Students' Engagement in Learning Programming Using a GenAI-Driven Chatbot: Insights from Sentiment and Epistemic Network Analysis

Ean Teng Khor
National Institute of Education, Nanyang Technological University
eanteng.khor@nie.edu.sg

Abstract: *The study examines the sentiment-related engagement of students interacting with a GenAI-driven chatbot in learning programming, focusing on two distinct groups: students with score improvement (Group A) and those without score improvement (Group B). This study leveraged sentiment analysis and epistemic network analysis (ENA) to examine the relationships between sentiment expressions and learning behaviors. The findings reveal that students in Group A exhibited greater diversity in sentiment expressions, characterized by more constructive use of feedback, whereas students in Group B predominantly displayed neutral and negative sentiments with limited feedback utilization, positing lower engagement. These results provide insights into how students' sentiment patterns relate to learning strategies and highlight the potential of ENA in capturing complex interactions between affective expressions and cognitive behaviors in learning programming.*

Keywords: GenAI, Chatbot, Learning Engagement, Sentiment Analysis, Epistemic Network Analysis

1. Introduction

Despite the increasing integration of chatbots in education, research examining students' sentiment trajectories during GenAI interactions remains limited, particularly in computing education. This study addresses the gap by analyzing students' sentiment patterns, comparing the distribution between different groups of students and exploring how these sentiment patterns connect with students' interaction behaviors through ENA. The study examines how learning outcomes are impacted by students' sentiment-related engagement that is enabled by an educational chatbot powered by GenAI, *MyBotBuddy* (Khor et al., 2026). Drawing on Vygotsky's Zone of Proximal Development (ZPD) (1978), *MyBotBuddy* uses a scaffolding instruction methodology to enhance students' learning while ENA provides a structural lens to capture how students' discourse elements co-occur during these interactions. This study offers insights into how GenAI-driven chatbots can support learners' engagement, particularly their positive and negative sentiment patterns, in complex subject areas such as programming, by utilizing sentiment analysis and ENA.

2. Research Design and Methods

Sentiment analysis guided the tailoring of chatbot responses according to users' sentiment signals. When negative sentiments were detected, the chatbot generated responses designed to be more supportive. These adaptations made the chatbot seem more responsive, which can boost user confidence and improve the quality of interactions. To minimize the cognitive load on students when reading the generated responses, *MyBotBuddy* breaks explanations of complex concepts into smaller sections that are revealed progressively (Khor & Chan, 2025). These require less mental effort to process at a time and are less overwhelming. Ethical approval was obtained from both the authors' institution and the Singapore government ministry to recruit student participants. A total of 49 Secondary school students (aged 15–16) enrolled in GCE 'O' Level Computing participated in this in-class study. In the pre-test, students applied computational thinking to decompose a problem, abstract key information, and design an algorithm to validate an ISBN-13 number, which they implemented in Python using Google Colaboratory. During the intervention, students interact with *MyBotBuddy* (Khor et al., 2025) to improve their code as well as discuss other computing questions. The post-test assessed their ability to validate an ISBN-10 number.

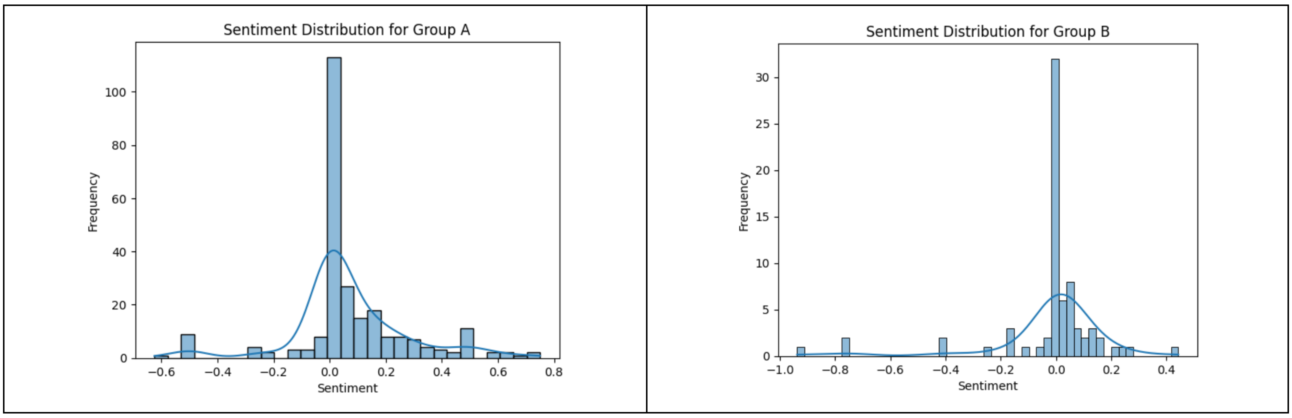
Sentiment analysis and ENA were conducted on conversational logs to compare students who improved (Group A) and those who did not (Group B). Interactions were classified as positive, neutral, or negative to examine differences in overall sentiment patterns between the two groups. ENA was used to model relationships among key learning behaviours, including feedback utilisation, problem identification, knowledge contribution, clarification requests, and solution attempts. The coding scheme was grounded in Vygotsky's sociocultural theory Mind in Society, particularly the concept of the ZPD, which emphasises learning through social interaction and scaffolding. Within this framework, *MyBotBuddy* functions as a More Knowledgeable Other, providing feedback and prompts that guide students beyond their current capabilities. These interactions support learners in progressing through their ZPD by encouraging more advanced problem-solving strategies. Students' sentiments toward feedback influenced their engagement: those with neutral or positive sentiment tended to sustain dialogue, while negative sentiment was associated with reduced engagement and fewer productive behaviours. Multiple ENA-compatible codes were applied to capture and map co-occurrence relationships among these learning actions.

3. Findings

As shown in Figure 1, Group A's histogram shows a wider spread of sentiment values, ranging approximately from −0.6 to 0.8, with multiple visible bars across both negative and positive ranges. There are noticeable positive peaks (around 0.1 to 0.5) and some negative values, alongside a strong central cluster near neutral. This indicates greater variability and emotional fluctuation, suggesting that students experienced and expressed a broader range of sentiments during interaction. In contrast, Group B's distribution is more tightly concentrated around neutral (close to 0), with a narrower range (approximately −1.0 to 0.4). The histogram shows a dominant central spike at neutral, with relatively few positive values and sparse negative outliers. Compared to Group A, there are fewer positive sentiment bars and lower overall variation, indicating more limited emotional engagement. Together, these patterns support the interpretation that Group A demonstrated higher affective engagement, while Group B exhibited more constrained and neutral interaction patterns.

Figure 1

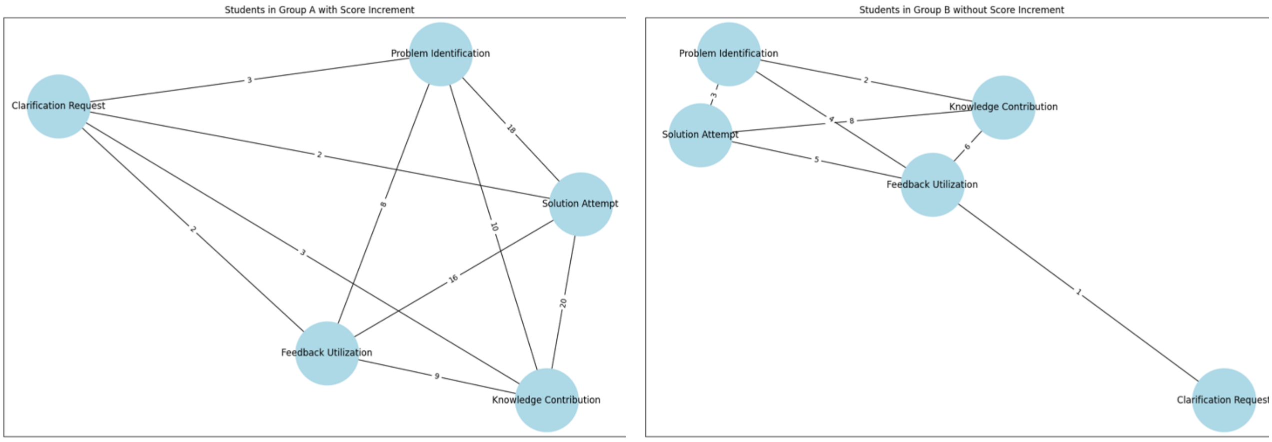
Sentiment distribution



ENA results further showed that solution attempts were the most frequent learning behaviour, followed by knowledge contribution and feedback utilization (Figure 2). Group A exhibited stronger co-occurrences between knowledge contribution and solution attempts (20 times), and between feedback utilisation and solution attempts (16 times), indicating active integration of feedback into problem-solving. This aligns with the feedback model proposed by Hattie and Timperley (2007), which emphasises the importance of using feedback to close the gap between current and desired performance. In contrast, Group B showed weaker co-occurrences between feedback utilisation and solution attempts (5 times), suggesting limited reflective engagement and possible disengagement from feedback processes (Carless & Boud, 2018). The frequent pairing of problem identification and solution attempts in Group A (18 times) points to stronger metacognitive regulation, which is a key predictor of learning success. Overall, Group A's more effective feedback utilisation and metacognitive engagement likely contributed to their improved performance.

Figure 2

ENA graph visualization



4. Discussion

The findings show that students in Group A and Group B exhibited different sentiment patterns when interacting with *MyBotBuddy*, highlighting the role of affective engagement in shaping learning outcomes. Group A demonstrated a wider range of sentiments, suggesting higher motivation and engagement. This aligns with flow theory (Csikszentmihalyi, 1990), where positive emotions support sustained effort in challenging tasks such as programming. In contrast, Group B displayed predominantly neutral and occasional negative sentiment, indicating lower affective engagement. Negative sentiment may reflect cognitive overload, which can hinder feedback processing, consistent with Cognitive Load Theory (Sweller, 2020). Correspondingly, Group B showed fewer learning behaviours across feedback utilisation, knowledge contribution, solution attempts, clarification requests, and problem identification. For example, solution attempts were substantially lower (28% vs. 71% in Group A), suggesting limited effort in iterating and refining problem-solving strategies, which may explain the lack of score improvement.

The ENA findings further reveal how crucial feedback utilization is for fostering reflective learning and problem-solving. Group A students demonstrated frequent feedback utilization, which allowed them to iteratively refine their solutions and develop deeper understanding. This suggests good feedback receptivity and action with productive feedback actions (Carless & Boud, 2018). Students were able to use the feedback from the chatbot effectively to make improvements, to utilize input to adjust their learning strategies and solve the problems. In contrast, Group B's inadequate use of feedback implies that they did not integrate input into their problem-solving efforts. Without engaging in metacognitive reflection, students B are less likely to identify knowledge gaps or areas for improvement. This highlights the need for chatbots to provide more targeted feedback prompts that encourage introspection and problem-solving in addition to motivating students to make changes.

The findings highlight key design implications for GenAI chatbots. Students in Group B showed lower engagement and more negative sentiment, alongside weaker feedback utilisation. This suggests chatbots should detect affective cues and provide targeted support, such as scaffolding, motivational prompts, or simplified explanations, to sustain engagement. This aligns with control-value theory, which links emotions to perceived control. Incorporating strength-based feedback and reflective prompts (Gradito Dubord et al., 2022) can further support learners. Students in Group A showed more positive sentiment, indicating that affirming feedback promotes persistence. Chatbots can reinforce this by highlighting progress and breaking tasks into manageable steps, especially in demanding subjects like programming.

5. Conclusion

The significance of sentiment-related engagement in influencing learning outcomes in chatbot-mediated environments is highlighted by this study. Compared to students in Group B, who expressed more neutral or negative sentiment and engaged with lesser feedback, students in Group A, who showed more positive sentiment and high feedback usage, showed better learning outcomes. These results imply that chatbots powered by GenAI may promote deeper learning by providing tailored assistance and maintaining students' motivation and engagement through difficult tasks. This study does, however, have limitations. The current study does not factor in cause-and-effect relationships in sentiment expression or temporal dynamics. Sequential sentiment analysis could be therefore explored for further studies. Nonetheless, this study still provides insights into the role of sentiment and ENA in learning with chatbots and highlights practical implications for designing more supportive and responsive GenAI-powered learning environments.

Acknowledgements

This research is supported by the Ministry of Education (MOE), Singapore, under its Academic Research Fund (RG89/22). Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the Singapore MOE and National Institute of Education, Nanyang Technological University, Singapore. IRB reference no.: IRB-2023-392.

References

Carless, D., & Boud, D. (2018). The Development of Student Feedback Literacy: Enabling Uptake of Feedback. *Assessment & Evaluation in Higher Education, 43*(8), 1315-1325.

Csikszentmihalyi, M. (1990). *Flow: The Psychology of Optimal Experience* (pp. 75-77). New York: Harper & Row.

Gradito Dubord, M. A., Forest, J., Balčiūnaitė, L. M., Rauen, E., & Jungert, T. (2022). The Power of Strength-oriented Feedback Enlightened by Self-determination Theory: A Positive Technology-Based Intervention. *Journal of Happiness Studies, 23*(6), 2827-2848.

Hattie, J., & Timperley, H. (2007). The Power of Feedback. *Review of Educational Research, 77*(1), 81-112.

Khor, E. T., & Chan, L. (2025, June). Exploring The Effect of Scaffolding Strategies in GenAI Chatbot on Student Engagement and Programming Skill Development. In *The Global Chinese Conference on Computers in Education (GCCCE) Proceedings* (Vol. 2025, pp. 32-39).

Khor, E. T., Chan, L., Koh, E., & Seow, P. (2026). Exploring Students' Perceptions of Generative AI-generated Feedback in Learning Programming. *Educational Psychology, 46*(1), 150–182.

Khor, E. T., Chan, L., & Seow, P. (2025). Students' Use and Perception of Educational GenAI Chatbot in High School Computing: Insights from The Decomposed Theory of Planned Behavior. *Education Sciences*, *15*(12), 1569.

Sweller, J. (2020). Cognitive Load Theory and Educational Technology. *Educational Technology Research and Development, 68*(1), 1-16.

Vygotsky, L. S. (1978). *Mind In Society: The Development of Higher Psychological Processes*. Cambridge, MA: Harvard University Press.