International Journal for Educational Media and Technology
2022, Vol.16, No. 1, pp.17-26

Are There Different Trends in Members' Use of Feedback Functions about Interactions?: Focusing on the HighNyammer Social Scanner

Masayuki Yamada
Kyushu Institute of Technology, Japan
yamada@lai.kyutech.ac.jp

Sayaka Tohyama
Shizuoka University, Japan
tohyama@inf.shizuoka.ac.jp

Hideki Kondo
Kanda University of International Studies, Japan
kondo-h@kanda.kuis.ac.jp

Ayano Ohsaki
Musashino University, Japan
a-ohsaki@musashino-u.ac.jp

The purpose of this study was to examine the differences in how members of a community get information about their colleagues. To do so, we developed the HighNyammer Social Scanner, which visualizes summative results of members' activities on a computer bulletin board system (BBS) used in a community. In the Social Scanner, three types of visualization functions were implemented: a chart of yearly changes in each member's betweenness centrality values, all members' betweenness centrality values in a week, and relationships among members in a week. The numerical values in each chart obtained by the social network analysis regarding the interaction of members were provided as feedback to each member in real time. How often they accessed this visualized feedback was examined. We analyzed the activities of seven members in a community that operates an active learning classroom on a BBS with Social Scanner for nine months. The log data of the members' use of a BBS suggested that the members could be divided into two categories based on the trends of their use of Social Scanner: those who continuously used the visualization function, and those who only used the function at the beginning of term, when the function was provided. The possibility was raised that members who continuously invoked the function were continuously interested in their colleagues' states as well.

Keywords: Visualization, Interaction, Social Network Analysis, Feedback

Introduction

Society is transforming greatly owing to the remarkable development of information communication technology (ICT). What we might now consider "conventional society" was established in the era of industry and industrialization wherein individuals were required to memorize knowledge and then process it quickly. Conversely, in our present society, individuals are required to have the ability to set up tasks, search for effective solutions, and create knowledge. In such a "knowledge-building community" (Scardamalia and Bereiter, 1991), education methods need to adapt in accordance with the changes in individuals' abilities that are being sought after. Specifically, we observe a shift away from an era wherein the educational purpose was for everyone to attend the same lecture and memorize content to one wherein the objective is to foster students' ability to build better knowledge through discussions with a diverse group of people. Along with such changes taking place regarding methods of education, the evaluation practices within education are also changing. It has become necessary to analyze students' transformation process over a long period of time, rather than simply relying on tests that measure their memory at a given point in time to assess whether the abilities are being developed (Scardamalia et al., 2012).

In current times, the evolution of ICT now enables the collection and processing of vast amounts of data at a fraction of the previous expenditure. One of the most impactful studies related hereto was a practical study conducted by Deb Roy (2009) of MIT. In this study, Roy presented the language acquisition process of a baby from birth, to the age of

3 years. Roy installed cameras in every room of his house to conduct the study. The study clarified how the support of a cohabitant changed during the process of the baby acquiring words using the automated voice recognition data gained from the enormous amounts of general video data. It should be noted that the data employed in Roy's study was different from collecting the Big Data as "data science." Although Roy's study only used data from a single-person case, it collected very thick data and could, thus, cause the study to be considered a case that persuasively displays the acquisition process of human language by pursuing a single individual's process. In and through such studies on longitudinal learning, we are beginning to see cases wherein such transformation processes are being suggested through the analysis of long-term data.

In this study, we implemented the visualized functions of interactions by members in a community as feedback. The functions calculated the number of interactions among community members and demonstrated how they are related among members.

Research Backgrounds

Asymmetricity of Interaction among Members in a Community

Community is a well-known tool for enhancing members' learning (Lave & Wenger, 1991). From an apprenticeship viewpoint, the degree of expertise of members is varied in each community. Novice members in communities are expected to be taught about the educational theme of each community by expert members from the legitimate peripheral participation (LPP) viewpoint (Lave & Wenger, 1991). In an LPP environment, experts are expected to observe their less-experienced colleagues' work to maintain community functions (Hutchins, 1995). Another study suggested that the visibility of support requests from novices to experts was important in a community. From observations at a call center, a support request sent by a novice worker was received by a senior member who solved the problem (Lothe & Filliettaz, 2019). However, novices in a community may have difficulty interacting with them even though they receive visible support requests from their colleagues, because novices have limited knowledge about how to do their work in a community. Further discussion about the asymmetricity of each community member based on their expertise is expected.

How experts get information about novices' states and how novices send help signals to experts in a community are important issues in a community of practice. According to previous studies, these signals and this information can be externalized by feedback. Schmidt (1991) classified feedback studies in three ways. First, researchers must consider the intrinsic feedback of learners, which is intuitive in nature. Then, there is extrinsic feedback, which exists in the external world surrounding learners. Extrinsic feedback can further be classified as relating to the knowledge of performance, pertaining to the linguistic feedback that learners receive from others, and the knowledge of results, which is linked to the knowledge of numerical results (e.g., specific scores). It should be noted that most of such feedback research has been conducted in the context of expertise research (e.g., Ericsson et al., 2006). Many such expertise studies, in turn, have been conducted by researchers comparing experts with novices.

Hutchins (1995) and Lothe and Filliettaz (2019) suggested that experts can effectively use visualizations of novices' activities or thinking to maintain their community functions. This may suggest that the visualizations of community interactions enhance expert workers' efficient task performance in a community. The tasks of experts may be smoothly performed when experts understand the community's situation.

Social Network Analysis for Visualization of Long-Term Learning Process

There is a high possibility that the features of interactions can be ascertained using a system that constantly records and visualizes them in long-term projects. In a study of longitudinal work by Zhang et al. (2009), wherein the authors practically compared the state of learning in classrooms over a three-year period, the difference of the education methods used during and across the given 3-year period was examined within fourth-grade classes where students were learning about light. Specifically, Zhang et al. (2009) examined the interactions between students and teachers through the learning support system using an electronic bulletin board. The authors then presented the recorded data as a social network diagram. The results showed that the role of teachers gradually decreased over the 3-year period, and that classes began to change toward becoming more student-centered. It is suggested, therefore, that the visualization of the process of interaction over a long period of time using ICT could be effectively used to evaluate children's learning.

Social network analysis (SNA) has presented many possibilities for visualizing and evaluating relevant interactions (Barabasi, 2016; Newman, 2010) as an analysis method. Zhang et al. (2009) and Ma et al. (2016) used SNA visualization results for analysis for research purposes, but there are also cases wherein learners have received SNA feedback. Ouyang et al. (2021) and Kondo et al. (2020a) used SNA visualization results as feedback for community members. Kondo et al. (2020a) used calculated betweenness centrality values based on visualizing the relationships among members through by using articles posted on a BBS and using them to give feedback to members to encourage their work. Kondo et al. (2020a) showed that the number of posts on BBS increases when members receive feedback on their posts' relevance through network visualization using SNA compared to feedback that is only a numerical value of SNA.

Ma et al. (2016) analyzed learners who studied science in a knowledge-building community and found that almost all the learners in the class acted as leaders, and that leadership roles rotated. Tao and Zhang (2021) revealed the process by which learners reframe and reconstruct community practices through collaborative discourses over time and as activities progress. To support the dynamic process of each member regulating their relationships within the community, it is worthwhile to consider giving these externalized results to members.

In previous studies, the visualization of such long-term interactions has only been practiced and made use of by researchers for the purpose of evaluation. In contrast, we argue in this study that giving learners access to the visualized information could prove useful for feedback. Therefore, the numerical value attained through the network analysis of interactions in a community was provided as feedback to members of the community in real time, with a further examination of their behaviors with respect to their utilization of visualized feedback.

Pros and Cons of Feedback

Data saved by students who use online tools can also be used to provide feedback to students. However, it is difficult to generate feedback data using students' learning when we only have a qualitative analysis method for trained researchers. If we analyze the data by qualitative analysis, such as a coding-and-counting analysis (Vogel & Weinberger, 2018), and then analyze the results using SNA, feedback to students is delayed. Simple numeric results, such as the number of articles posted by a student on BBS or the number of characters in a posted article, should be treated with caution if they are to be used as feedback for students because it is not easy to interpret these results. There is a risk of misleading students about the characteristics of an "ideal" learner.

Recent studies using machine learning (ML) or deep learning (DL) have become more accurate in coding learners' dialogues automatically (Fiacco et al., 2021). However, ML and DL have limitations in providing feedback in creative learning processes. When providing feedback on learners' function, automatically generated results are promising to improve learning trajectories. However, in the case of creative learning processes, ML or DL has limitations in providing feedback because ML and DL results depend on previous learner activities. In creative learning situations, learners are expected to develop new learning processes. In this sense, managing the granularity of feedback and selecting data for feedback are essential to avoid misleading learners.

It can be argued that we should find appropriate granularity of feedback that does not force students into a rigid "right way" of learning but rather improves their self-directed learning. In this sense, the idea of constructing feedback from a metacognitive viewpoint of students' activities may be promising. For example, metacognitive scaffolding has been effective in reading comprehension. Palincsar and Brown (1984) suggested that children who have difficulty reading were able to improve their reading abilities by "reciprocal teaching": the children read stories and answer a set of questions that scaffolds the focal point of the reading, such as "Who is the protagonist?" and "What is the problem the protagonist faced?" Further, the children still used these metacognitive strategies after the scaffold had faded. The same trend was observed in a children's writing support study conducted by Scardamalia et al. (1984), which provided cues for supporting children's writing, such as, "An even better idea is…" and "My purpose is.…" The effect of the proposed idea was observed, however, when they improved their scaffolding into a contextualized approach, because some students had difficulty applying the scaffolds in their actual writing situation (Scardamalia & Bereiter, 1987). Later, their idea was implemented as the Computer-Supported Intentional Learning Environment (CSILE) as the center of classroom discourse in children's online learning (Scardamalia & Bereiter, 1994). Knowledge Forum is a later, improved version of CSILE.

Research on Knowledge Forum has shown promising examples of feedback, including leading statements called "theory-building scaffolds" for supporting the externalization of students' ideas, such as "My theory is…" and "New information.…" Knowledge Forum also provides feedback on the number of articles in each category of theory-building scaffolds called a "scaffold meter." The scaffold meter encourages students to see their activities from a birds'-eye-view in their knowledge-building community (Scardamalia & Bereiter, 2014).

Research Question

As pointed it out in a previous study (Lave & Wenger, 1991), it can be argued that the length of experience in a specific community reflects some aspects of the degree of expertise. Additionally, members with long-term experience in a community frequently checked on their colleagues' states and relationships (Kondo et al. 2020b). Meanwhile, inexperienced members are likely to check their colleagues' states and relationships very often or on an ongoing basis.

Oppositely, it is possible that the length of experience is irrelevant when using feedback functions because the feedback function helps members to know other members' states and relationships from a group awareness viewpoint (Strauß and Rummel, 2021). In other words, members may be more interested in feedback when they are working in a community, regardless of their length of experience.

Meanwhile, many problem-solving interactions in a community are reported in authentic working situations. Xia and Borge (2019) suggested that learning through constituent interactions in communities needs further exploration and research on a longer term with authentic problem-solving. We also focused on an authentic community following these previous studies.

Accordingly, the research question of this study is "Are there any different trends in members' use of feedback functions about interactions among members especially in the length of experience?" We addressed this question by analyzing community members who operate an active learning classroom.

Hypotheses

We hypothesized that there are different trends among members when using the feedback function about members' state and relationships in a community. Experienced members may use the feedback function more often than less-experienced members because experienced members are expected to play an "expert" role in a community from the viewpoint of LPP. Experts in a community are expected to introduce novices into a "community of practice" (Lave & Wenger, 1991). However, the definition of "experienced member" is not limited to the length of their experience in a community because Hatano and Inagaki (1986) suggested that adaptive experts can be defined not only by the length of their experience but also its quality. We expected that the characteristics of such "experts" would be revealed through the analysis.

Methods

Participants and contexts

"MILAiS" is a facility for active learning classroom in a Japanese university (Kondo et al., 2020b), which has been operating since 2011. For both regular classes and informal learning, resident faculty and "student-staff members" who participate in operating MILAiS provide a variety of supports for classroom practices. These include routine tasks, individual consultations with each class instructor, technical problem solving, and suggestions for alternative teaching methods using MILAiS's ICT equipment. These supports can be considered creative work because they involve complex problem-solving processes. The student-staff members help each other perform these support tasks. During the problem-solving processes in the support tasks, the student-staff members are expected to acquire the knowledge to operate MILAiS and 21st century skills. Thus, the community of student-staff members functions as community of practice.

A study that used a community run by MILAiS as its subject included research by Yamada et al. (2019), which conducted SNA using log data gathered over a 4-year period. The results of studies including such data led to the features of interactions between students and teachers being examined. Later, Tohyama et al. (2021) focused on collective cognitive responsibility by analyzing the log data for a 7-year period. The data were specifically used for an evaluation method aimed at promoting the sustainable development of a given community. Each noted study also examined the characteristics of interactions in the respective communities after practice, and highlighted that it was necessary to provide relevant analysis results to members as feedback in real time. Based on this issue, we implemented real-time visualization feedback and examined how it was used by community members.

HighNyammer Social Scanner

The tasks are carried out both in face-to-face interactions and on an online thread-based electronic bulletin board system named "HighNyammer.". All the student-staff members can read and write replies to all articles in HighNyammer; thus, they can share trends in the community through HighNyammer. Furthermore, the student-staff members are expected to write daily reports and discuss their tasks proactively with colleagues in the system.

This study implemented the system called "Social Scanner" for HighNyammer. Social Scanner was developed to visualize the relationships of student-staff members on HighNyammer. To visualize the relationships, Social Scanner focused on betweenness centrality values as an indicator, calculated from weekly sub-graphs of student-staff members' relationships based on HighNyammer (Kondo et al., 2020). Each student-staff member could receive three types of graphical feedback, as detailed below.

Feature 1: Charting yearly changes in a student-staff member's betweenness centrality values (BC_Changes_Chart). It is noteworthy that SNA can be used to identify network characteristics by analyzing the degree of each node, distances between said nodes, and centrality of each node that comprises the network being targeted in the analysis. In particular, the centrality is often used to discriminate key nodes, with betweenness centrality frequently being used along with degree centrality. Betweenness centrality is also generally referred to as "fragility" or "load," as it is equal to the number of times a node acts as a bridge along the shortest path between two other nodes. Nodes with high betweenness centrality are then considered to play leadership roles in the community. Conversely, a community with only a few leaders at the helm is more at risk of collapse than a community where the load is evenly distributed. Betweenness centrality is expected to be used as a common method of learning analytics (LA) in the years to come since it is possible to visualize the reference relationship between log data stored in SNS and keywords in a post.

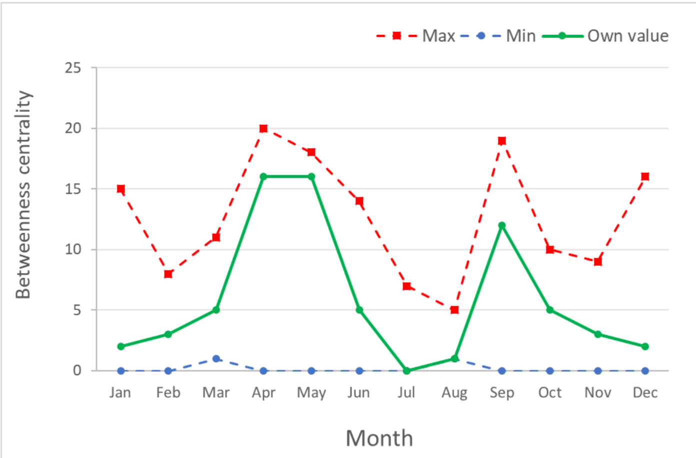

Figure 1. An Example of BC_Changes_Chart

This function visualizes the changes in the betweenness centrality values of one of student-staff members during one year (from January 1 to December 31). This function calculates the student-staff member's own betweenness centrality weekly for up to a year and displays the changes in a line chart (Figure 1). No one can see the charts of other members.

Feature 2: Charting multiple student-staff members' betweenness centrality values in a week (BC_Chart). This function visualizes the short-term positions of each student-staff member. The betweenness centrality values of each student-staff member are displayed as a bar chart to facilitate comparison of the student-staff members. This function helps the student-staff members to discover colleagues with high betweenness centrality values, thereby encouraging the student-staff members to imitate the practices of higher-value student-staff members' workstyles and discuss work processes with them. All student-staff members can see each other's values in the bar chart (Figure 2). The bars are presented in descending order. The bar of the logged-in person in the HighNyammer is highlighted in red.

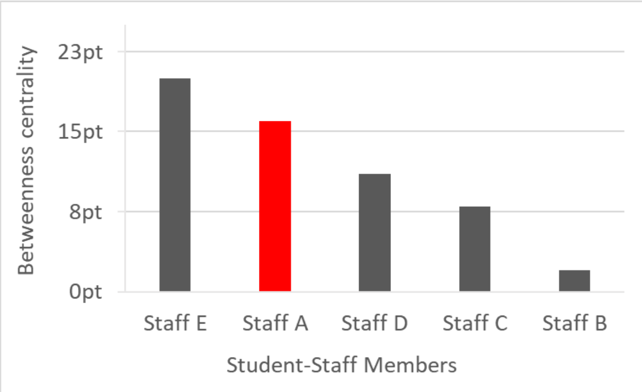

Figure 2. An Example of BC_ Chart

Feature 3: Relationships between student-staff members in a week (Social_Graph). This function extracts the weekly relationships between student-staff members on HighNyammer and displays them as a directed graph (Figure 3). The nodes represent the student-staff members, and the edges indicate relations between the respective student-staff members. Nodes without edges in the directed graph have had no interactions on HighNyammer.

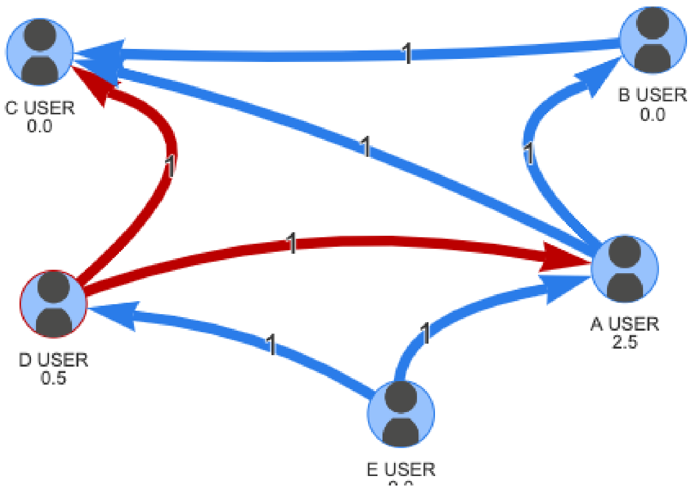

Figure 3. An Example of Social_Graph

Data collection and analysis.

Each function of Social Scanner was expected to encourage student–staff members to discover and examine the relationships among one another. When the student–staff members invoke these functions, it can be interpreted as members being interested in other members' states and relationships.

Kondo et al. (2022) analyzed the effectiveness of the developed feedback function using data from a 3-year period (i.e., 2018-2020) across three viewpoints. The first viewpoint was to test whether the feature was being used. The second related to the subjective evaluation of the feedback function. The third focused on a qualitative analysis of given posted articles. Through these examinations, the authors found that 1) student-staff members continuously utilized the feedback function, and 2) this function was useful.

However, the study only indicated that most members continuously used the visual feedback function. It did not examine the extent to which individual members used the function. For the purposes of the current study, it was therefore necessary to examine the degree to which members in the community are interested in such feedback.

In this study, we deployed Social Scanner functions in HighNyammer so that each student–staff member could execute them at any time, and we analyzed the frequency with which these functions were used during their actual work by using the system log. The analysis period was from January 1 to September 10 in 2020. Seven student-staff members were working at MILAiS during this period, and their length of experience is shown in Table 1. For these seven users, we extracted when and how frequently Social Scanner was used through HighNyammer, and analyzed the changes in their use throughout the study period.

Table 1

Months of experience of student-staff members

	Staff A	Staff B	Staff C	Staff D	Staff E	Staff F	Staff G
Months of experience	52	39	9	35	15	15	15

Results

To investigate the relationship between the number of months of experience of each student–staff member and the number of times each function of Social Scanner was invoked, we calculated Pearson's correlation coefficients using R (ver. 4.0.0). The coefficient values between the months of experience and invoked numbers of each visualization function were as follows: BC_Changes_Chart: $r = 0.616$, BC_Chart: $r = 0.739$, Social_Graph: $r = 0.760$. Further, the coefficient values between the month of experience and visiting to HighNyammer was $r = 0.866$. This indicates that months of experience and frequency of Social Scanner use and HighNyammer were correlated especially in HighNyammer use. However, since the sample size in this study was very small, references to such statistical analyses were limited. Therefore, the detailed analysis based on the visualized information has been added to offer a more appropriate discussion.

To investigate whether the frequency of use for each of the above functions differs by the student–staff members' months of experience, the frequency with which each function was invoked is shown in Figure 4. This shows a plot of the number of times HighNyammer and Social Scanner were used by each student–staff member, summed up weekly, and plotted in a time series. The left longitudinal axes on each graph are for the number of visiting to HighNyammer and the right longitudinal axes are for the numbers of invocations of each Social Scanner function.

Discussion

Decrease in the number of invocations since the beginning of April

The number of visits to HighNyammer decreased at the beginning of April (April is started from Week 15 to Week 18 in Figure 4) for all the members. This may be due to the lack of visibility of the university's overall course of action due to COVID-19. Normally, the new semester in Japan starts in April. However, in 2020, it was not possible to enter the university in April and there were no classes during April 2020. The number of visits increased during May (from Week 19 to Week 22) because the student–staff members changed their activities to prepare for the remote classes that began in June (from Week 23).

Correlation between months of experience and the number of Social Scanner function invocations

The correlation between months of experience and the number of times each function of Social Scanner and HighNyammer was used suggested that student–staff members with more experience invoked the social graph more and visited HighNyammer more often than the less-experienced student–staff members. It was suggested that more experienced members might have noticed the need to be aware of their relationships with other members when working in a community.

Trends in overall activity in the use of Social Scanner

The student–staff members can be divided into two categories based on the frequency of access to Social Scanner as shown in Figure 4. One category was generally increasing, and the other category was generally decreasing throughout the period. The frequency of accesses for student–staff members A, B, C, and D showed an increasing trend, while frequency of access for student–staff members E, F, and G generally decreased. The use of Social Scanner appears to have continued to increase throughout the entire period, although there were some interruptions. In contrast, although the student–staff members in the decreasing category used the system at the beginning of the period, though they did not use it continuously throughout the period.

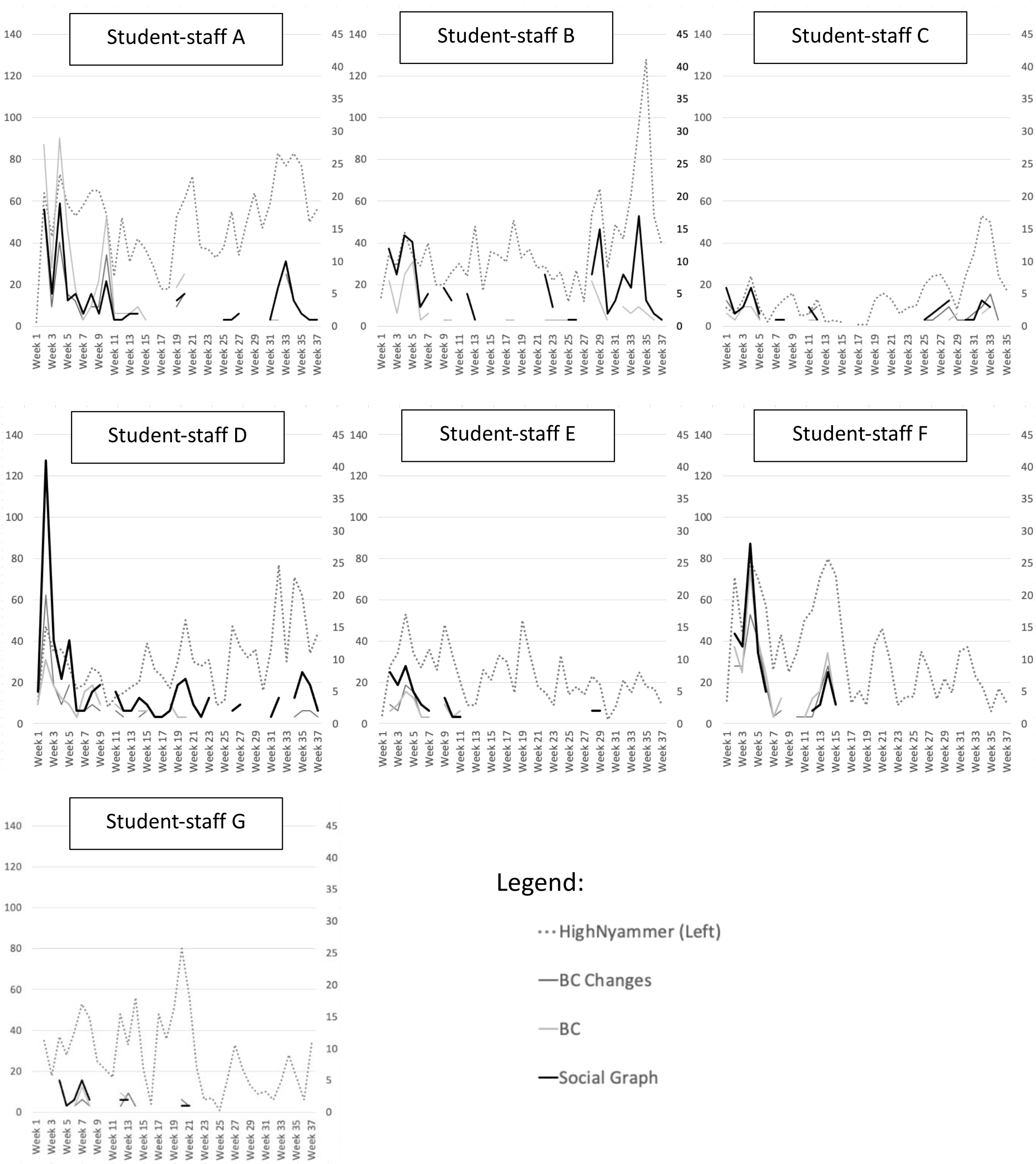

Figure 4. Numbers of visits and uses of HighNyammer and Social Scanner functions

We focused on months of experience in each group. In the increasing category, the mean was 33.75 months (SD=9.01), while in the decreasing category, the mean was 15 months (SD=0.0). The results suggested that student–staff members in the increasing category have more months of experience than student–staff members in the decreasing category.

However, there was the exception in the increasing group. Student–staff member C was the most inexperienced member in the analysis. Student–staff C had only one year of experience; the experience was less than members in the decreasing category. This result suggested two possibilities: the quality of experience of student–staff C differed from members in the decreasing group, or else the amount of the experience when C initially joined the community of student–staff C differed from the experience of decreasing group members. If the quality of experience of student–staff C was greater than that of the decreasing group members, years of experience do not determine the actual degree of expertise. As Hatano and Inagaki (1986) suggested, an adaptive expert is defined by the quality of their performance, not simply by the length of their experience. However, if the amount of student–staff C's experience at the beginning of his work differed from that of members in the decreasing group, the sort of experiences that contributed to his expertise has yet to be explained. One possible explanation is that the student–staff member may have experienced student-directed project-based learning previously. The ability of socially shared regulation has been shown to improve in projected-based learning (Järvelä and Hadwin, 2013).

Conclusion and future work

In this study, the numerical value obtained by the network analysis of interactions in the community of practice was provided as feedback to members of the community in real time. How these members utilized the visualized feedback was subsequently examined. Specifically, we analyzed how members were interested in how they interacted with others in their work through analyzing the frequency of Social Scanner use. We focused on trends in the frequency of use of Social Scanner by examining whether there was any difference in their experience.

The results showed that the student-staff members in the increasing category used Social Scanner more than student-staff members in the decreasing category. This suggests that the members in increasing group used continuously functions provided to them. This indicates that the members with continuously use of the functions may be interested in the community's interactions and suggests that they may interested in the conditions of the other members. Conversely, even if the members whose use of the functions decreasing were interested in their interactions, they often might find it difficult to spend time on using the functions.

The need for real-time feedback function was pointed out by Tohyama et al. (2021), and the implementation of the function in this study allows student–staff members to see the visualized externalization of each other's activities, even when the activities in the community changed. Real-time visual feedback can also be helpful for teachers. The teacher gets a holistic view of the community, making it easier to guide members to improve communication with each other. They may be able to give specific advice on how to use the feedback function with less-experienced members.

The main limitation of this study is that it remains unclear whether the student–staff members came to be interested in the relationships in their community through their expertise, or whether they became more expert in their work through collaborative work in their community. Interviewing the student–staff members is likely to provide qualitative insights into the motivations behind each of their respective behaviors.

A suggestion on how best to utilize feedback was obtained in this study. However, it is still necessary to examine whether such feedback encourages student-staff members' activities. Future researchers may also be interested in examining how they might be able to use the identified features in their experience as members.

This study showed how often the student–staff members used Social Scanner. Although a questionnaire survey of the student–staff about the use of Social Scanner suggested that some student–staff members tried to change their activities after watching the values showed in Social Scanner (Kondo et al., 2020a), more detailed interviews are needed to know how and why they used Social Scanner. Furthermore, future studies should address how to improve the use of Social Scanner, and how to help learners using the results from Social Scanner to improve their interactions.

Acknowledgements

This work was supported by JSPS KAKENHI (20K03066, 22K12315).

References

Barabasi, A.-L. (2016). *Network Science*. Cambridge University Press.

Ericsson, A., Charness, N., Felotovich, P., Hoffman, R. (2006). *Expertise and expert performance*. Cambridge University Press.

Fiacco, J., Haan, K.-W., Woolley, A. W., & Rosé, C. (2021). Taking transactivity detection to a new level. In Cindy E. Hmelo-Silver, C. E., Wever, B. D. & Oshima, J. (Eds). *Conference proceedings of 14th International Conference on Computer-Supported Collaborative Learning (CSCL),* 75-82.

Hatano, G., & Inagaki, K. (1986). Two courses of expertise. In H. Stevenson, H. Azuma, and K. Hakuta (Eds.) *Child*

Development and Education in Japan (pp.263-272), New York: W. H. Freeman.

Hutchins, E. (1995). *Cognition in the Wild.* The MIT Press.

Järvelä, S. and Hadwin, A. F. (2013). New Frontiers: Regulating Learning in CSCL, *Educational Psychologist*, 48(1), pp.25-39.

Kondo, H., Tohyama, S., Ohsaki, A., & Yamada, M. (2020a). HighNyammer Social Scanner: Collective cognitive responsibility visualization based on network analysis. *Proceedings of 2020 10th International Congress on Advanced Applied Informatics (IIAI-AAI)*, 149–154.

Kondo, H., Tohyama, S., Ohsaki, A., & Yamada, M. (2020b). HighNyammer: Metrics Feedback on BBS for Collaborative Improvement of Collective Cognitive Responsibilities. *International Journal of Learning Technologies and Learning Environments*, 3(1), 61-79.

Kondo, H., Tohyama, S., Ohsaki, A., & Yamada, M. (2022). Evaluation of the Support Function of a Knowledge-Creating Community: Visualizing Relationships between Members in an Online Situation. *Conference proceedings of 15th International Conference on Computer-Supported Collaborative Learning (CSCL),* (in printing).

Lave, J. & Wenger, E. (1991). *Situated Learning: Legitimate Peripheral Participation.* Cambridge University Press.

Lothe, V. & Filliettaz, L. (2019). Negotiation of Epistemic Territories and Collaborative Learning in Workplace Interactions: The Case of Requests for Assistance. *13th International Conference on Computer Supported Collaborative Learning*, 969-970.

Ma, L., Matsuzawa, Y., & Scardamalia, M. (2016). Rotating leadership and collective responsibility in a Grade 4 knowledge building classroom. *Journal of Organisational Design and Engineering,* 4(1/2), 54–84.

Newman, M. E. J. (2010). *Networks: An Introduction*, Oxford University Press.

Ouyang, F., Chen, S., & Li, X. (2021). Effect of three network visualizations on students' social-cognitive engagement in online discussions. British Journal of Educational Technology, 52(6), 2242–2262. https://doi.org/10.1111/bjet.13126

Palinscar, A. S., & L, B. A. (1984). Reciprocal Teaching of Comprehension-Fostering and Comprehension Monitoring Activities. *Cognition and Instruction*, 1(2), 117–175.

Roy, D. (2009). New Horizons in the study of child language acquisition. *Proceedings of Inter-speech 2009*.

Scardamalia, M., Bereiter, C., & Steinbach, R. (1984). Teachability of Reflective Processes in Written Composition. *Cognitive Science*, 8(2), 173–190. https://doi.org/10.1016/S0364-0213(84)80016-6.

Scardamalia, M., & Bereiter, C. (1987). Knowledge telling and knowledge transforming in written composition. In S.Rosenberg (Ed.), *Advances in applied psycholinguistics* (pp. 142–175), Cambridge University Press.

Scardamalia, M., Bereiter, C. (1991). Higher levels of agency for children in knowledge building: A challenge for the design of new knowledge media. *Journal of the Learning Sciences,* 1, 37-68.

Scardamalia, M., & Bereiter, C. (1994). Computer Support for Communities Computer Support for Knowledge-Building Communities. *The Journal of the Learning Sciences*, 3(3), 265–283.

Scardamalia, M., & Bereiter, C. (2014). Knowledge building and knowledge creation: Theory, pedagogy and technology. In K. Saywer (Ed.), *Cambridge handbook of the learning science (*2nd ed) (397-417). Cambridge University Press.

Scardamalia, M., Bransford, J., Kozma, B., et al. (2012). New Assessments and Environments for Knowledge Building, Griffin, P., McGaw, B., & Care, E. (Ed.), *Assessment and Teaching of 21st Century Skills*. Springer Netherlands.

Schmidt, R. A. (1991). *Motor Leaning and Human Performance.* Human Kinetis. Champain IL

Strauß, S., & Rummel, N. (2021). Promoting regulation of equal participation in online collaboration by combining a group awareness tool and adaptive prompts. But does it even matter?. *International Journal of Computer-Supported Collaborative Learning*, 16, 67–104.

Tao, D. & Zhang, J. (2021). Agency to transform: How did a grade 5 community co-configure dynamic knowledge building practices in a yearlong science inquiry?, *International Journal of Computer-Supported Collaborative Learning,* 16, 403–434. https://doi.org/10.1007/s11412-021-09353-7.

Tohyama, S., Yamada, M., Kondo, H., & Ohsaki, A. (2021). Examining an Evaluation Method for Sustainable Development of Communities Analyzing Data from Seven-Years Extracurricular Activities of University Students. *Transactions of Japanese Society for Information and Systems in Education*, 38(2), 137-149. (in Japanese).

Vogel, F. & Weinberger, A. (2018). Quantifying qualities of collaborative learning processes. In F. Fischer, C. E. Hmelo-Silver, S. R. Goldman, & P. Reimann (Eds.), *International hand- book of the learning sciences* (500–510). Routledge.

Xia, Y. & Borge, M. (2019). A Systematic Review of the Quantification of Qualitative Data in the Proceedings of International Conferences of CSCL from 2005 to 2017. *13th International Conference on Computer Supported Collaborative Learning*, 620-623.

Yamada, M., Tohyama, S., Kondo, H. & Ohsaki, A. (2019). A case study of multidimensional analysis for student staff collective cognitive responsibility in active learning classroom. *International Journal for Educational Media and Technology*, 13(1), 115-124.

Zhang, J., Scardamalia, M., Reeve, R., Messina, R. (2009). Designs for collective cognitive responsibility in knowledge building communities*,* 18(1), 7-44.