A Phygital Approach to Social-Emotional Learning: Effectiveness of a Generative AI Chatbot as a Digital Transitional Space for Junior High School Students

Tzu-Yin Liang[1], Su-Jian Yang[2], Chiu-Pin Lin[1]

[1] Institute of Learning Sciences and Technologies, National Tsing Hua University, Taiwan

[2]International Intercollegiate Ph.D. Program, National Tsing Hua University, Taiwan

* s0612004ii@gmail.com

Abstract: *Traditional large-class instruction often struggles to provide individualized guidance for Social and Emotional Learning (SEL). Addressing the theme of physical-digital integration (phygital), this study explores the effectiveness of introducing a generative AI chatbot as a "digital transitional space" for teaching Nonviolent Communication (NVC). Utilizing a quasi-experimental design, 40 eighth-grade students were assigned to either the experimental group (Baseline NVC AI, n=21) or the control group (Traditional Instruction, n=19). Quantitative results revealed that the system possessed an acceptable level of usability (p = .876 against the industry standard). The experimental group significantly outperformed the control group in the Nonviolent Communication Behaviors Scale (NVCBS) (p = .042) and performed comparably in the Situational Judgment Test (SJT) (p = .408). However, qualitative log analysis revealed a 95.2% dialogue survival rate. Despite this high completion rate, some students exhibited boundary-testing and passive harm behaviors when facing repeated objective corrections from a single-style AI. These findings provide empirical evidence for the limitations of a one-size-fits-all AI in a phygital ecosystem, highlighting the need for adaptive mechanisms based on the Stereotype Content Model (SCM) in future studies to buffer emotional frustration.*

Keywords: Collaborative Learning, Generative AI, Nonviolent Communication (NVC), Personalized Learning, Stereotype Content Model (SCM)

1. Introduction

The limbic system of adolescents develops rapidly, yet their prefrontal cortex remains immature, leading to the frequent use of "Jackal language" in interpersonal conflicts. The Nonviolent Communication (NVC) framework proposed by Rosenberg (2003) offers an effective intervention. However, its implementation in traditional large-class instruction often struggles to provide individualized guidance, and public role-playing triggers peer social anxiety, often hindering students' right to express their authentic voices in a safe, non-judgmental space (Lundy, 2007). This anxiety is particularly pronounced within high-context cultural environments, where adolescents frequently suppress their authentic emotions to maintain superficial group harmony and avoid losing face. When forced to practice vulnerable emotional disclosure in front of peers, adolescents often deploy defensive mechanisms—such as indifference or mockery—rendering traditional role-playing ineffective. Therefore, introducing a highly private, non-evaluative technological medium is not merely a matter of convenience, but a psychological necessity to bypass these cultural and developmental defense mechanisms. Aligning with the paradigm of phygital and seamless learning, AI chatbots can construct a safe "digital transitional space" to alleviate this anxiety by bridging physical classroom activities with intelligent digital scaffolding. This study employed a quasi-experimental design to examine the learning outcomes of two instructional conditions: a "Baseline NVC AI" approach and "Traditional Instruction." It further utilized empirical log data to explore the microgenetic learning process and to investigate whether integrating generative AI chatbots as a phygital transitional space, compared with traditional lecture-based instruction, can significantly improve junior high school students' NVC behaviors.

2. Theoretical Background

Traditional instruction often results in an "inert knowledge" problem, creating a knowing-doing gap where students comprehend concepts but fail to apply them in real-world conflicts (Brown et al., 1989). Generative AI can serve as a caring active listener to foster students' self-connection before resolving conflicts (Lee et al., 2025; Shao, 2023; Wolfe et al., 2025) and integrating NVC methodology into machine learning further enhances the explainability of these empathetic responses (Zhang et al., 2025). Furthermore, applying the Stereotype Content Model (SCM) allows users to perceive AI through the universal dimensions of Warmth and Competence (Fiske et al., 2002), which has been proven effective in pedagogical agent design (Baylor & Kim, 2005; Richter et al., 2025). While a baseline generative AI provides conversational scaffolds, Wang (2022) warned that interacting with a single-style AI might elicit annoyance and backfire effects if the system lacks adequate emotional buffering during error corrections. Therefore, assessing both learning effectiveness and qualitative interaction traces is crucial.

3. Research Method

3.1. Research Design and Participants

This study adopted a quasi-experimental design based on a preliminary validation phase. Participants were 40 eighth-grade students from two intact classes at a junior high school in northern Taiwan. The experimental group (n = 21) received AI-supported instruction, utilizing a "Baseline NVC AI" to conduct NVC dialogue practices. Conversely, the control group (n = 19) received traditional lecture-based instruction and engaged in paper-based NVC exercises with peer role-playing.

3.2. Assessment Tools

To evaluate the learning outcomes, system usability, and interaction processes, this study utilized the following quantitative scales and qualitative log analysis: (1) Nonviolent Communication Behaviors Scale (NVCBS): Used to assess students' self-connection and authentic expression (Cheung et al., 2023). The scale demonstrated good internal consistency (α = .754). (2) Situational Judgment Test (SJT): Evaluated students’ situational transfer of NVC skills into complex, novel conflict scenarios. (3) System Usability Scale (SUS): Evaluated the perceived ease of use and extraneous cognitive load of the AI system, adapted from Brooke (1996) (α = .820).

Furthermore, the study utilized Mixed-Methods Log Analysis, applying microgenetic analysis and the BIAS Map (Cuddy et al., 2007) to theorize interaction indicators, such as active facilitation (e.g., successful revisions) and passive harm (e.g., ignoring suggestions or dialogue breakdown).

The intervention consisted of a single 45-minute session for both groups to ensure instructional consistency. The research procedure began with an 8-minute conceptual explanation of NVC by the teacher. Subsequently, the experimental group engaged in 15 minutes of guided NVC dialogue practice with the Baseline NVC AI via tablets, while the control group engaged in 15 minutes of traditional paper-based role-play. Regarding the data collection process, all student-AI chat logs were automatically recorded in real time. Immediately following the practice phase, both groups were allotted 20 minutes to complete post-test assessments via online forms on their tablets. These quantitative assessments included the Nonviolent Communication Behaviors Scale (NVCBS) and a Situational Judgment Test (SJT), with the experimental group additionally completing the System Usability Scale (SUS). Finally, the session concluded with a 2-minute wrap-up.

4. Results

4.1. Quantitative Effectiveness: Usability and Situational Transfer

The experimental group's converted SUS scores averaged 67.74 (SD = 16.45). Due to the small sample size ($n < 30$), a one-sample Wilcoxon signed-rank test confirmed no significant difference from the acceptable industry standard of 68 ($p = .876$). The scale demonstrated good internal consistency ($\alpha = .820$), confirming the generative AI system is intuitive and minimizes extraneous cognitive load on students. In a phygital learning ecosystem, a "free-of-effort" interface is a pedagogical prerequisite. It ensures adolescents, easily overwhelmed during conflicts, can allocate limited cognitive resources entirely to deep emotional reflection rather than system navigation, sustaining the digital transitional space's psychological safety (Lee et al., 2025). Regarding learning outcomes (NVCBS overall $\alpha = .754$), normality was first examined. Although the sample size ($N = 40$) initially suggested a parametric independent-samples t-test, the experimental group's NVCBS post-test severely violated the normal distribution assumption. Specifically, data exhibited severe negative skewness (-1.218) and leptokurtic high kurtosis (3.759), with the Shapiro-Wilk test indicating significant deviation ($p = .047$). Employing a parametric t-test under such skewed conditions allows extreme values to distort the mean and reduce statistical power (Chiu, 2019; Hair et al., 2010). Consequently, a non-parametric Mann-Whitney U test was adopted for its robustness to skewed distributions. The test revealed a significant difference in NVCBS scores between the experimental ($M = 18.91$, $Mdn = 19.00$) and control groups ($M = 17.21$, $Mdn = 17.00$); $U = 125.00$, $Z = -2.035$, $p = .042$. This highlights the AI chatbot significantly outperformed traditional instruction in cultivating self-connection and authentic expression. Furthermore, in the SJT, the experimental group ($M = 8.19$, $Mdn = 9.00$) performed comparably to the control group ($M = 7.89$, $Mdn = 9.00$); $U = 170.00$, $Z = -0.827$, $p = .408$. These results demonstrate the baseline AI ensures adequate knowledge transfer and provides a more effective digital transitional space for internalizing NVC behaviors.

4.2. Qualitative Process: Survival Rate, Microgenesis, and Boundary Testing

Log analysis of 21 experimental group students showed a 95.2% dialogue survival rate (20/21 successfully completed the NVC request), averaging 5.3 turns (range: 2–11). Microgenetic analysis revealed three distinct interaction patterns: (1) Crossing the cognitive threshold: Students initially struggled to differentiate observations from judgments and needs from strategies. The AI successfully acted as a cognitive scaffold, using clarification and guided questioning to help students revise "Jackal language" into constructive NVC expressions. (2) Resolving intrapersonal conflicts: Before formulating objective peer requests, students used the AI as a safe buffer to process anger, highlighting NVC as an internal repair mechanism. This aligns with Cheung et al. (2023), emphasizing "self-connection" precedes authentic expression. The AI's non-judgmental presence induced an online disinhibition effect, allowing students to safely vent and regulate affect. This high survival rate reflects "sociality motivation" (Epley et al., 2007)—adolescents experiencing social pain anthropomorphize supportive agents for psychological comfort. The AI absorbed hostility without retaliation, triggering reciprocal self-disclosure (Nass & Moon, 2000). (3) Cognitive fatigue and boundary testing: Analysis revealed limitations of a one-size-fits-all AI. While only one student (A80604) failed completely after persisting with subjective judgments, others exhibited boundary-testing and "passive harm" (e.g., A80617 resisting with, "Whatever! I want you to practice!"). Although the AI eventually guided them to completion, these interactions verify Wang's (2022) finding that a single-style AI lacking warmth buffering triggers cognitive fatigue, highlighting the necessity for adaptive matching.

5. Conclusion

This study confirmed that integrating a generative AI chatbot as a phygital transitional space significantly improves junior high school students' NVC behaviors compared to traditional lecture-based instruction. However, the qualitative withdrawal behaviors observed echo Cronbach's (1957) warning that a single-style treatment is rarely optimal. It highlights the need for Phase 2: implicitly and adaptively matching students through SCM dimensions (Warmth vs. Competence) to provide tailored emotional or cognitive scaffolding, thereby eliminating passive harm and enhancing the overall seamless learning experience.

References

Baylor, A. L., & Kim, Y. (2005). Simulating instructional roles through pedagogical agents. *International Journal of Artificial Intelligence in Education, 15*(1), 95-115.

Brooke, J. (1996). SUS: A "quick and dirty" usability scale. In P. W. Jordan, B. Thomas, B. A. Weerdmeester, & I. L. McClelland (Eds.), *Usability evaluation in industry* (pp. 189–194). Taylor & Francis.

Brown, J. S., Collins, A., & Duguid, P. (1989). Situated cognition and the culture of learning. *Educational Researcher, 18*(1), 32-42.

Cheung, C. T. Y., Cheng, C. M.-H., Lam, S. K. K., Ling, H. W.-H., Lau, K. L., Hung, S. L., & Fung, H. W. (2023). Reliability and validity of a novel measure of nonviolent communication behaviors. *Research on Social Work Practice, 33*(7), 790–797.

Chiu, H. C. (2019). *Quantitative research and statistical analysis: Data analysis using SPSS* (6th ed.). Wunan.

Cronbach, L. J. (1957). The two disciplines of scientific psychology. *American Psychologist, 12*(11), 671–684.

Cuddy, A. J. C., Fiske, S. T., & Glick, P. (2007). The BIAS map: Behaviors from intergroup affect and stereotypes. *Journal of Personality and Social Psychology, 92*(4), 631-648.

Epley, N., Waytz, A., & Cacioppo, J. T. (2007). On seeing human: A three-factor theory of anthropomorphism. Psychological Review, 114(4), 864–886.

Fiske, S. T., Cuddy, A. J. C., Glick, P., & Xu, J. (2002). A model of (often mixed) stereotype content: Competence and warmth respectively follow from perceived status and competition. *Journal of Personality and Social Psychology, 82*(6), 878-902.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis* (7th ed.). Prentice Hall.

Lee, T., Park, S., Kim, D. H., Baek, S., Lee, J., You, B., Hur, J. W., Kim, M., & Lee, C. G. (2025). BetterMood: A human-like AI counseling service for adolescents and young adults. *Digital Health, 11*, 1–19.

Lundy, L. (2007). 'Voice' is not enough: Conceptualising Article 12 of the United Nations Convention on the Rights of the Child. *British Educational Research Journal, 33*(6), 927–942.

Nass, C., & Moon, Y. (2000). Machines and mindlessness: Social responses to computers. *Journal of Social Issues*, *56*(1), 81–103.

Richter, S., Kishore, S., Piven, I., Dodd, P., & Bate, G. (2025). Chatbots in tertiary education: Exploring the impact of warm and competent avatars on self-directed learning. *British Journal of Educational Technology, 56*(5), 2102-2124.

Rosenberg, M. B. (2003). *Nonviolent communication: A language of life* (2nd ed.). PuddleDancer Press.

Shao, R. (2023). An empathetic AI for mental health intervention: Conceptualizing and examining artificial empathy. In *Proceedings of the EmpathiCH workshop (EMPATHICH '23)*. Association for Computing Machinery.

Wang, R.-Y. (2022). *Can warmth breed competence? Double-edged effect of using social cues on human-AI interaction* [Unpublished master's thesis]. National Yang Ming Chiao Tung University.

Wolfe, R., Dangol, A., Kim, J., & Hiniker, A. (2025). Toward needs-conscious design: Co-designing a human-centered framework for AI-mediated communication. *Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society, 8*(3), 2718-2729.

Zhang, R., Khurshid, S. K., Tayfour, A. E., Jaleel, A., Ahmad, T., & Abbasi, M. (2025). Computational modeling of empathetic response types in textual communication: Integrating nonviolent communication methodology and machine learning for explainable AI. *Ain Shams Engineering Journal, 16*, 103813.