The Future of Engineering Education
2024 Annual Conference & Exposition
Oregon Convention Center
Portland, OR . June 23 - 26, 2024
ASEE
Paper ID #41294

Enhancing Student Participation in Online Global Project-Based Learnings (gPBLs) Through a Slack-Based Evaluation: A Student Perspective

Mr. Yujiro Iwata, Shibaura Institute of Technology

Yujiro Iwata received his Bachelor of Engineering in Science and Mechanics from the Shibaura Institute of Technology, Japan, in March 2024. He is currently a master's program student at the Shibaura Institute of Technology, majoring in Mechanical Engineering. His main research area is the fields of micro-fabrication and micro sensors.

Mr. Leo Kimura, Shibaura Institute of Technology

Leo Kimura received his Bachelor of Engineering in Science and Mechanics from the Shibaura Institute of Technology, Japan, in March 2024. He is currently a master's program student at the Shibaura Institute of Technology, majoring in Mechanical Engineering. His main research area is control systems for microrobots.

Prof. Hatsuko Yoshikubo Ph.D., Shibaura Institute of Technology

Dr. Hatsuko Yoshikubo obtained Ph. D in English Literature from Chiba University in Japan in 2002. She is currently a Professor in the Innovative Global Program, a research-based full English degree engineering program at the College of Engineering at Shibaura Institute of Technology, Tokyo, Japan. She is a Principal Investigator of the Japan Society for the Promotion of Science Research Grants 24K06133 and the Shibaura Institute of Technology Grants for Educational Reform and Research Activity in the AY2024. Her current main research interests are: 1) how including humanities courses in an engineering education curriculum can help students to gain flexibility, and an appreciation of equity, and a greater richness of ideas; and 2) systematic issues impacting the effectiveness of engineering education, specifically in the context of project-based learnings for the engineering education. Below are her recent presentations at international conferences: ASEE 2023, WERA 2023, 2022, 2019, APAIE 2023, 2022, IIAI DSIR 2021, 2020. She obtained the Multidisciplinary Engineering Division's Best Diversity Paper Award in ASEE 2023 and the Outstanding Paper Award in DSIR 2021.

Dr. Sumito Nagasawa Ph.D. in Engineering, Shibaura Institute of Technology

Dr. Sumito Nagasawa received Ph.D. in Engineering from the University of Tokyo in 2001. He is a Professor, College of Engineering at SIT. His research interests include miniaturized robots using Micro-Electro-Mechanical Systems technologies and robot education for STEM.

Enhancing Student Participation in Online Global Project-Based Learnings (gPBLs) Through a Slack-Based Evaluation: A Student Perspective

1. Introduction

In recent years, the field of engineering has become more globalized, necessitating that engineering students acquire the ability to collaborate with peers possessing expertise in other disciplines, while leveraging their own specialization [1][2][3]. However, in classes involving group activities, it is common for the final outcomes of student groups to be the only criteria used to evaluate students in that group - how well each student performed within the group is not really measured. In many cases, all group members receive the same score, regardless of differences individual contributions. This approach to evaluation can result in a lack of fairness, as students who take the initiative and contribute significantly to group activities end up with the same assessment grades as those who delegate tasks to others within the group and make minimal contributions. Other researchers in the field have explored alternative methods of evaluating group work and individual contributions within it. For example, in one study each member of a student group working on a particular project was given responsibility or 'ownership' of part of the end-of-project presentation, making it easier to ascertain different individuals' levels of involvement [4]. However, this approach still relies on student self- reporting, making it difficult to know how accurately the reports received match the reality of the group work environment. Under such a paradigm whereby assessment of group work typically involves large elements of self-reporting, students are often aware that they are not assessed as rigorously in group work as they are in the other parts of their courses where they are assessed as individuals. As a result, some choose not to fully utilize their expertise in group activities or even to reduce their participation to a bare minimum. Over time, it is also likely to decrease the students' satisfaction with their program. If this tendency continues throughout the workshop, it can create a negative loop whereby their willingness to participate in group activities reduces their ability to acquire team-working skills as well as specific subject knowledge related to that particular workshop. This in turn increases their reluctance to participate fully in the next set of workshops. Thus, we believe that a truly rigorous method for assessing individuals' commitment to group work should be further explored and developed in academia. These problems stem from a mixture of weaknesses in student assessment, issues with student management, and individual discipline; the following are some ways we have suggested to address this issue [4]:

- Regular feedback from students on a daily basis should be collected in order to make sure that they feel comfortable with the project, understand the instructions clearly, and feel comfortable working with the rest of their team.
- Continuous monitoring should be carried out, in order to make sure that the project

instructions are actually being followed and that the group project is progressing in the right direction.
- Workshop organizers should make it clear to the students that while they are working in a team on their project, they are also being assessed individually across each day of the workshop.

On the other hand, where the above strategies are implemented in large class-size settings (for example, with more than 20 students divided into multiple teams taking part in a workshop), it can be challenging for instructors to quickly gather accurate impressions of what is going on in all the groups, measure what each student is contributing individually as well as how the group is progressing as a whole, and thereby provide fair evaluations. Therefore, in this study, a method was developed for instructors to easily examine students' behavior in group work. The effectiveness of this method was validated using data from the Global Project Based Learning (gPBL) Online Robotics workshop at Shibaura Institute of Technology (SIT). SIT runs these gPBLs annually in collaboration with one of its international partner universities, and therefore the gPBLs feature student teams with members from diverse backgrounds both in terms of nationality and academic background - typical student teams are multinational and cross-disciplinary. The research objectives for this paper are as follows:
- To introduce a method for categorizing and analyzing student group-work communication on Slack, with MATLAB as the statistical analysis tool.
- To introduce a method for cross-analysing group and individual Slack communication scores against MGUDS-S global competence scores, also using MATLAB.
- To propose methods for identifying key factors for enhancing levels of student engagement and satisfaction in group activities, in the context of international, collaborative workshop involving students from diverse backgrounds.

During the online robotics workshops in AY2022 and 2023, the study's authors, Iwata and Kimura, were undergraduate students in the Department of Engineering Science and Mechanics at the College of Engineering at SIT, and had been serving as Student Teaching Assistants (TAs) on the Online Robotics workshop; they were then chosen to also be part of the team carrying out Slack-based evaluation. They worked under the supervision of the study authors, Prof. Nagasawa and Prof. Yoshikubo, to explore and decide on optimal data sorting methods, data analysis methods, and development of other processes and workflows for this study. From a data point of view, the study authors drew from assessments of students 'global competence' which were made using the MGUDS-S tool, and categorization and evaluation of students' behavior in group work which were made with particular focus on students' 'Slack' messages. Using these datasets, the Student TAs then carried out statistical analysis to explore the relationships between 'Slack' message quality, MGUDS-S global competence scores, and other factors relevant to group project work.

2. Methodology

Our method has two pillars, with the first being measurement of changes in students' 'global competence' using the MGUDS-S tool, and the second being evaluation of students' activity in their group over the 'Slack' messaging platform; we consider the latter to be the most important part of our approach as it is not based on self-reporting. 'Slack' is the main tool that students use to communicate with their teammates as they advance their project over the five days of the workshop - the main forms of communication are chat messages and sharing of relevant materials. All activity on Slack is logged in a way that makes it easy for educators to retrieve it and conduct analysis on it. Our analytical method assesses both the quantity and quality of each student's communication. As the most basic part of the analysis, we quantify the percentage of total communication (number of total messages sent) that is coming from each student in a group. Then, we assess the 'quality' of each student's contribution to team progress on the project, by categorising their messages into types 'A', 'B', or 'C' depending on how much the communication advances the project [5]. For example, for a student team working on a robotics project, sharing a proposed Tinkercad design for a new circuit would be classified as 'type A'. These methods provide us with detailed insights into the behavior of students within each group, enabling us to identify any issues as they arise - for example, we can identify whether particular students are disengaged from the project, or are having trouble understanding the project brief.

Next, a cross-analysis is presented which comprehensively analyses the relationships between changes in student's MGUDS-S scores before and after the program, and their 'post data' based on number and quality of posts on the Slack platform - both of these are considered and cross-analyses are done on a 'team' and 'individual' basis. We aimed to uncover not just how each student's own 'global competence' scores and communication style on Sack were related, but also how different levels of 'team' performance for these factors impacted individuals within that team - and we were indeed able to draw further insights into group dynamics that had previously gone unnoticed. 'Global competence' as measured by MGUDS-S is a well-established metric, used by universities across the world as a key way of evaluating the impact of courses on students; as such we were conscious that observing a strong correlation between MGUDS-S improvement and student Slack 'scores' would also lend weight to the idea that our new Slack evaluation tool is valuable in this space. To evaluate its study abroad programs, SIT developed a comprehensive global competency assessment framework. This framework utilizes the MGUDS-S, the English Proficiency Evaluation Rubric (CEFR) obtained from the Japanese Consortium of Universities for Institutional Research, and SIT's student satisfaction survey. These assessments are conducted before and after participation in gPBL [6].

To comprehensively analyze the student's post-data from their team Slack communication, their MGUDS-S data, and to learn more about the relationships between these, a cross-tabulation analysis was performed, and the Cramer's V coefficient was calculated. The Cramer's V coefficient is an indicator of the strength of the correlation between two items in a cross-tabulation table, and for all sets of items it takes a value between 0 ('no association between the variables') and 1 ('complete association'). The process of calculating the Cramer's V coefficient is described in steps 1 to 4 below a more detailed explanation is given in Section 3.1.

Step 1: Create a cross table.

Step 2: Calculate the measured frequency and expected frequency of each value.

Step 3: Calculate χ^2 value.

Step 4: Calculate the Cramer's V coefficient r_c .

For our study, Cramer's V coefficients were calculated for various combinations of paired values; more detail is given in the 'Experiment' section below.

3. Experiment

3.1. Cross analysis using Cramer's V coefficient

Next, a method for conducting cross-analysis using Cramer's V coefficient exhaustively to comprehensively analyze the students' MGUDS-S and the post-data will be introduced [7]. For our first example, consider a cross-tabulation table in which students' MGUDS-S score changes (grouped into ranges) are cross-analysed against the nature of their attendance to the workshop: face-to-face or online (with the element being the number of people).

Table 1: A cross-tabulation table comparing MGUDS-S score changes with face-to-face/online status of students (with the element being the number of total students in each MGUDS-S score category)

MGUDS-S	Face to Face	Online	Sum
-20 ~ -16	1 (100%)	0 (0%)	1 (100%)
-15 ~ -11	0 (0%)	1 (100%)	1 (100%)
-10 ~ -6	0 (0%)	2 (100%)	2 (100%)
-5 ~ -1	2 (25%)	6 (75%)	8 (100%)
0 ~ 4	2 (33%)	4 (66%)	6 (100%)
5 ~ 9	2 (50%)	2 (50%)	4 (100%)
10 ~ 14	1 (100%)	0 (0%)	1 (100%)
Sum	8 (35%)	15 (65%)	23 (100%)

The table 1 shows that students who participated in the workshop face-to-face had a higher percentage of MGUDS-S changes in the ranges of -20 to -16 and +10 to +14, compared to the students who participated online. When there is a difference like this, particularly across multiple values or ranges of the dependent variable, it suggests that there is a relationship between the factors being cross-analysed. For context we also calculate the expected value for each category of MGUDS-S score changes – this is the number of students that we would expect to see achieving scores within that range if there was no relationship between MGUDS-S and face-to-face / online participation. For example, if the total number of face-to-face students was the same as the total number of online students, then you would expect to see the same number of students from each 'learning style' in each MGUDS-S score range. This expected value for each MGUDS-S category is the number of students that would fall into the category if the data set satisfied the following conditions (1) and (2):

(1) The percentages of 'face-to-face' and 'online' students in each MGUDS-S range are the vertical total percentage for that attendance type - vertical total 1 being the percentage of total students who attended face-to-face, and vertical total 2 being the percentage who attended online. See Table 2.

Table 2: Expected outcomes in the case that the percentages of 'face-to-face' and 'online' students in each MGUDS-S range would match the vertical total

MGUDS-S	Face to Face [%]	Online [%]	
-20 ~ -16	35	65	
-15 ~ -11	35	65	
-10 ~ -6	35	65	
-5 ~ -1	35	65	
0 ~ 4	35	65	
5 ~ 9	35	65	
~ 14	35	65	
Sum	35	65	100
	↑		
	8 students	15 students	

(2) The percentages of students in each MGUDS-S range in the 'face-to-face' category is the same as the percentage in that range in the 'online' category, and this in turn is the same as the horizontal total - see Table 3.

Table 3: Expected outcomes in the case that the percentages of students in each MGUDS-S score range in the 'face-to-face' and 'online' categories would match the horizontal total of students in that score range

MGUDS-S	Face to Face [%]	Online [%]	Sum [%]	
-20 ~ -16	4.35	4.35	4.35	1 student
-15 ~ -11	4.35	4.35	4.35	1 student

-10 ~ -6	8.70	8.70	8.70		2 students
-5 ~ -1	34.8	34.8	34.8	←	8 students
0 ~ 4	26.1	26.1	26.1		6 students
5 ~ 9	17.4	17.4	17.4		4 students
10 ~ 14	4.35	4.35	4.35		1 student
			100		

The number of students satisfying the conditions (1) and (2) is obtained by multiplying the number of students in the vertical and horizontal totals and dividing by the total number of students.

Table 4: The number of students from each category ('face-to-face' and 'online') that would fall into each MGUDS-S score range if conditions (1) and (2) were satisfied.

MGUDS-S	Face to Face	Online
-20 ~ -16	8×1÷23 = 0.35	15×1÷23 = 0.65
-15 ~ -11	8×1÷23 = 0.35	15×1÷23 = 0.65
-10 ~ -6	8×2÷23 = 0.70	15×2÷23 = 1.30
-5 ~ -1	8×8÷23 = 2.78	15×8÷23 = 5.22
0 ~ 4	8×6÷23 = 2.09	15×6÷23 = 3.91
5 ~ 9	8×4÷23 = 1.39	15×4÷23 = 2.61
10 ~ 14	8×1÷23 = 0.35	15×1÷23 = 0.65

The number of students obtained in Table 4 is called the expected frequency. In contrast, the number of students in Table 1 is called the measured frequency. If the measured frequency is consistent with the expected frequency, there is no association, and if it is not consistent, there is an association.

Next, to determine the degree of agreement between the measured and expected frequencies, the following calculations are made for each cell.

$$\frac{(\text{Measured frequency} - \text{Expected frequency})^2}{\text{Expected frequency}}$$

Table 5: The degree of agreement between the measured and expected frequencies (across all categories of MGUDS-S score change and face-to-face/online status)

MGUDS-S	Face to Face	Online
-20 ~ -16	1.22	0.65
-15 ~ -11	0.35	0.19
-10 ~ -6	0.70	0.37

-5 ~ -1	0.22	0.12
0 ~ 4	0.004	0.002
5 ~ 9	0.27	0.14
10 ~ 14	1.22	0.65

The sum of all cells is calculated to be 6.10. This sum is called the χ^2 value. The higher the χ^2 value, the more strongly related the two items are.

Finally, Calculate the Cramer's V coefficient r_c is calculated by

$$r_c = \sqrt{\frac{\chi^2}{n(k-1)}} = \sqrt{\frac{6.10}{23(2-1)}} = 0.52$$

where n is the total number of categories and k is the number of the smaller of the two categories.

In general, the strength of association by the Cramer's V coefficient is defined as follows:

$$\left.\begin{array}{rll} r_c > 0.5 & \ldots & \text{Very strong correlation} \\ 0.25 \leq r_c < 0.5 & \ldots & \text{Slightly strong correlation} \\ 0.1 \leq r_c < 0.25 & \ldots & \text{Slightly weak correlation} \end{array}\right\} \rightarrow \text{There is a correlation.}$$

$$\begin{array}{rll} r_c < 0.1 & \ldots & \text{Very weak correlation} \end{array} \quad \rightarrow \text{There is no correlation.}$$

Therefore, there is a strong relationship between MGUDS-S and face-to-face/online. The above is the process of calculating the Cramer's V coefficient.

3.2. Cross analysis results

Various combinations of factors that could be related to students' MGUDS-S performance were subjected to pairwise cross-analysis, including project group size, face-to-face or online study, number of posts on Slack (per team and per individual), Slack post quality 'score' (as a team and as individuals), and others - please see Table 6 in appendix 2 for a full breakdown. The Cramer's V coefficients derived from this analysis are presented in Table 6 and also in Table 7 in appendix 2. The cross-analysis was conducted based on cross tables generated by analysing items 1 and 2, with the elements of the cross table being the post number unless otherwise specified. The investigation through cross-analysis identified four combinations with high Cramer's V coefficients, which are the focus of this paper.

- MGUDS-S Score Change × Group: This investigates whether there is a correlation between the post number within the group and the change in MGUDS-S scores based on the post number according to the change in MGUDS-S scores within the group.
- MGUDS-S Score Change × Individual Post score: This examines whether there is a correlation between the post number and the change in MGUDS-S scores based on the post number according to the change in MGUDS-S scores.

- MGUDS-S Score Change × Group (Number of Members): This examines whether there is a correlation between the group the student belonged to and the change in their MGUDS-S scores
- MGUDS-S Score Change × On/Offline Post number: This investigates whether there is a correlation between the post number made, based on whether the participation was in-person or online, and the change in MGUDS-S scores.

Upon investigating the correlation between MGUDS-S and the group's total post number, the Cramer's V coefficient was high at 0.616. This result indicates a very strong correlation between the number of posts made within the assigned group and the students' MGUDS-S scores. On the other hand, the correlation between MGUDS-S and individual post scores (when considering any given individual within the group) was relatively weak. From this, it was identified that individual contribution (in terms of making posts) and changes in MGUDS-S 'global competence' scores within a group were not directly related, but rather reflected differences in how activities were conducted in that group as a whole. The fact that several strong Cramer's V coefficients were found suggests that even in environments where educators have to manage large numbers of students, examining MGUDS-S can be used to identify groups with distinctive features and dynamics; this knowledge can in turn be used to facilitate improvements in group activities and course format.

Additionally, when we investigated the level of correlation between MGUDS-S score changes and the 'quality' score of individual students' posts, we found that the Cramer's V coefficient for this combination was also high at 0.411. This result indicates a strong correlation between individual contributions to group activities and MGUDS-S global competence scores. Identifying distinctive students based on MGUDS-S score changes (in either a positive or negative direction) can be of use in the ongoing process of improving group activities.

Regarding the correlation between 'MGUDS-S score change × Student group' (with group size as the element), the Cramer's V coefficient was high at 0.555. This result supports the empirical observation that there is a correlation between the group to which a student belongs and the student's MGUDS-S scores, providing additional evidence for the validity of the analysis method used in this study. The Cramer's V coefficient between 'MGUDS-S score changes' and 'Post number made in face-to-face / online settings' was 0.515, indicating a strong correlation. However, the fact is that in this study, most of the students from the study authors' university participated in face-to-face sessions whereas all students from the overseas partner universities participated online. Therefore, we cannot separate out the difference in face-to-face / online attendance from other possible differences between our students and partner university students. Therefore, the relationship between MGUDS-S and face-to-face /

online interactions is not fully demonstrated in this study.

3.3. Discussion: Student and TA benefits from using slack analysis

As mentioned earlier, Table 6 and 7 include all cross-analysis data for the four combinations validated in Section 3.3. From these experimental results, it is evident that Slack analysis is an effective method for observing and evaluating group activities. Furthermore, Slack analysis has the benefit that it can be conducted during the execution of group-work projects. Based on the above, the study authors propose that for maximum benefit to students and educators, Slack analysis should be carried out 'during' group projects rather than only at the end. Some of the benefits of ongoing Slack evaluation (from the perspective of the Student TAs who worked on this project) are summarised as follows:

- With Slack analysis, instructors and their assistants can quickly confirm the situation within a student group, allowing for early correction in the case that the group deviates from the intended project brief. This helps rectify misunderstandings promptly.
- Making students aware of the ongoing Slack analysis enables students to recognize that their activity within the group is indeed being evaluated on a daily basis; this enhances motivation to participate fully in group activities.
- Even if students have questions about the evaluation method, the ongoing nature of the Slack analysis gives them the opportunity to inquire about and potentially improve their own performance before the end of the group activity, preventing dissatisfaction and resentment.
- Slack analysis allows educators to promptly recognize and address issues such as conflicts within student project groups, maximising their ability to resolve these in a timely fashion and thus ensure that group work is as productive as possible for all the students involved.

The Student TAs who worked on this study also noted that individual evaluation and analysis of groupwork through Slack, as described in Section 3.1, involves the time-consuming process of reviewing each student's posts and converting the data drawn from them into quantitative assessments. This task required 2 TAs to each perform around 3 hours' work for one day's worth of posts from 23 participants. However, the part of the statistical analysis presented in Appendix 1 can be automated using the MATLAB software package, enabling the swift and non-manual analysis of activities within each group; the only part that needs to be 'manually' done by TAs is the initial classification of student posts. This issue - the fact that 'classifying' posts by quality is inherently a somewhat time-consuming process - could be addressed by hiring additional Student TAs according to the number of students and classes being assessed. Additionally, this solution brings numerous benefits to the employed Student TAs, as summarized below:

- By being involved on the organiser side, Students TAs can gain a comprehensive view of overall group activities and how these function within undergraduate programs.

- TAs can use this experience and the perpectives they gain from it as a reference for their own future participation in group projects - having had the experience of being a Student TA might lead them to get more from workshops they themselves take part in in future years, either as an undergraduate or postgraduate student.
- TAs identified a key factor in smoothing interpersonal relationships within the group: the role of a mediator.
- Collaborating on solving issues faced by students in group activities and having to choose when to occasionally seek advice from the class professor, similarly allowed TAs to broaden their skills.
- The experience of being a Student TA contributed to the improvement of TAs' English skills. As the participants were drawn from diverse international background, TAs learned how English speakers at a wide range of levels (from very basic to native speaker) express themselves in the language during group activities. This experience provided practical and everyday English learning that would be very difficult to obtain just by studying vocabulary in a textbook.

From our perspective as Student TAs, there is one remaining issue with the current evaluation method. At present, it does not really quantify the level of individual student contribution to tasks conducted outside of Slack, such as the creation of presentation slides - at the end of the workshop each group’s presentation receives one score for the group as a whole. In our next paper we aim to come up with a way assessing each student's contribution to the final presentation, reflecting the group dynamics seen within this part of the course and giving students fair and accurate scores for their involvement.

4. Conclusion

This study introduces a method for educators to effectively evaluate students' behavior in the context of team projects, using data drawn from their activity on the 'Slack' messaging platform and statistical techniques. By analyzing student posts on Slack, changes in student 'MGUDS-S' global competence scores, and other data related to their communication and group activity, we were able to identify significant correlations between students' contributions, MGUDS-S scores, and group dynamics. We believe that our findings underscore the importance of recognizing individual contributions within group settings, and the impact of such recognition on student satisfaction and engagement. The proposed method above enables instructors to promptly address issues in group work and provide feedback to students - during the period when workshops and other projects are taking place, not just retrospectively. Moreover, it offers valuable insights into both individual behaviors and the dynamics that arise within student teams; this can facilitate improvements in course design, enable more effective collaboration between partner universities, and enhance overall student satisfaction with workshops. While the study demonstrates the effectiveness of Slack-based analysis in evaluating group activities, there are still areas for further research and refinement. Future studies could explore additional factors influencing student satisfaction and engagement (for example, the relationship between students' performance in international workshops and their written and spoken English levels). We also intend to conduct further research on the scalability of the proposed method in settings where class sizes are very large. Overall, the research we have carried out contributes to ongoing efforts to enhance teaching effectiveness and the student experience in engineering education. It offers a substantial number of practical insights and methodologies for educators who have the desire to optimize the 'group work' aspect of their courses, and the need to foster student engagement in international, collaborative learning environments.

Reference

[1] Van den Beemt A, MacLeod M, Van der Veen J, et al., “Interdisciplinary engineering education: A review of vision, teaching, and support,” *Journal of Engineering Education*, vol. 109, issue 3, pp. 508-555, 2020.

[2] M.A. Clavert and M.S. Laakso, “Implementing design-based learning in engineering education Case Aalto University Design Factory,” in *European Society for Engineering Education: Proceedings of 41st Annual Conference of the European Society for Engineering Education,* Leuven, BEL, September 16-20, 2013.

[3] H.-W. Wang, “Multidisciplinary Efforts Addressing Problem-Based Learning in a Graduate Course,” in *American Society for Engineering Education: Proceedings of 2017 Annual Conference and Exposition,* Columbus, USA, June 24–28, 2017.

[4] P. P. Srinivasa, N.C. Niranjan and B.R. Shrinivasa, “Project Based Learning (PBL): Issues Faced by Faculty for its Effective Implementation,” Journal of Engineering Education Transformations, vol. 31, no. 3, pp.9-16, January 2018.

[5]H. Yoshikubo, S. Nagasawa, H. Ishizaki, “Creating Innovation for Interdisciplinary Robotics Workshops: Solving Issues in the Online Project-Based Learnings in Engineering Education,” in *American Society for Engineering Education: Proceedings of 2023 Annual Conference and Exposition,* Baltimore, USA, June 25–28, 2023.

[6] H. Yoshikubo, S. Aihara, M. Inoue, et al., “Assessment of Online Study Abroad Programs from the Students’ Perspectives,” Journal of JSEE, vol. 71(1), pp.18-26, January 2023.

[7] H. Cramér, *Mathematical Methods of Statistics*, Princeton University Press, 1999.

Appendix 1

An analysis method using MATLAB is introduced, to generate a table of the distribution of number of posts by students within each working group, categorized by Slack post quality

Step 1: Import data from an Excel file using the 'readtable' function, and convert names and Slack message scores to a nominal array.

```
ds=readtable('FileName.xlsx');
ds.name=nominal(ds.name);
ds.score=nominal(ds.score);
```

Step 2: Create a dataset.

```
% Create a dataset for the team to which the focused student belongs.
dst = ds(ds.team==Team_Number,:);
% Create a dataset for each member.
dsMember1=dst(dst.name=='Member1_Name',:);
…
dsMember4=dst(dst.name=='Member4_Name',:);
dsWithoutMember1=dst(dst.name~='Member1_Name',:);
```

Step 3: Display the history of Slack messaging / posting over time for individual students, using a histogram.

```
% Transition of post time. (Histogram comparison between Member1 and other members.)
createfigure01(dsMember1(dsMember1.date==320,:).time,dsWithoutMember1(dsWithout
Member1.date==320,:).time,'20 March, Team Number');
```

Step 4: Display the percentage of post of each quality 'score' that were made by each group member.

```
% Comparison of the quality of posts. (Percentage of each member's post evaluation.)
t320=[length(find(dsMember1(dsMember1.date==320,:).score=='A')),length(find(dsMemb
er2(dsMember2.date==320,:).score=='A')),...
length(find(dsMember3(dsMember3.date==320,:).score=='A')),length(find(dsMember4(ds
Member4.date==320,:).score=='A'));
length(find(dsMember1(dsMember1.date==320,:).score=='B')),length(find(dsMember2(ds
Member2.date==320,:).score=='B')),...
length(find(dsMember3(dsMember3.date==320,:).score=='B')),length(find(dsMember4(ds
Member4.date==320,:).score=='B'));
length(find(dsMember1(dsMember1.date==320,:).score=='C')),length(find(dsMember2(ds
Member2.date==320,:).score=='C')),...
```

```
length(find(dsMember3(dsMember3.date==320,:).score=='C')),length(find(dsMember4(ds
Member4.date==320,:).score=='C'))];
createfigure02(t320,'20 March, Team Number');
% Percentage of Member1's posts in each score.
[t320(1,1)/sum(t320(1,:))*100,t320(2,1)/sum(t320(2,:))*100,t320(3,1)/sum(t320(3,:))*100]
```

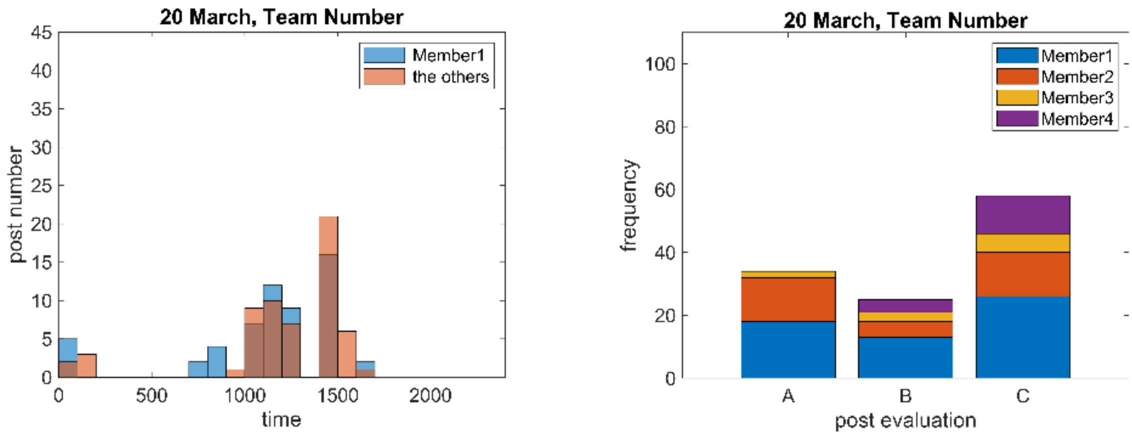

Fig. 1 Examples of diagrams that can be created by steps 3 (left figure) and 4 (right figure).

When following steps 3 and 4, the code can be simplified by creating functions as follows.

```
% Create ‘createfigure01’ function.
function createfigure01(data1, data2, titleinfo)
figure1 = figure('Name','Figure','Color',[1 1 1]);
axes1 = axes('Parent',figure1);
hold(axes1,'on');
histogram(data1,'DisplayName',' Member1','BinWidth',100);
histogram(data2,'DisplayName',[' the others'],'BinWidth',100);
xlabel({'time'},'FontName','Arial'); ylabel({'post number'},'FontName','Arial');
title({titleinfo});
xlim(axes1,[0 2400]); ylim(axes1,[0 45]);
box(axes1,'on');
hold(axes1,'off');
set(axes1,'FontName','Arial','FontSize',14,'TitleFontWeight','bold');
legend1 = legend(axes1,'show');
```

```
% Create ‘createfigure02’ function.
function createfigure02(ymatrix1,titleinfo)
figure1 = figure;
axes1 = axes('Parent',figure1);
hold(axes1,'on');
```

```
X = categorical({'A','B','C'}); X = reordercats(X,{'A','B','C'});
bar1 = bar(X,ymatrix1,'BarLayout','stacked','Parent',axes1);
set(bar1(4),'DisplayName','Member4'); set(bar1(3),'DisplayName','Member3');
set(bar1(2),'DisplayName','Member2'); set(bar1(1),'DisplayName','Member1');
xlabel({'post evaluation'},'FontName','Arial'); ylabel({'frequency'},'FontName','Arial');
title({titleinfo});
ylim(axes1,[0 110]);
box(axes1,'on'); hold(axes1,'off');
set(axes1,'FontName','Arial','FontSize',14,'TitleFontWeight','bold');
legend1 = legend(axes1,'show');
```

Appendix 2

Table 6: The Cramer's V coefficients derived from various combinations.

Analysis item 1	Analysis item 2	Cramer's V coefficient	Analyst
MGUDS-S score Change	Student's group	0.616	TA B
	Face-to-Face/Online	0.515	TA B
	Post number of Face-to-Face/Online	0.692	TA B
	Individual post score	0.411	TA A
	Group post score	Group 1: 0.191, Group 2: 0.130 Group 3: 0.216, Group 4: 0.079 Group 5: 0.190	TA B
	Face-to-Face/Online post score	Face-to-Face: 0.248 Online: 0.197	TA B
	Students' group (Element is number of students)	0.555	TA B
The date	Student's group	0.120	TA A
	Face-to-Face/Online	0.046	TA A
	All students	0.214	TA A
	Individual post score	Refer to Table 7	TA B
	Group post score	Group 1: 0.130, Group 2: 0.120 Group 3: 0.117, Group 4: 0.105 Group 5: 0.140	TA A
	Face-to-Face/Online post score	Face-to-Face: 0.120 Online: 0.118	TA A
Before/After eating	Face-to-Face/Online post number	0.092	TA B

	Individual post score	Refer to Table 7	TA B
	Group post score	Group 1: 0.289, Group 2: 0.413 Group 3: 0.286, Group 4: 0.255 Group 5: 0.341	TA B
	Face-to-Face/Online post score	Face-to-Face: 0.264 Online: 0.259	TA B
Student's group	Group post score	0.208	TA B
Individual	Individual post score	0.304	TA B
Face-to-Face/Online	Group post number	0.178	TA B
	Group post score	Group 1: 0.178, Group 2: 0.129 Group 3: 0.211, Group 4: 0.046 Group 5: 0.199	TA B
	Group post score	0.066	TA B

Table 7: The Cramer's V coefficients derived from combinations; 'Date and Individual post score' and 'Before/After eating and Individual post score'.

Student Number	The Cramer's V coefficient		Student Number	The Cramer's V coefficient	
	Date × Individual post score	Before/After eating × Individual post score		Date × Individual post score	Before/After eating × Individual post score
1	0.224	0.215	13	0	0
2	0.216	0.268	14	0.254	0.216
3	0.206	0.167	15	0.153	0.187
4	0.157	0.184	16	0.175	0.208
5	0.211	0.206	17	0.149	0.134
6	0.173	0.227	18	0.223	0.193
7	0.226	0.196	19	0.163	0.183
8	0.202	0.178	20	0.187	0.186
9	0.256	0.221	21	0.185	0.144
10	0.208	0.192	22	0.105	0.083
11	0.199	0.225	23	0.161	0.155
12	0.077	0.107			