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Towards Predictable Process and Consequence Attributes of Data-Driven Group Work: Primary Analysis for Assisting Teachers with Automatic Group Formation

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ABSTRACT: Data-driven platforms with rich data and learning analytics applications provide immense opportunities to support collaborative learning such as algorithmic group formation systems based on learning logs. However, teachers can still get overwhelmed since they have to manually set the parameters to create groups and it takes time to understand the meaning of each indicator. Therefore, it is imperative to explore predictive indicators for algorithmic group formation to release teachers from the dilemma with explainable group formation indicators and recommended settings based on group work purposes. Employing learning logs of group work from a reading-based university course, this study examines how learner indicators from different dimensions before the group work connect to the subsequent group work processes and consequences attributes through correlation analysis. Results find that the reading engagement and previous peer ratings can reveal individual achievement of the group work, and a homogeneous grouping strategy based on reading annotations and previous group work experience can predict desirable group performance for this learning context. In addition, it also proposes the potential of automatic group formation with recommended parameter settings that leverage the results of predictive indicators.

Keywords: Group work indicator, GLOBE, Correlation analysis, Group formation, CSCL, Group work prediction, Teacher assistance

1. Introduction

Group learning gets increasingly prevalent in pedagogical practice (Dinh et al., 2021) and prevalent online courses nowadays raise impetus to the demand for such interactive activities. Prevalent research on computer-supported collaborative learning (CSCL) (Stahl et al., 2006) and learning analytics (LA) (Siemens, 2012) bring about immense opportunities to scaffold group work nowadays. However, there are still obstacles that hinder teachers from using technical support due to unfamiliarity with digital systems and lack of learning data (Austin et al., 2010; Brusilovsky et al., 2015; van der Velde et al., 2021).

Current LA researches focus on LA tools during the orchestration phase of the group work that investigates the group dynamics for timely intervention or forecasting the learning outcomes (Van Leeuwen et al., 2014). The predictive analysis before the group work start is less discussed, which is equally meaningful for group work organization such as group formation (Wessner & Pfister, 2001).

With the accumulation of abundant learning log data, group formation systems using learning logs advent (Boticki et al., 2019; Liang et al., 2021). However, teachers still need to manually set the parameters to create groups, which can overwhelm them and take time to understand the meaning of each indicator. To simplify such work for teachers from complicated parameter selections, it is imperative to automatically recommend appropriate group formation indicators that are predictive of desirable group work performance. This study aims to present a step towards an automatic group formation system by analyzing the data of a reading-based university course with asynchronous forum group discussion so that the recommendations of parameter selection of similar group learning contexts can be made for teachers.

Throughout the correlation analysis, this study examines how learner indicators from different dimensions before the group work connect to the subsequent group work processes and consequences attributes. Based on the predictive learner indicators, our findings can help teachers with the detection of endangered students and group formation strategies in reading-based learning contexts. Meanwhile, it also contributes to the development of automatic group formation systems in a data-rich environment.

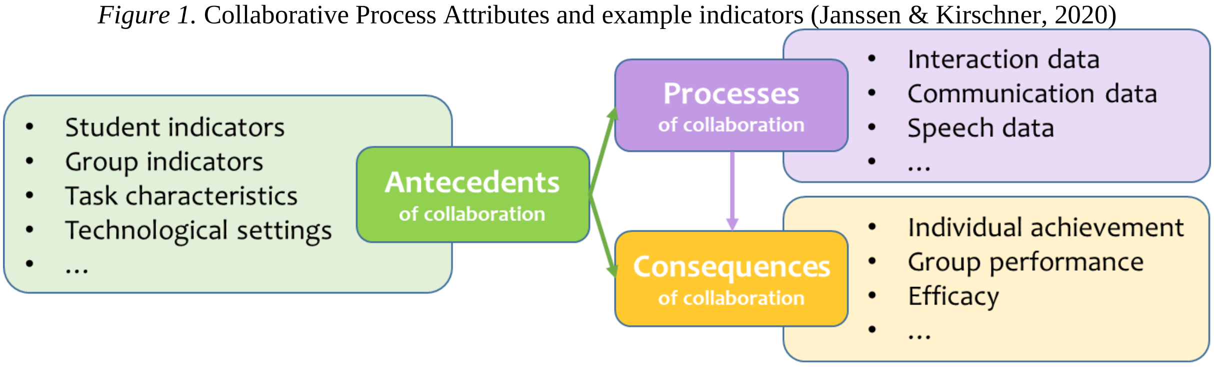
The following sections will first discourse on the research background based on related studies. Then we present correlation analysis based on data from a university reading course to explore the predictive indicators for desirable learning outcomes, followed by the discussion of results and implications for automatic group formation system design and teacher assistance.

2. Research background

2.1. Group work attributes and indicators

When conducting group work in pedagogy contexts, multiple issues should be considered in different stages (Urhahne et al., 2010). To characterize these issues with data, multiple indicators are proposed which reveal certain aspects of group work. Janssen and Kirschner (2020) put forward the concept of Collaborative Process Attributes that depict collaboration in three constructs: antecedents, processes, and consequences (see Figure 1). Indicators of antecedent attributes can pose an effect on processes and consequences of collaboration. However, which antecedent attributes influence the process and consequences of collaboration more was less discussed in previous studies, though it can be not only instructive for system innovation on automatic grouping, but also assist teachers to set groups appropriately with assorted student model data. In a digital learning environment with abundant learning log data, many of these indicators are recorded as learner models that depict the learning characteristics of students (Brusilovsky et al., 2015).

Figure 1. Collaborative Process Attributes and example indicators (Janssen & Kirschner, 2020)



For antecedents of collaboration, Janssen and Kirschner (2020) presented several typical instances based on what it describes. Student and group indicators are frequently-discussed (Saqr et al., 2020) and are prone to vary from group work tasks. Student indicators encompass all domain-specific and domain-independent information and as quantified indicators (Boticki et al., 2019), which can be easily derived from student model attributes under data-driven infrastructures. For example, gender, previous knowledge and task experience, preferences of learning styles, and personalities can be enveloped in the student indicators of group work (Savicki et al., 1996; Abnar et al., 2012; Zheng & Pinkwart, 2014; Sánchez et al., 2021). Group indicators describe characteristics of groups such as group size and intimacy (Amason & Sapienza, 1997; Huckman et al., 2009). Meanwhile, the heterogeneity distribution of student indicators within one group was also highlighted (Xu et al., 2020; Liang et al., 2021), which is closely connected to data-driven algorithmic group formation.

Processes of collaboration are an important part of CSCL research (Strode et al., 2022) since they can offer a holistic picture of the collaborative process that records the evidence during group work. The communication data, no matter in form of oral utterance (Liang et al., 2021) or online forums (Fidalgo-Blanco et al., 2015), assumes widely-used group learning evidence in related studies. Timeline sequence modeling, social network analysis (SNA), and epistemic network analysis (ENA) are conducted to further investigate the interaction data (Fidalgo-Blanco et al., 2015; Hoppe et al., 2021; Kaliisa et al., 2022). Using these interaction data during group work, it is feasible to use machine learning techniques to predict group performance (Cen et al., 2016). However, these data get available only when the current group work has started and the groups have been created.

Consequences of collaboration disclose the outcome of collaborative learning (Janssen & Kirschner, 2020). On the one hand, individual achievement estimates how much one has learned throughout the group work, especially for cognitive skills and knowledge acquisition. On the other hand, group performance is another indicator of collaboration quality, which can include the scores of group presentations and collaboratively composed reports.

Related research investigated the impact of specific student and group indicators in controlled experiments. For instance, previous knowledge and task experience proved to be closely related to group work performance in a collaborative programming context (Rentsch & Klimoski, 2001; Hsu et al., 2021). Similarly, Xu et al. (2020) also found the education level and domain knowledge of users can interactively predict users' knowledge gained in collaborative web searching sessions. In parallel, the heterogeneity of a group also affects the group work performance (Sánchez et al., 2021), and the impact of group heterogeneity can be different depending on the learning context (Liang et al., 2022b).

However, current studies seldom address these indicators from a comprehensive data-driven perspective, and it remains unclear which indicators of antecedent attributes get more predictive of the processes and consequences of collaborative learning in a certain learning context. Under the data-rich group work support system, Liang et al. (2022a) strategized a step to address this issue and provided explainable factors to teachers, while the group-level indicators were not incorporated. As it is significant to consider both student indicators and group indicators simultaneously according to Cress (2008), further studies remain imperative to detect the impact of group compositions.

2.2. Group formation based on student model data

Group formation is important since it can determine the quality of group work (Wessner & Pfister, 2001), and it was also found that collaborative learning with properly formed groups outperforms traditional teaching methods (Kyndt et al., 2013). However, creating collaborative learning groups remains challenging in CSCL studies due to the unfamiliarity of students and time-consuming procedures. Teachers can also get stuck due to little exposure to the CSCL tools in their daily routines. When creating groups, we need to determine three issues: the characteristics of group members, the context of the group work, and the group formation techniques according to Maqtary et al. (2019).

The characteristics of students lay the foundation to perform group formation algorithms. These student characteristics correspond to the antecedent attributes in the previous section and can be acquired in online learning platforms where multiple learning log data are accumulated. In the data-rich environment, student model data makes it possible to take student characteristics into account when creating groups.

The context is important as well since the optimal settings of group formation can differ from the purpose and traits of group work activity. For example, learning with peer help calls for heterogeneity of knowledge level, while homogeneous groups perform better in situations that encourage interaction and familiarity of group mates.

Based on different student model data and purposes, manifold techniques were employed for learning group creation. Clustering techniques underpinned by distance measurements are used for homogeneous groupings, such as the K-means algorithm that puts students in the same cluster together in the mobile learning context (Maqtary et al., 2019). In cases where students created abundant learner-generated content, the semantic method can group students (Isotani et al., 2009) based on textual features in terms of knowledge diversity, textual similarity as well as a semantic network of learner's interaction texts (Yoshida et al., 2023). It is hard to express the heterogeneity of groups under the semantic matchmakers in comparable values (Konert et al., 2014).

To deal with group formation from multiple student attributes, Moreno et al. (2012) put forward a genetic algorithm (GA) that can generate different group compositions (heterogeneous or homogeneous) in light of the calculated fitness values. The fitness values can be estimated by distance measures of vectors such as the sum of the squared differences (Moreno et al., 2012), which can reflect the heterogeneity of the student characteristics. In this way, homogeneous groups consisting of similar group members, or heterogeneous groups with dissimilar group members can be determined. The genetic algorithm presents flexibility owing to the fitness functions that can be adjusted to meet various grouping purposes and accommodate assorted input variables as was discussed in Flanagan et al. (2021) and Revelo et al. (2021). Liang et al. (2021) presented a group formation system that enables student models from different data sources underpinned by genetic algorithms and LEAF infrastructure (Flanagan & Ogata, 2017; Ogata et al., 2023) that aggregates multiple learning logs.

GroupAL is another relative project for group formation using a similar technique of vector optimization as GA (Konert et al., 2014). The GroupAL algorithm also provides flexible settings of parameters and criteria (heterogeneous or homogeneous) to meet different learning scenarios. Similar to the fitness function in GA, the optimal group allocation also relies on the defined metrics that depict the distance among participants and pairwise disjoint groups. However, without multiple iterations implemented in GA, GroupAL assigns

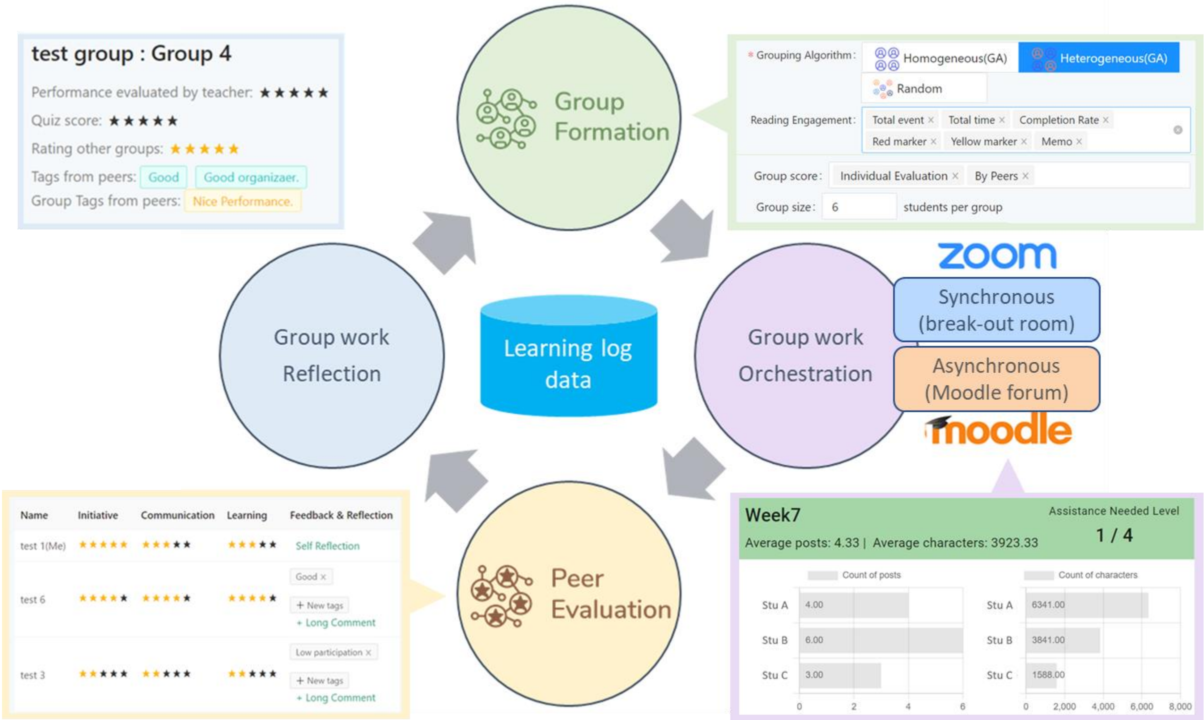
participants to learning groups only once. Under the same criteria and parameter settings, both GroupAL and GA can make different cohorts of groups since both approaches start from a randomized group allocation. Further, there were efforts of data integration to derive data from e-learning systems such as MoodlePeers as extensions of the GroupAL project (Konert et al., 2016).
In previous studies, the impact of algorithmic group formation using several student model indicators with heterogeneous or homogeneous compositions were investigated. However, which indicators play a more significant role to elicit desirable outcomes still deserve further inspection.

2.3. Continuous data-driven environment for group work conduction

The division of antecedents, processes, and consequences is not absolute since the previous learning logs reflecting the processes and consequences of collaboration can be employed as antecedents in the next round of group work. Group Learning Orchestration Based on Evidence (GLOBE) presents a data-driven environment (Liang et al., 2021) that enables such data re-usage. It also integrates group work-related learning logs from different sources to scaffold group work, hence suggesting further opportunities to explore the relationships among indicators of group work.

GLOBE utilizes data from Learning and Evidence Analytics Framework (LEAF), an overall technical framework integrating research and production systems to support learning analytic research as well as AI-driven services for effective teaching-learning (Ogata et al., 2023). The data covers learning records from learning management systems (LMS) such as Moodle, and reading interaction logs from learning material distribution platform BookRoll (Ogata et al., 2015).

Figure 2. GLOBE framework with continuous data-driven modules (Liang et al., 2021)



As illustrated in Figure 2, data-driven support consists of four phases: group formation, orchestration, evaluation, and reflection. An algorithmic group formation system, a forum discussion dashboard, and a peer evaluation system actuate the GLOBE framework utilizing the learning logs. In the group formation phase, teachers can create groups using multiple indicators, which play the roles of antecedents of collaboration. Then in the orchestration phase, the teacher can check the group work process in the dashboard and give timely interventions. For evaluation, both the teacher and students can give ratings in the evaluation module and check real-time feedback for reflection.

Table 1 lists the current indicators used in GLOBE with its pedagogical implications (the proxy for construct) in related studies. These indicators can be divided into several categories. Reading attributes from BookRoll reading logs (Ogata et al., 2015) can reflect learning engagement and also active reading behaviors (Toyokawa et al., 2021). These reading engagement data can also predict individual learning outcomes (Junco & Clem, 2015; Chen et al. 2021; Yang et al., 2021). Forum attributes talk about the interaction aspects in online group work, which covers passive participation with only view behaviors and positive participation indicated by post behaviors (Fidalgo-Blanco et al., 2015). The ratings from teachers and peers assess the performance of the group presentation and participation within each group, which also suggest the experience of collaborative learning as indicators of subsequent activities (Liang et al., 2022). Finally, the scores from external sources such as test scores and final course grades uploaded to the learning management systems (LMS) are of equal significance as an estimation of the individual learning outcome.

Table 1. Group work indicators in GLOBE systems

Indicators in GLOBE	Description	Collaborative process attributes	Data source	Proxy for construct (what does it convey)
*Reading time	Total time spent on the e-book reader	Antecedent	BookRoll	Reading engagement that can predict learning achievement and academic performance (Junco & Clem, 2015; Chen et al., 2021; Yang et al., 2021)
*Operation times	Total number of operation times in the e-book reader (e.g., flipping page)	Antecedent	BookRoll	
*Completion rate	Percentage of completion of the reading material	Antecedent	BookRoll	
*Red markers	Number of annotations of important parts in the reading material	Antecedent	BookRoll	Active reading skills (Khusniyah & Lustyantie, 2017; Toyokawa et al., 2021)
*Yellow markers	Number of annotations of difficult parts in the reading material	Antecedent	BookRoll	
*Memos	Number of memos in the reading material	Antecedent	BookRoll	
Forum views	Times of views in the forum	Process	Moodle forum	Engagement and active interactions (Fidalgo-Blanco et al., 2015)
Forum posts	Number of posting messages in the forum	Process	Moodle forum	
Forum characters	Number of characters in all the forum posts	Process	Moodle forum	
*Teacher's ratings	Teacher's rating scores of the group presentation	Antecedent & Consequence	Evaluation module	Group work experience and task experience
*Peer ratings (individual)	Peer rating scores of group members within the group	Antecedent & Consequence	GLOBE	
*Peer ratings (group)	Peer rating scores of presentations from other groups	Antecedent & Consequence	GLOBE	
Course scores	Test/quiz scores and final grades that reflect the learning outcome	Antecedent & Consequence	LMS	Academic performance and learning outcome

Note. *Heterogeneity of this indicator as an antecedent attribute within a group can be calculated by the squared differences (Flanagan et al., 2021) as a group-level indicator.

3. Method

To investigate the impact of each antecedent attribute, we run correlation analysis using an online reading course under the LEAF and GLOBE infrastructure. The study aims to detect the relationship between the antecedent attributes and that in the subsequent phases (processes and consequences), which can be utilized to assist teachers to create groups with a recommendation of optimal group formation settings.

We conducted a single group study with a pulled-in dataset of one university course. During the weekly learning activities in the online learning platforms, their Collaborative Process Attributes were anonymously recorded in the data repository of GLOBE. This study aims to find optimal predictors for desirable group work by analyzing the correlation of the antecedents with processes and consequences attributes of collaboration. The overarching research questions of this study are as follows:

- RQ1: What are the associations among individual-level indicators in different Collaborative Process Attributes?
- RQ2: What are the associations among group-level indicators in different Collaborative Process Attributes?

3.1. Research context and participants

The dataset came from a university course “Readings in Humanities and Social Sciences: Education Technology and AI” in Japan in the academic year 2022. On completing this course, students should understand the structure and expressions in academic articles. The course also allowed students to improve their English reading and presentation skills. Weekly reading and group work activities were implemented under the LEAF and GLOBE infrastructure. The course collected abundant data on Collaborative Process Attributes, thus producing enough data samples from real-world settings with routine practices. Hence it holds generalizability (Maissenhaelter et al., 2018) and convenience for extraction of evidence in further analysis (Kuromiya et al., 2020). Thirty-two (32) students registered for the course at the beginning, with 7 students withdrawing midway. 25 students finished the whole course and got a final course grade. 19 students came from the Faculty of Engineering, 3 students came from the Faculty of Integrated Human Study, and the remaining 3 students majored in Pharmacy, Economics, and Science respectively. There were 17 sophomores, 5 junior students, and 3 senior students among the participants.

In this course, group work was conducted several times from week 3 to week 11 across the 15-week semester. Following the GLOBE framework, students were grouped five times by the group formation system (Liang et al., 2021) across the course with different group formation indicators for different academic reading topics (see Table 2).

Figure 3. Workflow of the weekly activity implemented in the course

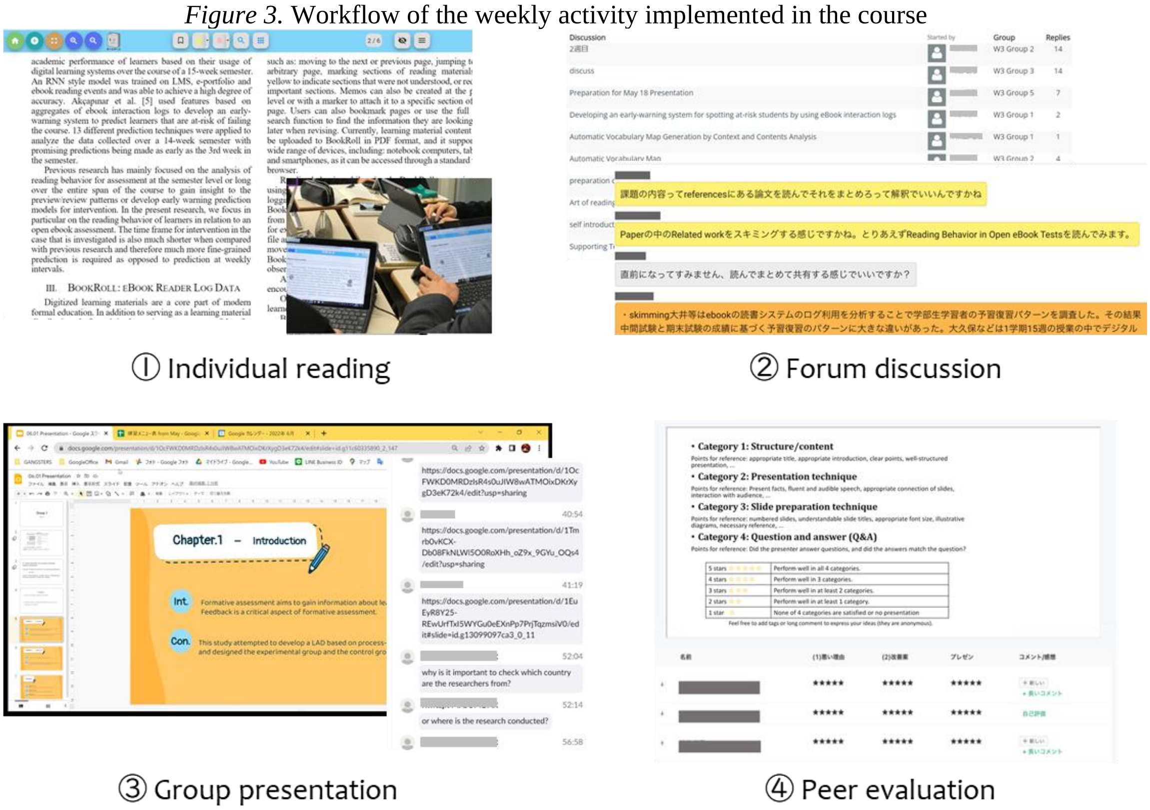


Figure 3 shows the workflow of the weekly activity implemented in the course. For each week, students were required to read several articles on BookRoll, an e-book reading system (Ogata et al., 2015) that can automatically collect learning data. Then, they should share and discuss their reading progress with their group members in the Moodle forum and prepare a brief presentation as a group for the next offline class. During the class, each group made presentations, which were peer-evaluated by the audience (both the instructor and students) in the classroom in the evaluation systems (Liang et al., 2021). In the meantime, asked to make peer ratings on the initiative and communication of their group mates in the peer evaluation system for each week as well.

Table 2. Group formation and group work topics in the course

	Input attributes	Group work topic	# of students	# of groups
Week 3-4	Reading engagement	Fast overview & reading strategy	32	6
Week 5-7	Reading engagement & previous group ratings and peer ratings	Related work & review design	32	5
Week 8-9	Reading engagement	Keywords & systematic survey	25	5
Week 10	Reading engagement & previous group ratings and peer ratings	Using group graphs	26	4
Week 11	Reading engagement & previous group ratings and peer ratings	Using group graphs & self-directed learning tools	26	4

3.2. Data collection

The data of 8 group work in 5 group compositions were pulled in for analysis since all of the group work followed the same procedure and identical rating rubrics. The individual indicators of antecedent attributes and process attributes were standardized into the range of 0 to 1 for the group formation input. For group-level indicators, antecedent attributes were estimated by the squared differences (Flanagan et al., 2021) as heterogeneity, and average scores were calculated for some process and consequence attributes (forum posts, forum characters, peer ratings of initiative, and peer ratings of communication). Table 3 summarizes all these indicators involved in the study.

Table 3. Indicators used in this study

Indicator	*N*	Mean	Max	Min
Antecedents				
Reading time	199	0.658	1	0.08
Operation times	199	0.653	1	0.06
Completion rate	199	0.483	0.65	0.05
Red markers	199	0.532	1	0
Yellow markers	199	0.551	1	0
Memos	199	0.384	1	0
*Heterogeneity of reading time	46	0.250	0.461	0.078
*Heterogeneity of operation times	46	0.239	0.409	0.035
*Heterogeneity of completion rate	46	0.123	0.218	0
*Heterogeneity of red markers	46	0.347	0.489	0.078
*Heterogeneity of yellow markers	46	0.335	0.526	0.064
*Heterogeneity of memos	46	0.388	0.509	0
Previous teacher’s ratings	121	0.876	1	0.6
Previous peer ratings (individual)	109	0.738	1	0.2
Previous peer ratings (group)	121	0.786	0.9	0.629
*Heterogeneity of previous teacher’s ratings	26	0.098	0.121	0.031
*Heterogeneity of previous peer ratings (individual)	26	0.243	0.312	0.076
*Heterogeneity of previous peer ratings (group)	26	0.091	0.132	0.017
Processes				
Forum posts	114	0.301	0.99	0
Forum characters	114	0.353	0.99	0
Consequences				
*Teacher’s ratings	46	4.413	5	3
Peer ratings of initiative	199	3.658	5	0.5
Peer ratings of communication	199	3.461	5	1
*Peer ratings (group)	46	4.055	4.667	2.857
Final course grades	25	69.8	100	30

Note. *Group-level indicators.

3.3. Data analysis

We used correlation analysis and calculated the Pearson correlation coefficient for each pair of antecedent-process and antecedent-consequence. To deal with missing values (e.g., in weeks 3-4 and 8-9, previous group ratings and peer ratings as antecedent attributes were not used for group formation), we exclude cases pairwise before the analysis.

According to the research questions, we investigate two levels of indicators in this study. For individual-level indicators, we inspect the correlation among values. Positive relations denote that the higher score of an indicator one possesses, the more predictive of the desired learning outcome this indicator can be, and vice versa. Insignificant correlation means low predictive power in this learning context.

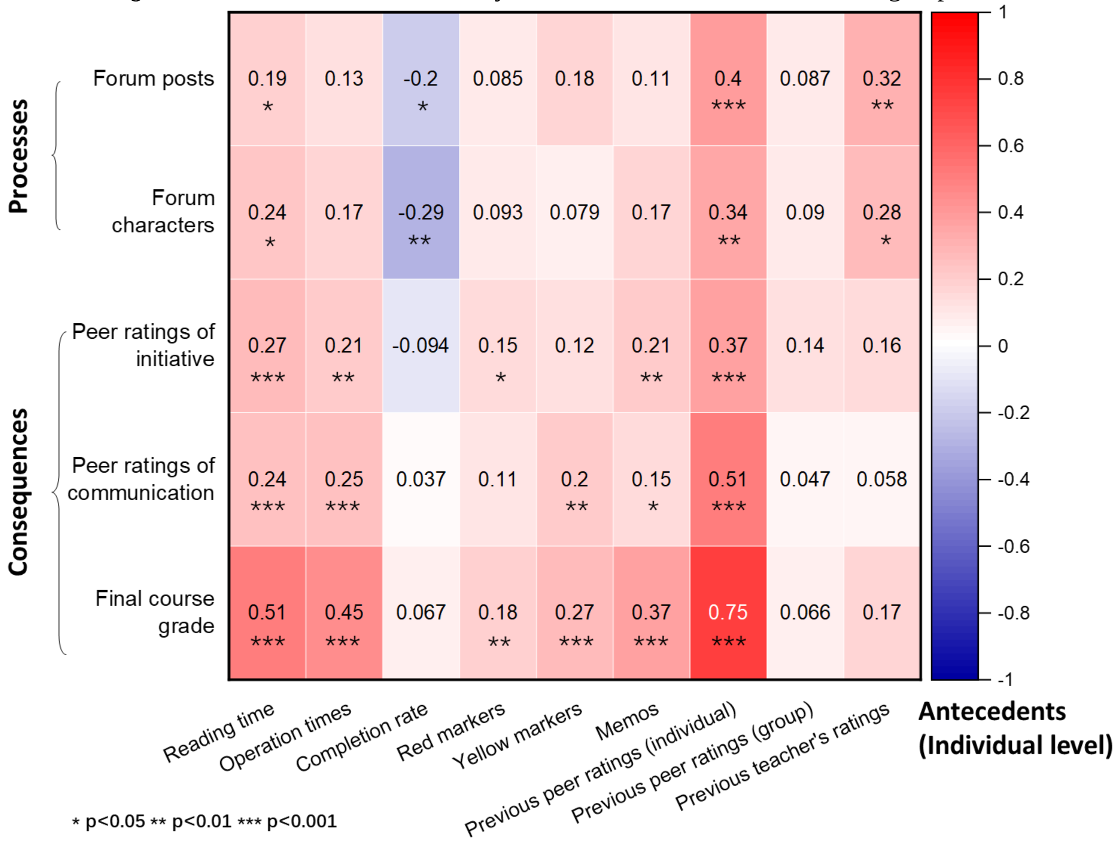
For group-level indicators, we examined their correlations with the group-level indicators of processes and consequences attributes that were calculated by aggregation of each group. The heterogeneity of each indicator as an antecedent attribute within a group is calculated by the squared differences, which are also used in the group formation algorithm to measure the heterogeneity of each group as the fitness function (Flanagan et al., 2021). As for the indicator of heterogeneity, the positive relation coefficient suggests the more heterogeneous the values of a certain indicator within a group, the better performance this group will have. On the contrary, negative correlations connote the more homogeneous the values of a certain indicator in a group, the more desirable the group-level outcome will be.

4. Results

4.1. Individual-level indicators

Figure 4 is the correlation diagram of individual-level indicators. As can be seen in the diagram, reading time and previous peer ratings for individuals show significant positive associations to all processes and consequences attributes. The association between previous peer ratings for individual and final course grades is strong (> 0.7). Operation times and the number of memos have significant positive correlations to all three consequence attributes, but their associations to process attributes are not found. Conversely, previous teachers' ratings of group work are related to the individual performance of two processes attributes, but not associated with all individual-level consequence scores. Both red markers and yellow markers take close relations to the final course grade. In addition, red markers show a weak significant association with initiative scores of peer ratings while yellow markers are weakly associated with communication scores of peer ratings. The completion rate connotes a weak adverse connection to the process attributes of forum utterance in this study and no significant correlation with all three consequence attributes. Meanwhile, previous peer ratings of group presentations indicate no significant relationship to any individual-level indicators.

Figure 4. Results of correlation analysis of individual-level indicators of group work

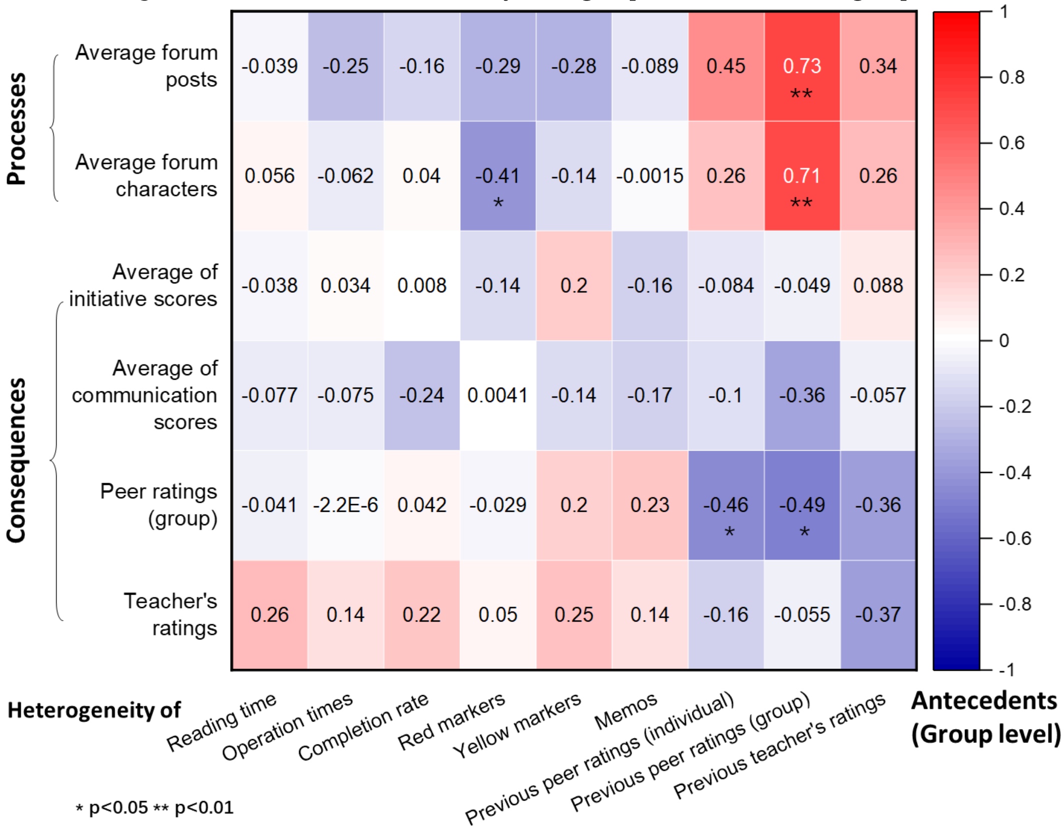


4.2. Group level indicators

Figure 5 illustrates the results of correlation analysis for group-level indicators. As a result, positive and strong associations are found between (1) heterogeneity of previous peer ratings (group) and average forum posts and (2) heterogeneity of peer ratings (group) and average forum characters. This means that the heterogeneous composition of these antecedent attributes can contribute to the performance of the group work processes.

Negative correlations are revealed between (1) heterogeneity of red markers and average forum characters, (2) heterogeneity of previous peer ratings (individual) and the peer ratings received of the current group presentation, and (3) heterogeneity of previous peer ratings (group) and the peer ratings received of the current group presentation. These three correlations are moderate. This denotes the potential of the homogeneous composition on these antecedent attributes to scaffold the performance of the group work processes. Apart from the former results, all other correlations are insignificant in statistics.

Figure 5. Results of correlation analysis of group-level indicators of group work



5. Discussion

5.1. Individual-level indicators and individual performance

Compared to the previous study, most correlations in this study remain the same with Liang et al. (2022a). The reading time and previous peer ratings received are still the most predictive indicators that suggest a significant positive correlation with all processes attributes of forum engagement and consequences attributes of peer ratings as well as the final course grade. These results are also in accord with Junco and Clem (2015) and Chen et al. (2021) that found reading time is predictive of the individual learning outcome. The active reading indicators such as memos and markers are also positively associated with desirable learning consequences as Yang et al. (2021) presented. In parallel, the reliability of peer ratings under the peer evaluation system can be approved as well, suggesting that students of the online university course can give a fair assessment to their peers based on rubrics. However, the completion rate showed an adverse association with the forum engagement indicators. This can be caused by the pull-in operation when we aggregate data. Since this study used all data from the course, the overall completion rate got lower due to the abundant reading materials as can be seen in the descriptive statistics in Table 3.

We can also find that, as for previous peer ratings and the teacher's ratings of group presentations, the predictive power is relatively low in that only the teacher's ratings of group presentations have a weak correlation to the forum engagement indicators. Since these two ratings are group-level assessments of previous group work, their reliability can be reduced by social loafing and free riding (Forsell et al., 2020), which can elicit less predictive power when modeling each individual using such scores. Apart from this, it also shows the necessity for analysis of group-level indicators as was mentioned by Cress (2008).

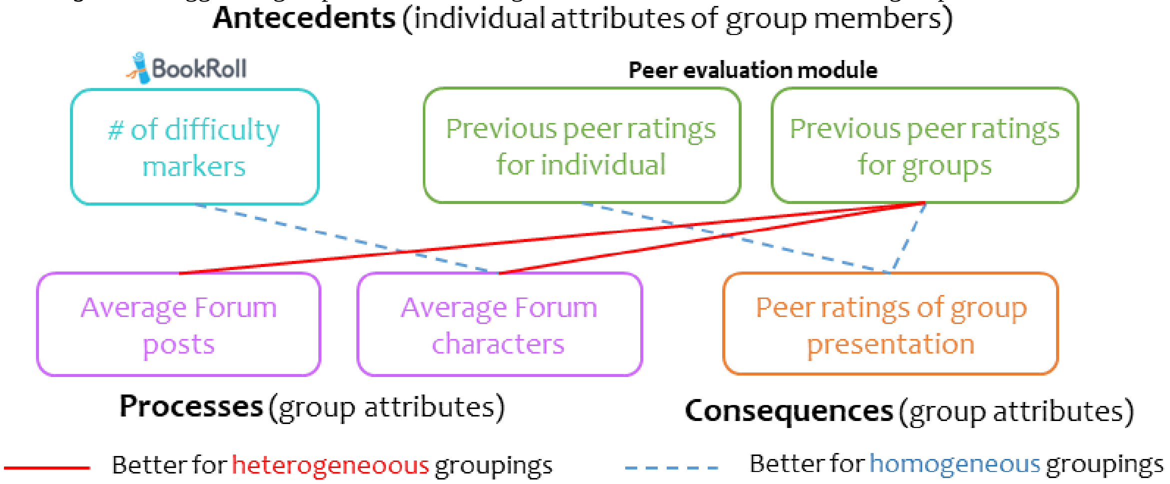
In sum, in the context of reading-based group work, the reading engagement attributes and peer ratings received in previous group work that indicates group work experience are closely connected to the individual performance of subsequent forum discussions and learning outcomes, which can guide group formation settings and intervention suggestions in the similar context such as language learning and academic reading. In parallel, from the participation of reading and previous group work performance, teachers can take timely measures to help these endangered students predicted by the GLOBE system (Liang et al., 2022b).

5.2. Group level indicators on group work performance

The group-level analysis focuses on the heterogeneity of each antecedent attribute within each group and aims to explore group dynamics. First, the average forum engagement of a group indicated by posts and characters is strongly positively correlated with its heterogeneity of previous group performance rated by peers. While no correlation was detected at the individual level between these two indicators. These findings support the strategy to heterogeneously group students so that we can guarantee that at least one outperforming student with desirable previous group work experience is assigned to each group, thus avoiding absolute silence in groups with all underperforming students. Such a positive effect of heterogeneous strategy on previous performance indicators agrees with group work in the classroom scenario as well (Liang et al., 2022).

As for annotation data that indicate the records of active reading strategy, we found the groups with more homogeneous red markers indicating highlights tend to have more forum discussions, though for individuals more markers did not indicate more posts. As an indicator of active reading engagement, the effect of grouping students with homogeneous engagement levels agrees with the other research on online courses and MOOCs (Abou-Khalil & Ogata, 2021; Sánchez et al., 2021), which can be explained by reduced social loafing for lack of proactive students to count on (Wichmann et al., 2016). Furthermore, the homogeneous grouping can be more promising when considering the annotated contents, since students with common annotations can show joint interest that can facilitate the interaction of the participants (Toyokawa et al., 2021).

Figure 6. Suggested group formation strategies based on correlations between group-level attributes



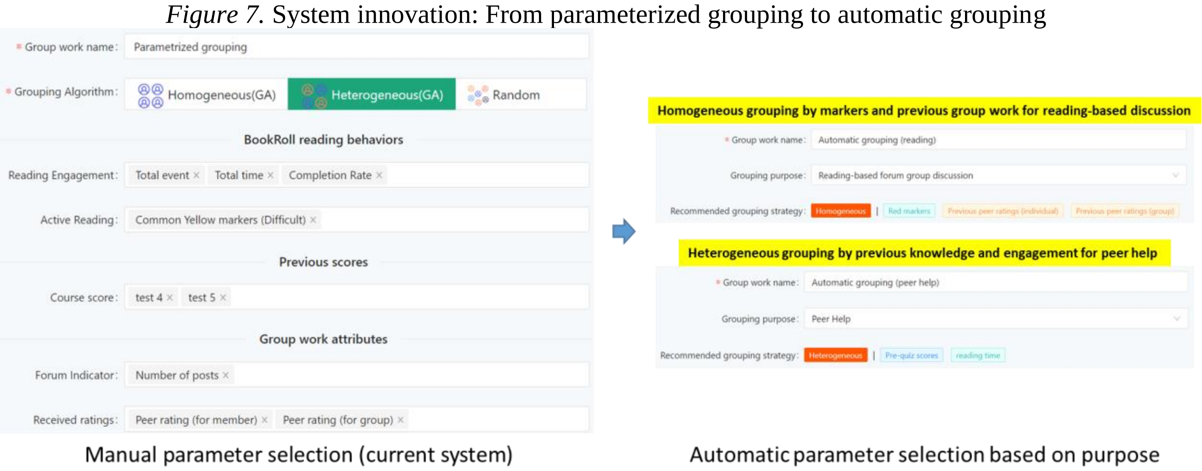
Another finding that deserves our attention is that the heterogeneity of previous ratings, both for individuals and groups, are of moderate negative related to the peer rating scores of the final group presentation. The result denotes that though a group with heterogeneity in the previous group experience tends to have more discussion and engagement when it comes to the cooperative for a group-level output, it can become hard to reach a consensus, thus resulting in undesirable performance on group presentations. The heterogeneous groups with unbalanced knowledge of the task encourage peer help that facilitates individual achievement (Kanika et al., 2022), but it may not contribute to the cooperation and synergistic output of a group. To figure out the reason, further analysis of forum discussions is required to investigate the relationship between processes and consequences indicators of group work in the orchestration phase of GLOBE.

According to our primary analysis (see Figure 6), we have identified appropriate group formation strategies for teacher assistance in the data-driven environment of LEAF. A homogeneous grouping strategy, considering the number of difficulty markers and previous peer ratings, has the potential to enhance the number of forum characters and peer ratings of group presentation. This finding provides guidance for subsequent group formation in the context of active reading-based group work. On the other hand, heterogeneous grouping based on previous peer ratings for groups can facilitate more detailed forum discussions with more characters in forum posts. This strategy can be useful for online courses where online reading and forum discussion are closely connected.

5.3. Automatic group formation with optimal indicators to assist teachers

For technical implications, the research provides supportive evidence for the innovation of the current group formation system. Although we only addressed reading-based group discussions herein, similar research on other contexts can be done in the same way under the GLOBE framework. As is shown in Figure 7, teachers have to manually choose multiple indicators when creating groups currently. With the accumulation of evidence from studies on the predictive antecedent in different learning contexts, the strengthened system can automatically select input parameters based on the selected learning purpose and context in the future. For example, homogeneous algorithms with red markers and previous peer ratings are suggested based on the results of this study, as they are associated with better group performance. Conversely, in contexts that underscore individual learning with peer help design, heterogeneous groups with reading engagement and test scores that indicate previous knowledge are recommended in the automatic grouping according to Liang et al. (2021) and Liang et al. (2022b).

Figure 7. System innovation: From parameterized grouping to automatic grouping



For pedagogical implications, a pivotal goal of this study is to help teachers to determine the optimal group formation indicators in data-driven digital systems. This study discloses predictive antecedent indicators to the performance of subsequent group work in a forum-supported academic reading course, which can guide teachers in similar contexts. The automatic group formation function will further release teachers from selecting assorted variables in the system and reduce the time for creating groups. Further studies to examine the effectiveness of the automatic grouping will become necessary then.

5.4. Limitations

The indicators incorporated in this study are still limited. Under the data-driven platforms, most of the indicators are from learner models that reflect learning-related characteristics, but the social-emotional indicators are less addressed in the current systems. These issues should also be addressed by uploaded scores and social network data as quantitative input for group formation. However, how to incorporate these data with different granularity and formats into the group formation algorithm remains unclear, and deserves future investigation. In parallel, the objective behavior data of previous group work was not used as the antecedent for the next round following the continuous data flow, which may reduce the reliability of previous group work performance indicators.

Meanwhile, though we got a larger sample size using pulled-in data of all group work throughout a semester in a university course compared to the previous study (Liang et al., 2022a), the learning context is confined to reading-based tasks with asynchronous forum discussions. Hence the predictive indicators in other learning conditions and cultures can vary. Therefore, the results of the current study need further validation in other learning scenarios.

6. Conclusion and future work

In conclusion, this study investigated the connections between antecedent attributes and the processes/consequences of group work in an asynchronous online reading course. We considered both individual-level and group-level indicators in the correlation analysis and found predictive indicators for algorithmic group formation. The reading engagement and previous peer ratings can reveal individual achievement of the group work, and a homogeneous grouping strategy based on reading annotations and previous group work experience can predict desirable group performance for this learning context. This study also provides avenues for future research to find predictive indicators in more learning contexts, and in turn, orchestrate an automatic group formation system that can mitigate teachers' trivial work from manual grouping. Meanwhile, how to make the antecedent indicators of groups created by algorithms explainable to teachers with adequate illustrations also deserves further consideration.

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