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What does process mining of feedback-behavior reveal about problem-solving in chemistry undergraduates?

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Abstract: Feedback is known to play a powerful role in the process of learning and problem-solving. In a problem-solving context where feedback is expected to positively influence the process of achieving the target goal, feedback information can be elicited through feedback-seeking questions. In this study, we analyze different purposes for which feedback is both sought and given by chemistry undergraduate students (n=3) as they solved representational problems concerning a medicinal drug. The students were left unsupervised and, with their consent, were video-recorded to capture their problem-solving process. We used the transcript of the video data and coded students' interactions to identify feedback events concerning 'the task', 'process', and 'regulation' of the problem-solving activity. These events were then used to generate process models of feedback behavior of students, individually and collaboratively, through ProM- a process mining tool. Our models suggest that feedback questions on tasks and processes dominate the beginning of the problem-solving activity, while feedback responses on processes and regulation dominate the end phase. Our work has implications for designing activity problems. We suggest designing well-thought-out focus questions at the beginning of problem-solving exercises to both scaffold and facilitate students' learning because it aligns with the natural unsupervised flow of problem-solving, as is observed in this study.

Keywords: Feedback, feedback-seeking, questions, responses, process mining

1. Introduction

We seek feedback because, as humans, we are inherently curious and want to know how we are doing and how we have done (Cutumisu, & Lou, 2020). The process of seeking feedback and the corresponding gathered response positively influences learning (Rattan et al., 2015). It helps learners to verify their position, gather insights about strategies that can be used, and/or provide appropriate metacognitive support (Wang & Wu, 2008). In their feedback model, Hattie & Timperley (2007) identified that feedback questions were concerned with tasks, processes, self-regulation, and self, while feedback responses were concerned with answering questions about goal-directed action, overall progression (say, about a concept), and future possibilities. In this study, we draw upon this feedback model to map the trajectories of individual students as they are involved in feedback behavior during a problem-solving task.

We use ProM (Günther & Van Der Aalst, 2007), an open-source process mining tool to analyze and visualize the process of interaction between individual student's feedback-seeking questions and responses. It uses multiple algorithms to shed light on the sequence in which a process occurs. Here, we use the Directly Follows Graph, Extended Causal Graph Miner algorithm, and Heuristics Miner algorithm (Weijters, Van Der Aalst, & De Medeiros, 2006) to visualize the trajectories of interaction among different feedback behaviors.

2. Research Questions

This study addresses the following research questions-

- With no specific instructions on collaboration, do students engage in feedback behavior during a problem-solving activity?

- If yes, could we map the sequence of flow in which feedback behavior is manifested?
- What does the sequence reveal about the trajectory of individual students' feedback behavior in a problem-solving activity?

3. Methods

3.1 Participants, Data Sources & Task

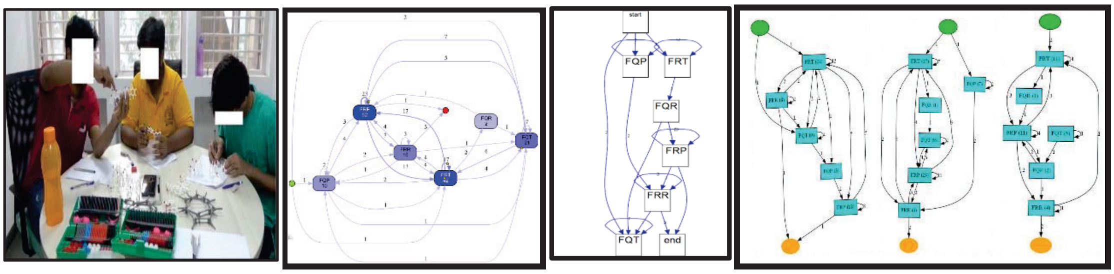
Three male post-graduate chemistry students, who had completed an introductory course on stereochemistry, volunteered for a study based on tasks about representations of a medicinal drug. Students were seated at a round table and were individually given task-specific worksheets. They were free to work individually or collaboratively and the activity was video-recorded with minimal presence of the researcher. The video data formed the primary data source for this study. The video (1.5 hours) was transcribed using a combination of 'Otter', an online transcribing interface, and manual transcription. The study was approved by the IRB of the institute and students' consent were received before the conduct of the study.

3.2 Data Coding

Following Hattie & Timperley (2007), we used codes to map feedback questions and responses pertaining to- a) form and structure of tasks (FQT & FRT- *F*eedback-seeking *Q*uestion about the *T*ask and *F*eedback *R*esponse on the *T*ask), b) processes involved (FQP & FRP: *F*eedback-seeking Question about the *P*rocessing and *F*eedback *R*esponse about the *P*rocessing of the task), and c) monitoring (FQR & FRR: *F*eedback-seeking *Q*uestion about *R*egulation and *F*eedback *R*esponse about *R*egulation of the task). We use codes S1, S2, & S3 for the three students.

4. Analysis and Findings

4.1 Students engage in feedback behavior on their own and PRoM algorithms mapped the sequence of the flow of feedback questions and responses



a) b) c) d)

Figure 1. a) *A feedback-seeking episode (Adapted from Swamy et al., 2022), b) a 'Directly Follows Graph' (DFG) representing the path for all the participants, (c) an Extended Causal Activity Graph, d) Heuristic Net Graphs for each student*

Figure 1 a) depicts two students engaging in feedback behavior during the activity even in the absence of no specific instructions on collaboration. Further, a Directly Follows Graph ('DFG'; Figure 1 b)) and an Extended Causal Graph (Figure 1 c)) mapped the overall flow of feedback events moving from the start (green circle in Figure 1 b) & 'start' box in 1 c) to the end (red circle in 1 b) & 'end' box in 1 c) of the problem-solving task for the participants. The nodes and the lines in the two graphs represent feedback behavior (questions or responses) and the transitions in these behaviors respectively. The numbers within the DFG nodes give the count of the events. Nodes with the greatest number of events are depicted in darker shades and vice-versa. The graphs reveal that the maximum number of feedback-seeking questions were asked about the task (FQT-21) and the maximum number of feedback responses were given on the process (FRP-52), suggestive of a potential emphasis on process strategies to tackle questions on task. Further, from both graphs, we find that FQT (21 events) & FQP (10 events) behavior dominate the beginning phase and FRP (52) & FRR (16) behavior dominate the end phase of the problem-solving activity, suggesting that

4.2 Individual differences in interaction trajectories

Heuristic Net Graphs (Fig. 1 d)) mapped the trajectory of all students' interaction between feedback questions and responses from the start (green circle) to the end (orange circle) of the problem-solving task. We find that S3 had only 34 events of feedback exchange, while S1 & S2 had more than 60 events for the process. We also find that S3 asked extremely few questions (7) overall. Thus, we can conclude that S1 and S2 were more actively involved in feedback behavior than S1. Thus, the graph gives an insight into the dynamics of interaction among the participants during the problem-solving process.

5. Discussion

In summary, we found that the participants naturally drifted toward collaborative problem-solving. The use of PRoM tools revealed that feedback-seeking questions on 'task' and 'process' dominated the start of the activity, while feedback responses on 'process' and 'regulation' dominated the end of the activity. Based on this, we suggest designing well-thought-out focus questions at the beginning of problem-solving exercises to both scaffold and facilitate students' learning. The Heuristics Net graph revealed answers to broader questions like- 'Who was more/least engaged in the feedback event?' to finer questions like- 'What form of feedback event was prominent in an individual's interaction with the other group members?' Our work contributes to the field by visualizing the process of feedback behavior and mapping the sequence of feedback events at both individual and aggregate levels. It has implications for both pedagogy and research, where such insights could be used to design scaffolds to promote scientific discourse (Seng & Hill, 2014), infer design principles for facilitating collaborations, and/or use/design tools to better visualize problem-solving behavior.

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ICCE 2023 Learning Outcomes of Computer Programming and Information Technology - Integrated Courses for Non-Computer Science Majors: Case Study of a Public Research University in Taiwan

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Abstract: This study investigates non-CS major students' performance in computer programming and Information Technology-integrated (ITI) courses at a Taiwanese research university. Non-CS students struggle in introductory programming due to syntax and logical thinking limitations, resulting in lower grades compared to advanced programming. Similarly, ITI course grades are lower due to subject-specific demands. Gender and entry channels impact outcomes, with females excelling in informal learning. Favorable results are seen in individual applications and Multi-star Projects. Challenges include different learning paces and cultural adjustments. Regression analysis shows Introduction to Computer Programming (ICP), Advanced Computer Programming (ACP) and gender significantly affect ITI performance, explaining 24% of its variance. Recommendations include diverse teaching methods, problem-solving guidance, practical programming, collaboration, and project participation to enhance skills.

Keywords: Computer programming, Information technology-integrated courses, learning outcomes, entrance channels, longitudinal study

1. Introduction and Key Questions

The 2016-2020 Information Education Blueprint aimed to enhance deep learning and digital citizenship through IT tools, aligning with Taiwan's emphasis on computational thinking for problem-solving (Kalelioglu et al., 2016). The "Higher education sprout project" achieved 60% participation by June 2020, indicating successful non-CS programming course implementation (Ministry of Education, 2020). However, non-CS students face challenges in programming due to logic, syntax, and abstract thinking (Weng et al., 2014). Therefore, the research questions for this study are as follows:

- Are there grade differences among non-CS students in ITI courses, including programming skills in other subjects?
- Do gender and entrance channels influence the learning outcomes of non-CS students in ITI and programming courses?
- Is it possible to predict non-CS students' performance in ITI courses using their programming course grades and relevant background factors?

2. Methodology

2.1 Participants and Computer Programming Implementation Courses Information

The participants in this study are non-information field professionals who have successfully completed three types of courses: ICP, ACP, and ITI courses. The total number of participants is 367. Among these students, 69% were male and 31% were female. Entrance channels included individual applications (39%), Multi-star projects (15%), exams (35%), and special programs/transfer/international admissions (11%). This reflects the Ministry of Education's admission policies and highlights effective recruitment and selection strategies.

According to the curriculum design of the individual school, the course is divided into the following three parts:

1. ICP Course: Students will learn basic concepts of computer programming, including syntax, fundamental logic, and programming skills.
2. ACP Course: Students will delve into more complex programming techniques and strive to achieve specific programming goals.
3. ITI Course: The ITI course integrates subject knowledge with program analysis, including topics such as statistics. This will enable students to apply computer programming skills to specific disciplinary areas and solve relevant problems.

Grades earned by students may be obtained repeatedly in these classes, and these grades will be represented through the calculation of average semester grades. Performance differences were analyzed using weighted adjustments: ICP (15%), ACP (25%), and ITI (60%) of Computer and Technology (CT) Grades.

2.2 Statistical Analysis Tools

For data analysis, descriptive statistics compare grade differences. An independent t-test assesses gender disparities in CT, followed by mean comparisons. One-way ANOVA explores diverse non-CS major backgrounds, with post hoc tests. ICP and ACP predict ITI grades. JASP 0.16 conducts all analyses.

3. Results

3.1 Analysis of Computer Programming and ITI Course Performance of non-CS Majors.

Table 1 displays a performance comparison of Non-CS students based on grades in ICP, ACP, and ITI courses using repeated measures ANOVA ($p<0.05$ or F-value=14.27). Results highlight a significant performance difference among these course categories. Post hoc analysis indicates superior performance in ACP compared to ICP and ITI courses. Meanwhile, ICP and ITI course grades were comparable, suggesting support is needed for students in comprehending unfamiliar subjects within their respective disciplines.

Table 1. *Comparison of course grade and background variables*

	F	P	Post hoc
Courses	14.27	<0.01	ACP > ICP & ITI grade
	T	P	Post hoc
Gender	-3.76	<0.01	Female >Male
Entrance channels	F	P	Individual Application Channel >Oversea & Transfer
	12.03	<0.01	Multi-star Project >Exam-based channel & Oversea& Transfer

3.2 To compare the learning effectiveness of the CT Grades among students with different background variables.

Historically, there existed a perception of gender-based inclinations toward literature and art, posing challenges in STEM fields for females (Wrigley-Asante, C et al., 2023). Gender's impact on CT grades was examined using a pair sample t-test (t-value=0.001<0.05), The results demonstrated that female non-CS students outperformed males, as presented in Table 1.

Entrance channels' influence on academic performance was investigated through one-way ANOVA (F value=12.03, p<0.05). Post-hoc analysis revealed higher grades for individual applications and "multi-star project" students compared to overseas and transfer students. "Multi-star project" entrants also outperformed exam-based entrants, as presented in Table 1. Notably, individual application and "multi-star project" students demonstrated stable IT and academic performance, while overseas and transfer students made additional efforts to reach similar levels.

3.3 The Relationship Between Student Variables and ITI Grade

Multiple regression analyses showed that ICP grades, ACP grades, and gender collectively explain 24% of the variance in ITI grades, which is statistically significant. Post hoc comparisons revealed significant contributions from ICP grades (t=6.03, p<0.001), ACP grades (t=4.16, p<0.001), and gender (t=-3.1, p<0.001) to the explanatory power. ICP grades had the highest influence (β=0.32), followed by ACP (β=0.2), and then gender (β=0.15). Entrance channel didn't significantly impact the model. Multicollinearity was assessed using VIF, with values well below 5 (ICP: VIF=1.21, ACP: VIF=1.21, Gender: VIF=1.02), indicating no multicollinearity issues, as presented in Table 2.

The regression equation is: ITI grade = 48.59 + (0.23) * ICP grade + (0.17) * ACP + (-3.53) * Gender. Gender is a dummy variable; when 0, it represents female students' influence, and when 1, it represents male students. Female students outperform male students by an average of 3.53 points in ITI grades.

Table 2. *Linear Regression of ITI Grade*

	Coef	Std err	T	p-value	VIF
Const	48.59	3.87	12.54	<0.001	
ICP	0.23	0.04	6.03	<0.001	1.21
ACP	0.17	0.04	4.16	<0.001	1.21
Gender (male)	-3.53	1.11	-3.1	0.002	1.02
Entrance channels	0.02	0.41	0.05	0.96	1.06

4. Conclusion and Recommendations

Non-CS students struggle in ICP and ITI courses compared to those skilled in ACP due to unfamiliar syntax and initial lack of logical thinking training. Females excel, challenging stereotypes. Individual applications yield better outcomes than transfers or overseas recruitment. Multi-star Projects outperform exams and overseas recruitment, showcasing diverse experiences. Regression analysis explains 24% of ITI grade variance; ICP grade, ACP grade, and gender influence ITI grade. Recommendations encompass diverse teaching methods, promoting practical programming, fostering collaboration, and encouraging participation in information competitions. Interactive learning environments and providing support for overseas students are essential to enhance the learning experience.

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