Analysing Peer Assessment Interactions and Their Temporal Dynamics Using a Graphlet-Based Method

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Abstract. Engaging students in peer assessment is an innovative assessment process which has a positive impact on students learning experience. However, the adoption of peer assessment can be slow and uncomfortably experienced by students. Moreover, peer assessment can be prone to several biases. In this paper, we argue that the analysis of peer assessment interactions and phenomena can benefit from the social network analysis domain. We applied a graphlet-based method to a dataset collected during in-class courses integrating a peer assessment platform. This allowed for the interpretation of networking structures shaping the peer assessment interactions, leading for the description of consequent peer assessment roles and their temporal dynamics. Results showed that students develop a positive tendency towards adopting the peer assessment process, and engage gradually with well-balanced roles, even though, initially they choose mostly to be assessed by teachers and more likely by peers they know. This study contributes to research insights into peer assessment learning analytics, and motivates future work to scaffold peer learning in similar contexts.

Keywords: Peer Assessment, Temporal Networks, Graphlets.

1 Introduction

Peer assessment has emerged as a peer learning approach, which is an important research topic in education [15]. It has been presented as part of the concept of peer tutoring [27] or peer education [7], which is a specific form of student's engagement, having a powerful impact on active student participation [15].

A key way to bring learning and teaching together by engaging students in peer learning is through the assessment process [14]. Assessment used with students has been argued to have a significant impact on what, how and how much students study [13] and is therefore an essential element in the learning and teaching process. Bringing students into interactive learning and peer feedback around assessment activities is a good way for students to identify the strengthens and weaknesses of their work [30]. Allowing students to develop their own assessment activities is suggested as an innovative assessment practice enhancing tutor experience [2]. More importantly, engaging students in peer assessment has a positive impact on students learning experience, and helps improvement of performance [2]. Despite prior work in this field, the intrinsic mechanisms and temporal dynamics of peer interactions that drive peer assessment in hybrid classes remain understudied. A few online tools exist for supporting peer assessment [35], and support for transparent and meaningful peer assessment learning analytics is lacking [9]. For instance, such learning analytics may allow for reliability check of assessment [9].

This paper aims to provide insights on how students engage in peer assessment and address the following main questions: 1) How peer assessment interactions occur ? 2) What are the consequent student roles regarding the peer assessment process ? 3) How the student assessment roles evolve temporally ? To this end, we applied a graphlet-based method, a meaningful and expressive network analysis approach, to a dataset collected across seven in-class courses integrating an online peer assessment platform called Sqily. This method allowed for the description of peer assessment roles students engage with, as well as their temporal dynamics, leading to a more understanding on how students involve in peer assessment.

In the following sections, we first present a state of research and practical issues in peer assessment. We describe the peer learning platform we used and how it implements peer assessment (Sqily). We also introduce the graphlet concept in the domain of Social Network Analysis. We then describe the graphlet-based method we adopt to analyse peer assessment interactions, and detect student roles and their temporal dynamics. We report our observations, and finally we discuss our contributions and pedagogical implications of this work.

2 Background

2.1 Peer Assessment Findings

Peer assessment is seen as a powerful tool to achieve evaluation of complex students' assignments at a large scale, as in the context of Massive Open Online Courses (MOOCs) [6], [20]. Scalability in the evaluation is achieved since peer feedback is available in greater volume and with greater immediacy than teacher feedback [34]. It is also assumed that peer assessment is most generally formative, with the intent to make students help each other plan their learning, identify their strengths and weaknesses, target areas for remedial actions, and develop metacognitive, personal and professional skills [34].

This may seem to be an enriching system, but peer assessment evaluations can be prone to many biases. As it is reported in [35], biases for students can include inexperience in grading, but also friendship between peers [8], which implies rating friends favourably and making pacts with others [21]. A recent study [11] revealed that friendship-based favouritism in peer judgements was one of the most frequently cited by students, as posing a barrier for improvement, and so, a negative aspect of peer assessment. This is closely related to the problem of reliability and validity of students' peer assessment, which is one of the major concerns for both educators and researchers, that is rising in the literature, and which is mostly dealing with peer grading. For example, [5] found that when students are given guidance on peer assessment, they take the grading tasks seriously and their results are highly reliable and as valid as instructors' assessments. Other studies [35], [17], [33] indicated that peer assessment is of adequate reliability and validity compared to instructor or teacher assessments, when the process is carefully prepared and conducted.

It has also been expressed that peer assessment is a time-intensive process, as it requires students to engage in intellectually challenging tasks, and that students can feel socially uncomfortable [24]. The process of peer assessment may also take time before being adopted by students. It was reported that students, especially in the initial stages of peer assessment, are often critical of their peers' ability in assessing their work [1]. However, it was observed that although students have doubts and initially tend to resist being involved in peer assessment, such resistance subsides over time [1].

2.2 Peer Assessment Using the Platform Sqily

One of the objectives of Sqily [26] is to draw benefit from the peer assessment approach, by providing peer feedback (comments, documentation, ...) and certifying learning skills. Sqily also facilitates interactions between peers, by providing tools for sharing learning contents and engaging discussions. The platform enables to define a set of skills that can be certified by completing related assessment activities. An assessment activity can be an open question or an exercise created by a teacher or a peer. The creator of the activity, based on his or her own expertise and his own scoring, decides whether or not to validate the associated skill for another peer. A skill refers to a knowledge, a know-how or an ability. Each skill is added to the platform by a teacher or a peer who masters the related competency. Each learner refers to the platform, to acquire a new skill by interacting directly with the teacher or the tutor who acts as a teacher for that skill. Once a learner gets an activity certified, he can himself tutor other peers.

In the context of a classroom, this enables organising topics, or skills, to be learned as a tree of learning objectives' sequences. A learner progression is explicit, and interactions between peers are organised around skills through an assessment process. The learner is invited to progress in a learning path which is not imposed, since students can choose their own sequencing to certify skills (Fig. 1). Initially, the learning path is set by a teacher, but can be extended by

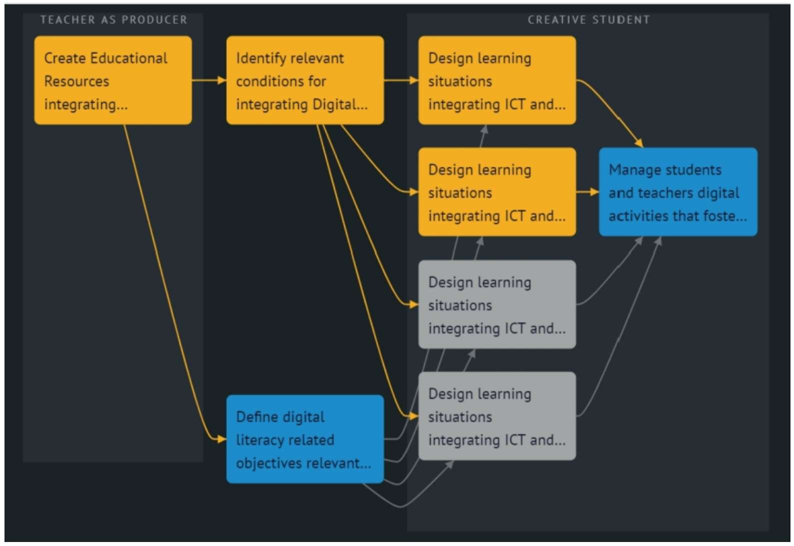


Fig. 1. A learning path in the Sqily platform: the skills coloured in yellow, blue and grey are respectively skills that have been certified, skills that are being certified, and skills that are not yet certified.

the learners, i.e. learners are assessed either by teachers or peers, according to the activities they choose.

The objective of peer assessment using the platform Sqily is to encourage the learner to adopt a peer tutoring approach: he must mobilise his newly acquired skills in order to explain them and help other students acquiring them. Thus, the learner puts himself into the role traditionally assigned to the teacher and deepens his skills [29]. In summary, students are encouraged to design their own assessment activities, ask for assessments to acquire new skills or give assessments and feedback on skills they master. Around assessment activities, students will alternatively assume both tutor (assessor) and tutee (assessed) roles.

2.3 Graphlet in the Social Network Domain and Potential for Peer Assessment Analysis

Since peer assessment involves social interactions and provides networking data, it is very worthy to look for the opportunities the domain of Social Network Analysis (SNA) may provide to analyse peer learning interactions. In fact, SNA is already known to be powerful at describing and analysing interaction behaviours in the field of learning analytics. SNA has mostly been applied to analyse student discussions in forums, a systematic review of literature covers more than 30 studies that analyse patterns of student discussions [3]. For example, the study [31] exhibits popular students who provide comments to others, who are reflectors and good communicators in the learning process. Graphlets have also potential to provide an automatic way to detect relevant, sometimes, non-obvious configurations of interaction inside complex networks [23]. By counting the positions in which the nodes appear (position enumeration), the graphlets offer a way to compare their topological role inside a social network. A previous study on the Sqily platform data [4] showed the relevance of the graphlet-based approach to detect roles. However, the limited number of graphlets used did not allow to differentiate the behaviors of students and teachers and thus to highlight statistically significant changes in behavior.

A social network, represented as an undirected or directed graph, consists, minimally, of a set of nodes (also referred to as vertices) representing social actors and a set of arcs (edges or ties) between pairs of nodes, representing social relations between actors [12]. Recently in the network analysis domain, methods that explicitly look at the connections between nodes inside subgraphs, called graphlets or motifs, have emerged [23]. Graphlets have been used in many tasks such as network comparison, link prediction, and network clustering, mainly in the computational biology domain (biological networks) [32, 25]. On a more global perspective, graphlets have shown to be able to classify superfamilies of networks [22, 37]. Graphlets are a collection of subgraphs representing all possible configurations of interconnection between a small number of k nodes, usually k is set to three in the case of a directed graph. Triadic configurations (directed graphlets with 3 nodes) represent a fundamental tool for social network theories and methodologies [16, 12, 36].

Fig. 2 illustrates the process by which positions are enumerated in a directed graph. In this example, position enumeration is completed by visiting an initial complex graph (social network), to determine all the constitutive subgraphs of 3 nodes, classify the isomorphic ones and determine and count the nodes having equivalent positions. Each class defines a new graphlet, which is distinguished by the way the nodes are connected each other. We can also know for each graphlet, the number of its occurrences which is given by the count of isomorphic subgraphs defining the graphlet. An isomorphism between two subgraphs means that the subgraphs have the same number of nodes and are connected in the same way. In other words, if the two subgraphs were drawn, then we would only have to highlight their nodes, and keep the direction of connection between the nodes to get the exact copies (Fig. 2, (c)). Depicting the nodes inside each graphlet allows highlighting equivalent positions of nodes within a graphlet (Fig. 2, (d), (e)).

3 Method

Our work aims to examine interactions between students, that occur during peer assessment on the Sqily platform. We first consider the student interactions within the same time baseline, then we vectorise the student peer interactions, on the basis of their topological positions within graphlets (Question 1). To obtain student distinct roles, we applied a clustering over the aggregated vectors

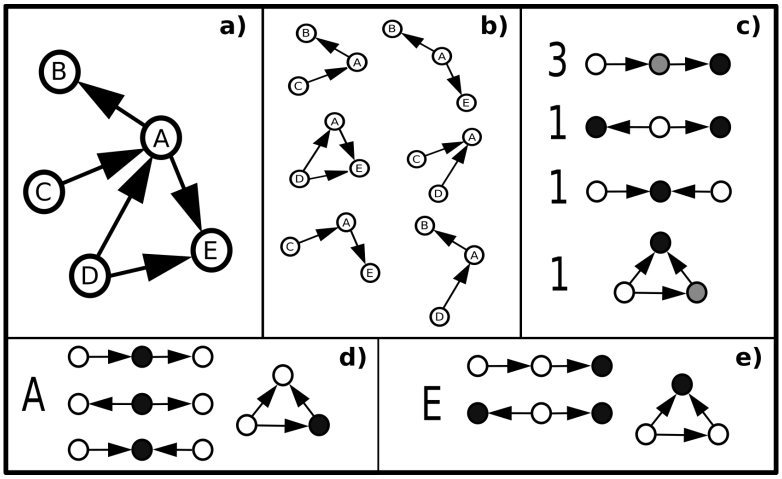


Fig. 2. Example illustrating the position enumeration process: a) initial directed graph; b) constitutive subgraphs of 3 nodes; c) classes of isomorphic subgraphs expressing the resulting graphlets, positions of nodes are depicted in shades of grey; d) node "A" in four positions; e) node "E" in 3 positions. Note that node "E" appears once in the same position as another node, hence the depicting of 4 nodes.

(Question 2), and finally we applied a likelihood metric to investigate relationships between two consecutive temporally unfolding roles (Question 3).

3.1 Context

The study was situated in seven courses that took place in a classroom using the Sqily platform in HEP Vaud (Lausanne, Switzerland), a higher education school that offers a university-level training to future teachers and educators. The courses were about the fields of mathematics, integration of ICT in teaching, web exploration and documentation, as well as images and media in teaching. Each of the courses involved different amounts of students rising from 11 to 171 students per course, and up to 7 teachers per course (this distribution is specific to the training program and the courses). Each course contains different assessment activities designed either by teachers or peers. To get involved in a peer assessment process, students are invited to certify exiting skills or to create their own assessment activities in the platform. Teachers are creators of skills and assessment activities, assessors and facilitators. Table 1 shows for each course, the proportions of assessment activities that have been created by peers in the platform.

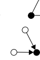
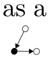
3.2 Data Analysis

A Unique Time Baseline for Interaction Observation. In order to facilitate analysis of peer assessment interactions within the different courses and

Table 1. Number of teachers and students enrolled in each course, and the proportion of assessment activities created by peers.

Course	Nb. Teachers	Nb. Students	Nb. Assessments	Peer assessments (%)
Maths 1	1	16	45	27
Maths 2	1	12	35	97
ICT 1	5	48	243	47
ICT 2	7	151	865	68
ICT 3	6	171	831	79
WebExplo	1	11	24	92
Image&Media	1	13	99	67

allow comprehensive comparisons, we first set an observation period to one week, to get observations with the same time baseline (time discretisation). Then, over each time period, we aggregate all the interactions between peers, as well as between teachers and students, to create a directed graph, where nodes are representing teachers or peers, and arcs the assessment interactions, i.e., a teacher assesses a student or a peer assesses another peer to certify at least one student skill. The obtained graphs are not weighted, i.e. there is no numerical values (weights) on the arcs, associated to the count of assessment interactions between the same individuals, and within the same time period.

Graphlets Shaping Student Interactions. Graphlets provide a meaningful way to express the student peer assessment roles. In each graphlet, peers are represented by nodes, the positions of nodes are visually depicted, and the arcs are directed from the peers taking the assessor role to the peers taking the assessed role. For instance, the graphlet  , expresses a student who assesses other peers (depicted as a black node),  expresses a student who is assessed by other peers, and  expresses a student who assesses a peer after being assessed by another peer.

In order to be computed, the graph data obtained from the previous step of time discretisation, is structured using vectors. Each vector stores for each student, during a period of time, the ratio of the number of appearances of the student in a given position, with the total number of his appearances in other positions. More specifically, we defined all possible configurations of graphlets of size 3, which distinguish teachers (shown as a ☆) from students (shown as a ○). We obtained 20 graphlets allowing highlighting 48 distinct positions for the nodes, depicted with shades of grey (Fig. 3). Therefore, each student is characterised regarding these 48 distinct positions.

Student Roles. In order to determine peer assessment roles, we applied the kMeans clustering algorithm over the vectors obtained from the previous step. Each vector stores for each student information about its enumerated positions within a period of time. By applying the kMeans algorithm [18, 19] to these

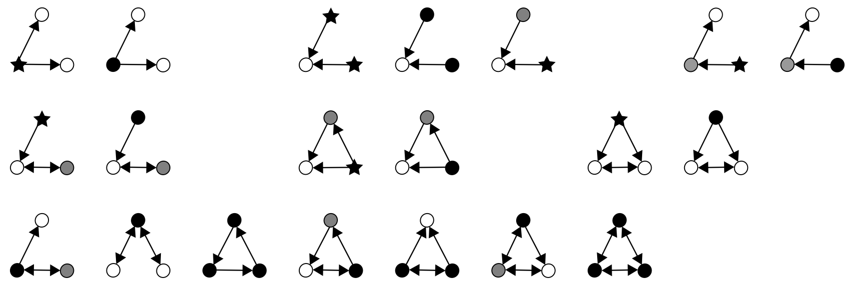


Fig. 3. The 48 possible positions expressed by 20 directed graphlets of size three, depicted by shades of grey. In each graphlet, the nodes with the same colour are in the same position. Students are represented by circles and teachers by stars.

vectors, we obtain clusters of similar distributions of positions. The clustering produced by this algorithm is dependent on its initialisation step and the number of clusters c that is given as a parameter. Therefore, we ran the algorithm a hundred times for each value of c between 1 and 20 and kept the best result according to the silhouette score [28].

Peer Assessments Temporal Dynamics. In order to characterise student behaviours over time and analyse peer assessment dynamics, we analyse, for each student, transitions between two different roles at two consecutive time periods.

We applied a likelihood metric named a measure of transition likelihood, as proposed in [10]. In our context, the likelihood metric is expressed as $L(R_t \rightarrow R_{t+1})$ (equation 1). It measures to what extent the student roles R_t and R_{t+1} are associated, where R_t represents a student role at a current time t, and R_{t+1} a student role at the next time, t+1.

$$L(R_t \rightarrow R_{t+1}) = \frac{Pr(R_{t+1}|R_t) - Pr(R_{t+1})}{1 - Pr(R_t)} \tag{1}$$

The Likelihood metric, looks for association between two states R_t and R_{t+1}, using a conditional probability measure $Pr(R_{t+1}|R_t)$. The expected degree of association is $Pr(R_{t+1})$, because if R_{t+1} and R_t are independent, then $Pr(R_{t+1}|R_t) = Pr(R_{t+1})$. Therefore, the numerator of equation 1 is null, and so $L(R_t \rightarrow R_{t+1}) = 0$, i.e. no relationship between immediate role and next role [10].

The numerator of the likelihood may be interpreted as the degree of the association between the two consecutive roles minus the degree of the expected association between these roles at independence. If $Pr(R_{t+1}|R_t)$ is lesser than $Pr(R_{t+1})$ then $L(R_t \rightarrow R_{t+1}) < 0$, i.e. the association is less frequent than what would be expected under the hypothesis of independence (null hypothesis). On the contrary, if $Pr(R_{t+1}|R_t)$ is greater than $Pr(R_{t+1})$ then $L(R_t \rightarrow R_{t+1}) > 0$, i.e. the association is more frequent than what would be expected under the hypothesis of independence.

Likelihood is then averaged for each transition over the student population. In order to determine whether the average of our sample is statistically different from a null likelihood hypothesis, we perform a one-sample t-test (see equation 2) where $\bar{x}$ is the average of the likelihood for our population, S the standard deviation of the likelihood for the population, n the size of the population and $\mu = 0$ our hypothesis statement.

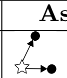
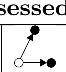
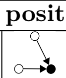
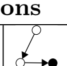
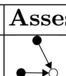
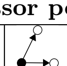
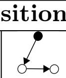
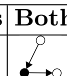
$$t = \frac{\bar{x} - \mu}{\frac{S}{\sqrt{n}}} \tag{2}$$

4 Results and Discussion

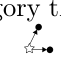
4.1 Student Peer Assessment Roles

The clustering of the aggregated peer interaction data based on graphlets and positions enumeration led to four different categories of student positions, defining four distinct student roles (Table 2). Instead of focusing on all 48 possible positions (see Fig. 3), and in order to describe in a meaningful way each role category, we only keep the most frequent positions representing at least 75% of the positions within a cluster. We keep eight positions expressed with eight distinct graphlets to characterise the student peer assessment roles. Table 2 gives for each role, the statistical frequency of each of the eight positions, as well as the size of each role category.

Table 2. Resulting peer assessment roles described with the most frequent positions. Black depicted nodes represent distinct positions. Teachers are distinguished from students by star-shaped nodes.

		Assessed positions				**Assessor positions**			**Both**
Role	**Size**								
teacher-assessed	270	**0.92**	0.02	0	0	0	0.01	0	0
peer-assessed	412	0.04	**0.70**	0.07	0.07	0.01	0	0	0.01
assessor	260	0	0	0	0	**0.80**	0.07	0.05	0.02
assessed-and-assessor	459	0.05	0.09	0.08	0.06	0.10	**0.23**	0.09	0.08

We interpreted the four distinct roles on the basis of graphlet and position enumeration, as follows:

– **teacher-assessed**: This role is defined by a category that includes students who have been mostly assessed by the teacher  (in 92% of cases). This shows that teachers are significantly present across courses, and that students choose to be assessed by teachers rather than peers at certain time periods.

- **peer-assessed**: This role is defined by a category that includes students who are mostly assessed by other peers (at least in 84% of cases). We note that it is common for the peers being assessed to have the same assessor (70%), but that it is quite rare to be assessed by several peers (7%), or to be assessed by a peer that has been himself assessed by another peer (a sequence of two assessments) (7%). This can be explained by the fact that, over one week of observation, peers remain focused on one learning objective and do not move to other peer assessment activities.
- **assessor**: This role is defined by a category that includes peers who are assessors in 93% of the positions they hold, over a period of time. The majority of these students assess the same peers (80%), more rarely different peers (7%), and it is also uncommon that when a student assesses a peer, this peer assesses in turn another peer (5%). This can be explained by the fact that students may know each other and favour their friends first in the assessments.
- **assessed-and-assessor**: This role is defined by a category that includes students who have the most balanced peer assessment interactions. This role is related to peers characterised by, at least, 42% of assessor positions and 28% of assessed positions. In contrast to what we observed for the category of assessor roles, students with this role are more likely to assess different peers (23%), instead of assessing peers who are being assessed by other students (10%).

  Furthermore, in this role students are more likely to appear as first assessors of peers that are in turn assessors of other peers (9%). They are less likely to be assessed by teachers (5%), but they are rather assessed by other peers. They are assessed by the same peers (9%), or different peers (8%). They are also assessed by peers that have been assessed before by other peers (6%). Finally, this role is characterised by the most frequent positions expressing both assessor and assessed peer interactions (8% of the cases). These students, therefore, present a role that could be described as being strongly committed to peer assessment, both by creating assessments activities, and also mainly interacting with their peers as assessors or to be assessed and get skills certified.

4.2 Student Peer Assessment Dynamics

Equation 1 was used to compute the likelihood of all possible role transitions excluding repetitions between roles, leading to 3×4 or 12 possible transitions. Descriptive statistics on the transition likelihood and the results of the t-tests are presented in Table 3. We performed one-sample t-tests to test whether likelihood measures were significantly greater than or equivalent to zero, i.e. no relationship between immediate and next role.

Significance testing led to five transitions that occur above chance ($p<0.05$, $\bar{x}>0$), namely (teacher-assessed → peer-assessed / assessed-and-assessor; peer-assessed → assessed-and-assessor; assessor → peer-assessed / teacher-assessed), and three transitions whose occurrence was expected at chance levels ($p<0.05$, $\bar{x}<0$), namely (peer-assessed → assessor; assessed-and-assessor → assessor / teacher-assessed).

The first five transitions expressed an association between specific roles. This showed that peers assumed different roles as assessed and assessors after being assessed from the teacher or another peer. They also engage with their peers with assessed roles after being assessors. On the other hand, the three other transitions showed that peers engage as assessors more frequently regardless of their previous peer assessment roles. Moreover, students who are assessed by teachers are not most likely those who are engaging in peer assessment beforehand.

From these results, we can observe that peers have a positive tendency towards a more balancing role and engage in the peer assessment process progressively. We observe that teachers are significantly present in the courses, and students may need to be assessed by teachers before engaging themselves in reciprocal activities with peers. Another interesting result, is that students who are assessing first their friends (assessing frequently the same peers), are not likely those who have experienced peer assessment in a more balanced way. This shows that students may need time before feeling comfortable to interact with new peers, and so the process of peer assessment may take time before being adopted by students.

Table 3. Descriptive statistics of transition likelihood between two roles and results of the t-tests. **p < 0.05

				One-sample t-test	
Transitions	n	$\bar{x}$	S	t	p
From teacher-assessed role					
teacher-assessed → assessor	267	-0.000	0.409	-0.02	0.988
teacher-assessed → peer-assessed**	267	0.110	0.590	3.05	0.002
teacher-assessed → assessed-and-assessor**	267	0.061	0.401	2.48	0.014
From peer-assessed role					
peer-assessed → assessor**	250	-0.129	0.357	-5.70	0.000
peer-assessed → teacher-assessed	250	0.038	0.624	0.97	0.332
peer-assessed → assessed-and-assessor**	250	0.229	0.475	7.64	0.000
From assessor role					
assessor → peer-assessed**	168	0.251	0.578	5.62	0.000
assessor → teacher-assessed**	168	0.105	0.534	2.55	0.012
assessor → assessed-and-assessor	168	0.020	0.425	0.62	0.539
From assessed and assessor role					
assessed-and-assessor → assessor**	149	-0.200	0.293	-8.31	0.000
assessed-and-assessor → peer-assessed	149	-0.022	0.616	-0.44	0.659
assessed-and-assessor → teacher-assessed**	149	-0.218	0.411	-6.47	0.000

5 Conclusion and Implications

In this work, we have presented a graphlet-based method to analyse peer assessment interactions and their temporal dynamics, in the context of hybrid courses using a peer learning platform called Sqily. The graphlets allowed to shape peer interactions and provide a meaningful way to detect peer assessment roles, over the same time baseline. This approach makes it possible to meaningfully observe how students engage in peer assessment activities. And finally, examining dynamics brings insights on how peers adopt different roles over time. We observed that peers have a positive tendency to adopt the peer assessment process and engage progressively in reciprocal activities towards peers. Teacher presence was observed significantly across courses, and this may lead to enhance initial assessment activities between peers.

This study contributes fresh insights into better understanding how peer assessment occurs for informing future research. One of the main interesting empirical findings of this work is that students need some support to engage in a peer-assessment process, and that a direct guidance from a teacher can help them to initiate interactions with peers. Another main contribution of this paper consists in the effectiveness and expressiveness of the graphlet-based method used for analysing and interpreting assessment interactions between peers. This method has a great potential to address meany state of the art issues regarding peer assessment, such as friendship based favouritism between peers and resistance to being involved in peer assessment. This method would also be transferable to analyse other learning issues in similar contexts, as it allows shaping interactions between peers. One could focus, for example, on cooperation between students, such as co-development of learning content or analysing team work [14].

The work presented in this paper is of scholarly and practical implications. This work brings interesting insights on the design of learning analytics tools that allow for a meaningful reporting of peer learning dynamics. This may strengthen formative evaluation and provide learners with quick feedback during their learning. Future work is motivated to scaffold peer learning. Moreover, further information is required to improve peer interaction analysis and better understand peer learning phenomena. For example, it would be relevant to adapt the size of the observation time window to the intensity of interactions during a course, to get more rich information and improve the analysis of peer learning. It would be also interesting to analyse the quantity and the quality of feedback made to peers. This can extent the relative research on peer learning and peer assessment.

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