INVISIBLE STUDENT PARTICIPATION IN ONLINE COLLABORATIVE LEARNING: IMPLICATIONS FOR SCAFFOLDING AND ASSESSMENT

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Abstract

Participation in computer-supported collaborative learning (CSCL) can be challenging for many students. Therefore, timely and proper facilitation and assessment is crucial. In the context of online collaborative learning, the course instructor may often not receive any visual cues and have to rely on the written contributions left by the learners in the discussion forum in. This way, the instructor gets access to certain parts of the learning process, while some important components may remain invisible. Learning analytics and log data have an immense potential to assist educators in assessing student participation and the level of cognitive engagement, closing some of these gaps and shedding more light on the group learning processes. On the other hand, these data can be misleading and impose a risk of misinterpretation. The paper discusses four scenarios of invisible student participation in online collaborative learning based on a case of a one-year online collaborative learning course and illustrated by data from a focus group interview with 14 course participants. Thus, invisible participation can stem from students' lack of technical experience, lack of established group norms, Internet access issues, and involvement in informal learning groups and alternative communication channels. The paper then discusses how learning analytics and log data can assist educators in scaffolding and assessing such participation. The paper also outlines several critical issues in the area of learning analytics and log data application.

Keywords: Learning Analytics, Computer-supported Collaborative Learning (CSCL), Learning Management Systems (LMS), Student Roles, Student Assessment, Ethics.

1 INTRODUCTION

Computer-supported collaborative learning (CSCL) is believed to be beneficial for educational practice due to both technological advancements in digital learning and better opportunities for students' active knowledge construction. In CSCL learners are usually expected to work on complex phenomena with little interference from teachers [1]. In CSCL, interactions among peers represent the most crucial aspect of learning, in addition to other factors such as interactions with teachers and learning materials [2]. While CSCL can be characterized by multiple opportunities which would not be available for students in a traditional classroom setting, many learners experience significant challenges when they are simply assigned to groups and left with devices. As CSCL environments often turn out to be motivationally and cognitively much more demanding, proper facilitation becomes crucial [1].

In the context of online collaborative learning, the course instructor may often not receive any visual cues whatsoever and must assess the learning process based on the written contributions and comments left by the learners in the discussion forum in the learning management system (LMS). It can be challenging for the instructor to make an evaluation of whether the student is overwhelmed by the learning materials, bored, or temporarily absent [3]. Here, learning analytics functionality has an immense potential to assist educators in student assessment, both in terms of participation and the level of cognitive engagement.

Learning analytics can be defined as "measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs" [3, p. 305]. Analytic insights can be helpful at multiple levels of the educational system. In addition to helping educators in developing their practice and providing effective support to their students, learning analytics dashboards can also help individual students in developing their own learning, as well as administrators in understanding and mapping organizational needs [4].

There are various computational methods of data analysis. Hoppe [5] discusses the "trinity of methods", which includes analytics of network structures, analytics of processes, and analytics of content. *Network-analytic approaches* view the actors or artefacts as nodes in a network, representing social or actor-

artefact relations. *Process-oriented analysis* is based on action logs. This type of analysis can detect action patterns. This technique can be applied in a CSCL context to detect the occurrence of specific collaboration patterns (e.g., co-construction or conflict). Finally, *content analysis* uses text-mining methods and is especially interesting in the case of artefacts produced by learners. This technique can be used in a CSCL context to investigate students' understanding of concepts.

However, the number of institutions where large-scale learning analytic programs have been implemented with significant impact on teaching and learning outcomes is relatively small. Still, for many institutions, the adoption of learning analytics remains limited in scope and impact, while for some institutions, organizational adoption of learning analytics remains only conceptual [6]. Multiple factors may affect learning analytics implementations in an institution, such as technological readiness, leadership, organizational culture, staff and institutional capacity [7]. In Norway, for example, Canvas LMS has been recently adopted by several higher education institutions. In this LMS, learning analytics and log data can be retrieved in several ways. *Course analytics* provide an overview of the amount of times students viewed course pages and/ or participated in course activities and submitted assignments. Here, the distribution of grades in the course can also be viewed. These data can be displayed on the aggregated level for all course participants or for an individual course participant. *Course statistics* provide a general summary of the course such as the amount of discussions, assignments, active students in the course room, etc. Finally, *access report* provides a summary of each action a certain student carried out on the platform (e.g., which page was viewed, how many times this was done, and when). This provides the instructor with a great amount of detail.

Some critical issues and challenges related to the use of learning analytics and log data to enhance education and learning has been identified by researchers. Thus, skills, as well as other latent traits, can be hard to characterise with the help of a statistical model [8]. While a statistical model can describe the regularities in the sequences of argumentative moves, it may be lacking understanding of the evolving issues. For example, independently applying codes to utterances in a dialogue can be problematic if one wants to study meaning making, since in a dialogue each utterance is placed in the context and is related to other utterances. Therefore, while interpretative approaches can be criticized for analysing small sets of collaborative exchanges with little opportunity for generalization, analytical approaches can be as well criticized for not being sensitive to contextual changes [9]. Kop, Fournier, and Durand [8] raise a question about what learning analytics data *cannot* tell about complex learning processes. The issue here is virtually unlimited amount of data and information that can be accessed quickly and easily. In doing so, researchers need to establish trustable techniques for translating these data into meaningful modes of representation for them to be understandable and usable for the target audience [8]. Moreover, ethical issues in the context of learning analytics is an important concern and will be discussed in more detail in Section 4.2 of the paper.

To sum it up, learning analytics and log data can provide educators with much information on students learning [10]. Such near-real-time data can help educators not only understand but also support CSCL [9]. To describe the characteristics of students to be able to provide more effective and targeted instruction is, in fact, one of the goals of learning analytics [11].

The aim of this conceptual paper is twofold. First, the paper aims to approach an ambiguous case of invisible student participation in an online collaborative learning course and discuss the possible scenarios and reasons of invisible student participation. Second, the paper aims to discuss how learning analytics and log data can assist educators in scaffolding and assessing such participation. Invisible student participation is understood here as such participation where an individual student follows up on the learning activities and assignments, however, without actively or regularly contributing to the course discussion forum over time. The discussion in the paper is focused on an online collaborative learning course where participants reside in different geographical locations.

This discussion is supported by the data collected through a focus group interview with 14 participants of an online CSCL course (the context is discussed in more detail in Section 2). Four cases of invisible participation are identified and described in Section 3, caused by participants' lack of technical experience, lack of established group norms, access issues, and involvement in informal learning groups. The implications for scaffolding and assessment are further discussed in Section 4, elaborating on the opportunities and challenges the learning analytics and log data may provide. The discussion demonstrates that, on one hand, the learning analytics and log data can be very helpful for the educator in understanding learning behaviour, providing proper support and carrying out student assessment appropriately. On the other hand, these data can be misleading and impose a risk of misinterpretation. Concluding remarks are presented in Section 5 of the paper.

2 CONTEXT AND EMPIRICAL DATA

To obtain first-hand insights into the group processes in an online collaborative learning course, excerpts from a focus group interview are included in the paper. The interview was conducted with a group of participants of a one-year Social Science online collaborative learning course at Master's degree level run by a university in Norway. While most course participants were based in Norway, also learners from collaborating universities based abroad (e.g., in Sri Lanka and Uganda) took part in the course. As the course employed collaborative learning methods, participants from the different universities were assigned in small multicultural groups to work online throughout the course. Due to the differences in the time zones as well as participants' schedules (some of the participants being full-time students and some students combining the study with 100% employment), the main form of communication among the participants and teaching team was text-based. The discussion areas were organized in the university LMS Fronter. While encouraged to run their discussions on the formal learning platform, students could also use alternative means of communication in cases they considered it necessary or significantly more efficient.

At the time of the data collection, two rounds of the course had been completed. The data used in this paper were collected during a focus group interview with the Ugandan participants in May 2016 held at the university in Uganda. Fourteen people participated in the interview, including students from both the first and second rounds of the course. Eight participants were female, and six were male. The interview lasted around 1,5 hours. The interviewer provided several general guiding questions for the students to reflect upon. The discussion evolved mainly around the issues of using the course learning management system Fronter and interactions with peers. Fronter used to be the university LMS before the transition to Canvas LMS in 2018.

The interview excerpts included in this paper are meant to serve as an illustration to the identified cases of invisible student participation in an online collaborative learning course.

3 RESULTS

Based on the focus group interview data, four scenarios of invisible student participation were identified (see Figure 1). In the first two scenarios, the participants leave traces of their presence in the learning platform (e.g., they visit pages, read other participants' contributions, and spend some amount of time on the platform) but do not necessarily actively contribute to the discussion forum themselves. In the last two scenarios, on the other hand, the participants leave fewer traces of their presence (e.g., they spend little time on the platform and do not have many page (re)visits). They may have somewhat more contributions on the discussion forum, although their number remaining limited. The four scenarios are described below.

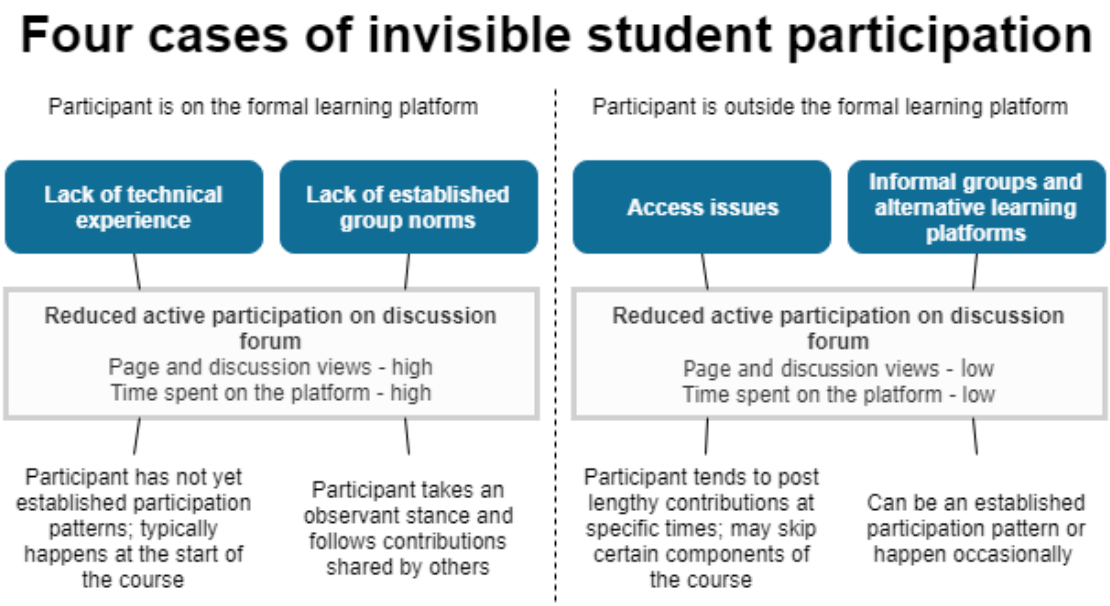

Figure 1. Four cases of invisible student participation in an online collaborative learning course identified through the focus group data.

3.1 Participants' lack of technical experience

Participants joining the online course possessed different levels of skills when it comes to the use of technology. For many participants, it was the first experience in online learning. For example, interviewee 1 shares: "*I was doing the course online for the first time, and on the first day I didn't have any hurdles because I had somebody to ask. My challenge came the next day onwards because I couldn't remember where to go and where to navigate. Even if I have gone through them on previous day, I was not able to recall how the process was. I learned through gambling. I kept on gambling and somehow I managed to get what I wanted to get*."

While the discussion forum may seem quite in the first days or even weeks after the course start, there can be immense work going on "behind the scenes" as the participants are exploring the learning platform to later settle down with their participation routines.

3.2 Lack of established group norms or participants' insecurity

At the start of collaboration in a newly formed group, some participants felt insecure about the accepted norms of communication. Interviewee 2 shares that she was insecure about how to proceed with further interactions in the group when her contribution was not taken up by peers: *"When you realize your contribution is not there… Without a tutor coming in, you don't know whether you make sense."*

Some misunderstandings may have become especially critical due to the multicultural dimension, where participants prior experience and expectations from the communication process are likely to be different. For example, interviewee 1 shares: *"From my background, even if somebody's argument is not good enough, you kind of appreciate it. It is different from their side: if it's not good – it is not good! But I understood that could be cultural."*

Such misunderstandings and incidents in the collaboration process may lead to some of the participants taking a more observant stance, decreasing their active participation on the forum but rather following what their peers are sharing instead.

3.3 Access issues

The participants residing in remote areas and thus not having stable Internet access naturally spent more time working offline. These participants would log in occasionally, to read their peers' contributions, upload their own responses, and check the upcoming assignments. Therefore, they spent less time on the platform overall, when compared to the students with stable Internet access who could work on the discussion forums directly in the online mode. Interviewee 3 discusses how challenging it can be to be online when traveling to remote areas in Uganda: "*I went for field work and I knew that I wouldn't be in [name of the city] all the time. Then I said "Well, I have to buy Internet". I bought 5 GB and tried to stay online to make sure that things are OK. But you know – 5 GB in two days on Fronter – it just got finished! I mean, that was too expensive…*"

Interviewee 3 later discusses that it can also be challenging to access specific components of the online learning environment: "*I also noticed that some of the Norwegian students have access to all this. For example, the video lectures – they couldn't open! For me, I've never succeeded in one*."

Thus, access issues may lead to some students downloading learning materials and doing most part of the work offline before going online and sharing their contributions. Moreover, the restrictions in the Internet connection can also lead to some students "skipping" specific components included in the learning environment.

3.4 Informal groups and alternative learning platforms

In the following excerpt, Interviewee 3 continues discussing how access issues made their group find alternative communication channels: "*We created a WhatsApp group for ourselves. Before even you go to Fronter, someone is already reminding you on the activity ahead, and I think that was nice. We ended up working on WhatsApp, because again, it was another access issue. Sometimes I would ask another colleague "Can you please help me to paste this in Fronter?" I remember many times I was also asking them to take all this discussion back to Fronter because I also knew that participation would be visible, but sometimes we were tempted to work on WhatsApp.*"

Thus, students may choose to use alternative learning platforms to communicate new contributions to peers and, as this excerpt demonstrates, even ask to post their contributions on the formal learning

platform on their behalf. Interviewee 4 was at the time employed as an online tutor, and commented on the tutor's perspective on informal learning arenas: "*The informal groups are very good, but it becomes very hard for the tutor to monitor your activities as students. Yet, even if the tutor may not add to what you are discussing, they have to look at what you are discussing. So, as a teacher on this other end, you keep wondering – what is happening? Are these people really doing the work? They keep telling you "We are in Google docs, we are doing this…" but without your knowledge of the extent to how far they have gone, there is a bit of challenge there*."

These excerpts demonstrate that while students may appear inactive or little engaged on the formal learning platform, they may be highly engaged in their assignments elsewhere without their instructor being able to assess their process.

4 DISCUSSION

The discussion section first addresses how learning analytics and log data can assist educators in scaffolding and assessing invisible student participation in an online collaborative learning course. Secondly, the issue of ethics in the context of learning analytics is addressed.

4.1 Learning analytics and log data for scaffolding and assessment of invisible student participation

At the start of the course activities, learning analytics and log data may help the instructor track which components of the learning environment are being most and least revised by the students. This may be helpful for the instructor in making preliminary judgements on the accessibility and intuitivity of the course structure and learning materials. Use of such aggregated and non-personalized data is in general of crucial importance in ensuring appropriate teaching and instruction [12]. It may become especially relevant at the start of the course when a high degree of scaffolding is important to help the participants establish effective participation routines. While multiple affordances are normally present in the learning environment, the crucial question is whether they are appropriated by students as meaningful for the activity [13].

Often, the instructor would expect that learners joining a course will gradually identify with other participants as a learning community [14], [15]. However, students do not always want to participate actively [14] or have little knowledge on how to engage in the discussions productively [1].

Some of the typical roles observed in collaborative learning are so-called "lurkers" (i.e., students providing short comments rather than contributing with new knowledge) and "free-riders" (i.e., students minimizing own efforts unless other group members directly ask for a contribution). Interestingly, lurking and free-riding are often not considered as a proper role in a group, because those are not assigned by the instructor [16]. A lurker would typically leave a brief comment or encouragement to other participants' ideas previously elaborated on the forum. That would hardly contribute to the discussion content-wise, but the learning analytics and log data would suggest that the student is participating actively (even though, most likely not spending too much time on the platform).

Along with lurkers and free-riders, there can be participants willing to actively engage in the collaborative learning process but lacking the strategies to do so. Reasons can be many, such as lack of prior experience in collaboration setting [17], socio-emotional issues of group formation, dynamics, and trust [15], feeling unsafe taking risks and sharing ideas [2], inability to interpret other people's emotions in virtual settings [18], or lack of social skills [19]. Gasson and Waters [14] distinguish between different levels of social engagement:

1. *Thought-leaders* demonstrating higher-order role behaviour (e.g., mobilizing, critiquing and reframing the ongoing debates);
2. *Active members of the peripheral learning community* actively engaging in the debates;
3. *Passive members of the peripheral learning community* who learn passively by reading and reflecting on peers' contributions.

Distinguishing between free-riders/ lurkers and such "passive members of the peripheral learning community" may be important for the instructor both when selecting an appropriate instructional approach and carrying out student assessment. Such "passive members of the peripheral learning community" are likely to establish participation patterns where they reduce their active contribution to the discussion forum and take a more observative stance following what their peers are sharing. Such

learners may need extra support to become actively involved in the learning process [14], for example, through scripted roles [20]. It could also mean that these students are insecure when it comes to sharing own opinions, and the online tutor's encouragement and establishment of an open learning environment would be crucial in this case [21].

Learning analytics and log data also have immense potential in assisting the course instructor in carrying out student assessment in CSCL. It is widely known that assessment in CSCL is challenging. Ideally, both individual and group levels should be targeted, and both collaboration process and product should be evaluated. The evaluation should be conducted before, during and after the collaborative learning activity. Finally, it should address not only cognitive aspects but also social and motivational [22]. Therefore, various assessment components need to be combined to ensure effective and valid assessment in CSCL. Typically, the instructor has access to parts of the learning process, with several important components being unavailable for evaluation. Such components, however, could play an important role when conducting student assessment, and learning analytics and log data have the potential to close some of these gaps and shed some light on the group learning processes and dynamics by characterizing each participant's level of commitment.

However, the last two scenarios identified in Section 3 imply that students participate in learning activities elsewhere than the formal learning platform (either offline or in alternative informal groups). This can be explained by both Internet access issues, as well as other factors. For example, earlier research demonstrates that learning groups have more varied types of interaction when using alternative chat tools. These also include more social interaction [23].

Log data specifying how much time each of the participants spent on the platform can be a useful tool for assessing student participation. However, since in CSCL much of student learning happens outside of the learning platform, the records and log data are distributed across different sites [3]. Therefore, low amount of time spent on the formal learning platform does not necessarily reflect a student's lack of commitment or participation.

Due to the wide use of social media and alternative platforms for communication and collaboration, the application of learning analytics becomes somewhat limited. The data need to be contextualized and used in combination with other information available to the instructor. There is a need for a shift towards a more challenging combination of datasets, which would include analytics outside the LMS [3]. Turning to complex data sources (i.e., big data) and combining various data types and analytic techniques becomes necessary to provide effective feedback on student performance or intervene during the learning process with scaffolding or support [24].

4.2 Ethical issues in the use of learning analytics

The issue of ethics in the context of learning analytics has been discussed as a problematic area for a long time. In the early years of the field, ethics and the need to question how student data are used was a marginal issue [12]. Research literature did not make it clear what rights learners themselves had in relation to the learning analytics data. It had not been agreed on a unified method on how the information can be obtained, and whether consent had to be collected. There were no procedures for the learners to opt out at all or have their analytic record cleared. All in all, there was no ethical platform to base on [3]. However, now these issues are becoming more established as the ethical frameworks have been developed (for an overview, see Prinsloo & Slade [12]).

Prinsloo and Slade [12], pointing to the mandate of higher education institutions which is to provide effective and appropriate support to their students' learning experiences, state that there is "broad agreement that institutions have a right to collect and use student information". What is still questionable, according to them, is the position around consent. Therefore, more work is necessary to explore possible conflicts between students' right to opt-out of the collection, analysis, and use of their data, and the implications this may have for the mandate of higher education to make interventions at an individual level based on these data [12]. Moreover, there is a special ethical concern when it comes to the use of such student data (without giving specific consent) in cases where students learning does not necessarily benefit directly [4].

5 CONCLUSION

In CSCL, interactions among peers are of crucial importance [2], as students are expected to actively engage in meaning making and knowledge co-construction with only limited interference from the instructor in their learning process. In online collaborative learning, the instructor normally has access

to parts of the learning process, while some important components may remain invisible. This imposes certain challenges on the provision of scaffolding and ensuring effective student assessment. Learning analytics and log data can provide valuable information on student cognitive engagement and participation in a CSCL course. On the other hand, such data can also impose a risk of misinterpretation.

This paper discusses four scenarios of invisible student participation in an online collaborative learning course based on a case of a one-year online collaborative learning course and supported by data from a focus group interview with 14 course participants. The paper then discusses how learning analytics and log data can assist educators in scaffolding and assessing such participation. At the beginning of the course, students' active contribution to the discussion forum may be reduced due to *the lack of technical experience*. The course instructor may use aggregated learning analytics and log data to make preliminary judgements on the accessibility and intuitivity of the course structure and learning materials to make necessary improvements. As the course progresses, students gradually establish participation patters to adhere to. Due to the lack of established group norms, some students may reduce their active participation and take a more observant stance. Learning analytics and log data may help the instructor to distinguish such learners from lurkers and free-riders, which has important implications for providing scaffolding and ensuring valid student assessment. Finally, some students may switch to working elsewhere than the formal learning platform. This can be caused by *access issues* and limited Internet access, when participants choose to carry out large parts of learning assignments offline. Moreover, some students may find it more efficient to use *informal learning groups and alternative communication channels*. In the latter two cases, the application of learning analytics and log data becomes somewhat limited and turning to more complex data sources becomes necessary for enabling effective feedback and intervention in the learning process.

The field of learning analytics has been rapidly developing. Various computational methods of data analysis have been discussed (for an overview, see Hoppe [5]). Yet, when it comes to practice, a clear understanding of how such data traces can most productively serve as indicators of good or bad collaboration for the teacher to make an informed decision, is still being shaped. Classroom is not very often considered as a practical context and is usually treated theoretically [9]. Therefore, there is much work remaining in translating theoretically sound studies into applications leading to positive educational changes.

Learning management system (LMS) software is employed widely by higher education institutions to deliver courses of different formats, including online courses based on the collaborative learning approach. It is frequently used to deliver learning materials in various formats, organize online discussion forums, collect and grade student assignments, incorporate online lecturing sessions, to name a few. However, learning analytics functionality seems to remain underutilized. As mentioned in the Introduction section of the paper, the adoption of learning analytics remains limited in scope in many institutions [6]. Learning analytics and log files are *data*, and the task of interpreting what these data mean may in the end be left to individual educators. Thus, institutions need to develop practical guidelines on the use of learning analytics and log data for instructors involved in teaching and/ or assessment of online collaborative learning courses. Moreover, these guidelines should also include a common ethical platform for the use of such data.

Currently, it is mainly computer scientists and mathematicians who produce the learning analytics applications. However, social scientists, too, have important insights to offer. Researchers should work in teams across the disciplines to avoid some of the biases in their work to enhance the value of learning analytics applications and log data in the educational context [8].

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