task interaction. While we observed strong patterns of bursty behavior in our data, modelling burstiness *per se* as a mechanism influencing event formation yielded non-significant results. Hence, the observed burstiness in the groups was probably caused by the windowed reciprocity, transitivity, and cyclicity effects, as these stem from recent previous interactions and lead to new interactions. We further found interaction in group work to be largely influenced by friendship ties between students, with students giving strong preference to initiating interactions with those they consider friends. We found evidence that those students who talk a lot during regular whole-classroom lessons and students with high levels of literacy tend to both initiate and receive more interactions in group work, and students similar in these attributes prefer to interact with each other. Finally, we found tentative evidence that the vocality composition of the groups moderated the effects of unequal student interaction based on their level of vocality. We found that higher average group vocality was related to lower tendency of vocal students to be more active in initiating interactions and higher group vocality heterogeneity was related to lower tendency of students to choose groupmates with similar levels of vocality when initiating interactions.

The strong presence of the structural endogenous mechanisms in interaction mirrors our expectations and previous research of interpersonal and communication ties (Kossinets and Watts, 2006; Le et al., 2018; Rivera et al., 2010; Slavin et al., 2003; Ten Bosch et al., 2005). Our results suggest that while many aspects might influence interaction in group work, the endogenous mechanisms influence it the most. The presence of the temporal mechanisms in interaction including the preference for repeated on-task interactions and the influence of off-task interactions on-task interactions also mirror our expectations and previous research on group dynamics (Miritello, 2013; Langer-Osuna et al., 2020). Taken together, our findings show that ignoring the relational and dynamic nature of small group interaction in educational settings leads to neglecting a substantial portion of the mechanisms driving group interactions.

The strong preference of students to interact with friends makes the inconclusive results found in previous literature more conclusive. Previous research found that friends in group work frequently engage in off-task activities (Chiriac and Granström, 2012; Myers, 2012). While this might be true; we found friendships ties to enhance on-task communication as well. The question is how our finding relates to the previously described tendency of students to exclude students with whom they do not have good relationships (Cullingford, 1988). We believe our findings support this thesis. If there is a group of four students and three of those students consider each other friends, our strong positive estimate of friendship ties suggests that those three students will give strong preference to interaction with each other, while the fourth student will remain excluded. The results of our meta-regression model further support the thesis that a student is most likely to be excluded from interaction if they are without friends in groups of three. In a more equal scenario – a group of four in which two of the students consider each other friends, while the other two are not friends with anyone in the group – the two students who are not friends with anyone are also more likely to be excluded from interaction because they are less likely to communicate with the two students who are friends as well as less likely to communicate with each other. In a scenario with two pairs of friends, students may end up interact mostly within the friendship pairs, with the group virtually operating as two groups.

Our findings related to the effects of student attributes support expectation states theory (Berger and Conner, 1969; Correll and Ridgeway, 2003) suggesting that pre-existing status characteristics influence group work dynamics. Furthermore, our findings suggest that certain groups of students tend to be disadvantaged in group work by actively engaging in communication less and these groups of students are those who are already disadvantaged in education. Both silent (Sedova et al., 2019) and low-literacy (Meneghetti et al., 2006) students have worse academic performances than their vocal and high-literacy counterparts. If we accept the proposition that those who actively engage in group work most are those who benefit from group work most, we may interpret our findings as indicating that group work acts as another mechanism through which disadvantaged students in education get more disadvantaged, while those who are already successful accumulate even more advantages.

Our findings related to the effect of group size and composition in interaction dynamics generally do not support earlier findings. We found little support for the thesis that smaller groups allow more even participation of all students (Kutnick et al., 2002; Kutnick and Blatchford, 2014). However, it is important to note that we operationalized even participation as low preferential attachment tendencies, which differs from measures used in other studies. Our approach to even participation emphasizes the effect of cumulative advantage of active and popular students in time, rather than the raw distribution of contributions. Also, we modelled only the differences among groups of three, four, and five students; we are therefore unable to capture any effect of group size if group size becomes significant with a larger number of students.

Our findings related to the effect of group vocality composition on equality of interaction suggest that communication group norms may shift with changing group compositions. When the average group level of vocality is high, the effect of vocal students to initiate more interactions is less pronounced. At the same time, when the group comprises students with a diverse range of vocality levels, the effect of vocality homophily is less pronounced. This pattern may be attributed to the diffusion of expectations across members when overall group vocality is high, diluting the influence of any single vocal student. In such settings, the collective confidence to speak up may encourage even the typically less vocal students to participate more actively. Conversely, in groups with a diverse range of vocality levels, students may be more likely to modulate their participation to match their peers, which could diminish the vocality-based homophily.

5.1. Limitations

Our study has limitations stemming from the sample characteristics and from the study design. Our models are based on a non-representative sample of students from the Czech Republic, which makes generalizations of our findings difficult. Furthermore, because our groups were small, often had students with collinear characteristics, and because we applied the DyNAMs to the groups individually, we were unable to fit the full model testing all our hypotheses to all groups. We were also unable to model the effects of demographic student characteristics, as including them made model convergence impossible. Finally, when dealing with interactions addressed to the whole group, we had to rely on a workaround involving the permutation method, as DyNAMs are not currently able to work with both dyadic and multicast interactions. It may be argued that interactions aimed at the whole group are qualitatively different than dyadic interactions, however, we treated them as qualitatively same as incorporating multiplex network structures into DyNAMs in currently not implemented and beyond the scope of this paper. Having an extension to DyNAMs making it possible to model both dyadic and multicast interactions would therefore be beneficial for modeling of many real-world situations.

5.2. Implications

Our study has several implications for practice. The strong effect of friendship ties on interaction in group work implies that when teachers form groups, they should not mix friends with non-friends together in the same group as those who are not friends with others in the group are at the risk of being excluded from the interaction. We therefore recommend forming either groups comprising only friends or groups comprising only non-friends. Moreover, the moderating role of group vocality composition on equal interaction implies that it may be more beneficial to form groups so that they contain a diverse range of vocality levels.

Our study has several implications for future research. We show that DyNAMs are a very useful tool for the study of real-world interaction between students. We show that DyNAMs are suitable to be fitted to groups ranging from three to five actors. In combination with the established meta-analytical procedures from social network models, we show that DyNAMs can be used to get effect estimates from several groups independently, with the results pooled to get overall estimates. We therefore believe that DyNAMs have the potential to serve as a strong analytical tool for the study of interaction in group work and for the study of interaction in whole-classroom settings. Given that structural endogenous mechanisms seem to influence interaction in group work more than any relational or attribute effects, any research aiming to explore interaction in group work should account for them, as the results may otherwise be invalid. Finally, because the size and composition of the groups prevented us from fitting the full model specification to all groups, in the future, it might be useful to get estimates from multiple groups using a multi-level framework with random-effects parameters (Uzaheta et al., 2023), and to compare the estimates from the meta-analytical framework with the estimates from the multi-level framework.

CRediT authorship contribution statement

Tomáš Lintner: Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Barbora Nekardová:** Investigation, Writing – review & editing. **Tomas Diviák:** Formal analysis, Investigation, Methodology, Writing – review & editing.

Declaration of Competing Interest

The authors declared no competing interests.

Data availability

The data that the paper is based on are publicly available in Mendeley Data here: https://doi.org/10.17632/9c3dth6cwp.3 and a Data in Brief article describing the data has been published here: https://doi.org/10.1016/j.dib.2023.109641.

Acknowledgements

This work was supported by GA21-16021S research grant of the Czech Science Foundation. This work was also supported by the NPO 'Systemic Risk Institute' number LX22NPO5101, funded by European Union—Next Generation EU (Ministry of Education, Youth and Sports, NPO: EXCELES).

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.socnet.2024.05.002.

References

Barabasi, A.L., 2005. The origin of bursts and heavy tails in human dynamics. Nature 435 (7039), 207–211. https://doi.org/10.1038/nature03459.
Bearman, P., 1997. Generalized exchange. Am. J. Sociol. 102 (5), 1383–1415. https://doi.org/10.1086/231087.
Berger, J., Conner, T.L., 1969. Performance expectations and behavior in small groups. Acta Sociol. 12 (4), 186–198. https://doi.org/10.1177/000169936901200403.
Block, P., Grund, T., 2014. Multidimensional homophily in friendship networks. Netw. Sci. 2 (2), 189–212. https://doi.org/10.1017/nws.2014.17.
Butts, C.T., 2008. A relational event framework for social action. Sociol. Methodol. 38 (1), 155–200. https://doi.org/10.1111/j.1467-9531.2008.00203.x.
van Buuren, S., 2018. Flexible Imputation of Missing Data, 2nd Ed. CRC Press.
van Buuren, S., Groothuis-Oudshoorn, K., 2011. mice: multivariate imputation by chained equations in R. J. Stat. Softw. 45, 1–67. https://doi.org/10.18637/jss.v045.i03.
Byrne, D.E., 1971. The Attraction Paradigm. Academic Press, New York.
Chiriac, E.H., Granström, K., 2012. Teachers' leadership and students' experience of group work. Teach. Teach. 18 (3), 345–363. https://doi.org/10.1080/13540602.2012.629842.
Correll, S.J., Ridgeway, C.L., 2003. Expectation states theory. In Handbook of social psychology. Springer, Boston, MA, pp. 29–51.
Cullingford, C., 1988. Children's views about working together. Education 3-13 16 (1), 29–34. https://doi.org/10.1080/03004278885200071.
Felder, R.M., Brent, R., 1996. Navigating the bumpy road to student-centered instruction. Coll. Teach. 44 (2), 43–47. https://doi.org/10.1080/87567555.1996.9933425.
Fung, D., 2022. Achieving individual and collaborative success: an investigation of guided group work and teacher participation in junior secondary science classrooms. Int. J. Educ. Res. 111, 101908 https://doi.org/10.1016/j.ijer.2021.101908.
Gillies, R.M., Boyle, M., 2010. Teachers' reflections on cooperative learning: issues of implementation. Teach. Teach. Educ. 26 (4), 933–940. https://doi.org/10.1016/j.tate.2009.10.034.
Hollway, J., Stadtfeld, C., 2022. goldfish: statistical network models for dynamic network data. R. Package Version 1. 6. 4. ⟨www.social-networks.ethz.ch/research/goldfish.html⟩.
Karsai, M., Kaski, K., Barabási, A.L., Kertész, J., 2012. Universal features of correlated bursty behaviour. Sci. Rep. 2 (1), 397. https://doi.org/10.1038/srep00397.
Kossinets, G., Watts, D.J., 2006. Empirical analysis of an evolving social network. Science 311 (5757), 88–90. https://doi.org/10.1126/science.1116869.
Kutnick, P., Blatchford, P., 2014. Effective Group Work in Primary School Classrooms. Springer, Dordrecht. https://doi.org/10.1007/978-94-007-6991-5.
Kutnick, P., Blatchford, P., Baines, E., 2002. Pupil groupings in primary school classrooms: sites for learning and social pedagogy? Br. Educ. Res. J. 28 (2), 187–206. https://doi.org/10.1080/01411920120122149.
Langer-Osuna, J.M., Gargroetzi, E., Munson, J., Chavez, R., 2020. Exploring the role of off-task activity on students' collaborative dynamics. J. Educ. Psychol. 112 (3), 514–532. https://doi.org/10.1037/edu0000464.
Le, H., Janssen, J., Wubbels, T., 2018. Collaborative learning practices: teacher and student perceived obstacles to effective student collaboration. Camb. J. Educ. 48 (1), 103–122. https://doi.org/10.1080/0305764X.2016.1259389.
Lehmann, S., 2019. Fundamental structures in temporal communication networks. In: Holme, P., Saramäki, J. (Eds.), Computational Social Sciences, *Temporal Network Theory*. Springer, Cham. https://doi.org/10.1007/978-3-030-23495-9_2.
Little, R.J., 1988. Missing-data adjustments in large surveys. J. Bus. Econ. Stat. 6 (3), 287–296. https://doi.org/10.2307/1391878.
Lou, Y., Abrami, P.C., Spence, J.C., Poulsen, C., Chambers, B., d'Apollonia, S., 1996. Within-class grouping: a meta-analysis. Rev. Educ. Res. 66 (4), 423–458. https://doi.org/10.3102/00346543066004423.
Mameli, C., Mazzoni, E., Molinari, L., 2015. Patterns of discursive interactions in primary classrooms: an application of social network analysis. Res. Pap. Educ. 30 (5), 546–566. https://doi.org/10.1080/02671522.2015.1027727.
Meneghetti, C., Carretti, B., De Beni, R., 2006. Components of reading comprehension and scholastic achievement. Learn. Individ. Differ. 16 (4), 291–301. https://doi.org/10.1016/j.lindif.2006.11.001.
Miritello, G., 2013. Temporal Patterns of Communication in Social Networks. Springer. https://doi.org/10.1007/978-3-319-00110-4.
Myers, S.A., 2012. Students' perceptions of classroom group work as a function of group member selection. Commun. Teach. 26 (1), 50–64. https://doi.org/10.1080/17404622.2011.625368.
Navarro, H., Miritello, G., Canales, A., Moro, E., 2017. Temporal patterns behind the strength of persistent ties. EPJ Data Sci. 6 (31), 1–19. https://doi.org/10.1140/epjds/s13688-017-0127-3.
R Core Team, 2021. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. ⟨https://www.R-project.org/⟩.
Rivera, M.T., Soderstrom, S.B., Uzzi, B., 2010. Dynamics of dyads in social networks: assortative, relational, and proximity mechanisms. Annu. Rev. Sociol. 36, 91–115. https://doi.org/10.1146/annurev.soc.34.040507.134743.
Rubin, D.B., 1987. Multiple Imputation for Nonresponse in Surveys. John Wiley and Sons, New York.
Ryu, S., Lombardi, D., 2015. Coding classroom interactions for collective and individual engagement. Educ. Psychol. 50 (1), 70–83. https://doi.org/10.1080/00461520.2014.1001891.
SCIO, 2023. Proj. Sch. ⟨https://www.scio.cz/english/project-schools12.asp⟩.
Sedova, K., Sedlacek, M., Svaricek, R., Majcik, M., Navratilova, J., Drexlerova, A., Salamounova, Z., 2019. Do those who talk more learn more? The relationship between student classroom talk and student achievement. Learn. Instr. 63, 101217 https://doi.org/10.1016/j.learninstruc.2019.101217.
Slavin, R., Hurley, E.A., Chamberlain, A., 2003. Cooperative learning and achievement: theory and research. In: Reynolds, W.M., Miller, G.E. (Eds.), In Handbook of psychology: Educational psychology, Vol.7. Wiley, New York, pp. 177–198.
Snijders, T.A., 2001. The statistical evaluation of social network dynamics. Sociol. Methodol. 31 (1), 361–395. https://doi.org/10.1111/0081-1750.00099.

Stadtfeld, C., Block, P., 2017. Interactions, actors, and time: dynamic network actor models for relational events. Sociol. Sci. 4, 318–352. https://doi.org/10.15195/v4.a14.

Staudt, A., L'Ecuyer, P., 2020. icr: Compute Krippendorff's Alpha. R. Package Version 0 6, 2. ⟨https://github.com/staudtlex/icr⟩.

Švaříček, R., Chmelík, J., 2018. EduCoM (2.2) [Mobile application software]. Masaryk University.

Ten Bosch, L., Oostdijk, N., Boves, L., 2005. On temporal aspects of turn taking in conversational dialogues. Speech Commun. 47 (1-2), 80–86. https://doi.org/10.1016/j.specom.2005.05.009.

Tolochko, P., Boomgaarden, H.G., 2024. Same but different: a comparison of estimation approaches for exponential random graph models for multiple networks. Soc. Netw. 76, 1–11. https://doi.org/10.1016/j.socnet.2023.05.003.

Turner, J.C., Hogg, M.A., Oakes, P.J., Reicher, S.D., Wetherell, M.S., 1987. Rediscovering the Social Group: A Self-categorization theory. Blackwell.

Uzaheta, A., Amati, V., Stadtfeld, C., 2023. Random effects in dynamic network actor models. Netw. Sci. 1–18. https://doi.org/10.1017/nws.2022.37.

Viechtbauer, W., 2010. Conducting meta-analyses in R with the metafor package. J. Stat. Softw. 36 (3), 1–48. https://doi.org/10.18637/jss.v036.i03.

Wagner, C.J., González-Howard, M., 2018. Studying discourse as social interaction: the potential of social network analysis for discourse studies. Educ. Res. 47 (6), 375–383. https://doi.org/10.3102/0013189×18777741.

Webb, N.M., 1991. Task-related verbal interaction and mathematics learning in small groups. J. Res. Math. Educ. 22 (5), 366–389. https://doi.org/10.5951/jresematheduc.22.5.0366.

Webb, N.M., 2009. The teacher's role in promoting collaborative dialogue in the classroom. Br. J. Educ. Psychol. 79 (1), 1–28. https://doi.org/10.1348/000709908×380772.