Koh, E., et al. (Eds.) (2026). Proceedings of the 2nd International Conference on Learning Evidence and Analytics. Asia-Pacific Society for Computers in Education.

Development of Introductory Generative AI course for University Students: Assessment of learning achievement and acceptance of GenAI

Mohammed Galib Hasan ABIR [a*], Mayumi SUGIURA [b], Katsusuke SHIGETA [c]
[a]*Graduate School of Science, Hokkaido University, Japan*
[b]*Center for Open Education, Hokkaido University, Japan*
[c]*Information Initiative Center, Hokkaido University, Japan*
*mohammedgalibhasan.abir.t3@elms.hokudai.ac.jp

Abstract: The rapid adoption of Generative Artificial Intelligence (GenAI) in higher education has raised significant ethical, copyright, and data privacy concerns. Responding to calls for responsible AI education, this study evaluates an introductory GenAI online course that integrates literacy with AI basics, copyright, critical thinking, ethics and privacy. Using a pre–post survey design, the study examines learning achievement, changes in student acceptance of GenAI, and the effect of prior GenAI experience. Results indicate significant improvements in learning outcomes and acceptance, alongside increased awareness of ethical risks and privacy responsibilities across diverse learners. These findings support embedding ethics and privacy-by-design principles in GenAI curricula to foster responsible use and effective utilization.

Keywords: e-learning development, Generative AI, learning achievement, Privacy

1. Introduction

The rapid integration of Generative Artificial Intelligence (GenAI) in higher education is reshaping student learning, writing, and engagement. While these tools offer significant opportunities, their widespread use raises concerns about learning quality, academic integrity, copyright, data privacy, and ethics (Floridi et al., 2018). This highlights the need for structured approaches that support both effective learning and responsible use. Educational research emphasizes that meaningful learning depends on well-designed instruction, clear objectives, and alignment between teaching and assessment (Bloom, 1956; Biggs, 1996). Without proper guidance, student interaction with GenAI may remain superficial, limiting deeper cognitive outcomes (Hattie, 2009). Studies suggest that learning benefits are greatest when GenAI is integrated into structured curricula that encourage reflection and critical thinking (Zawacki-Richter et al., 2019; Kasneci et al., 2023). However, empirical evaluations of foundational GenAI courses remain limited. Scholars also stress the importance of incorporating ethics, privacy, and legal considerations into GenAI education. Existing frameworks advocate responsible and transparent AI use, yet many programs still prioritize technical skills over ethical awareness (Floridi et al., 2018; Cavoukian, 2011). Additionally, prior experience with GenAI influences learning outcomes, as existing knowledge shapes how students understand new concepts (Ausubel, 1968; Hattie & Donoghue, 2016). To address these gaps, this study evaluates an introductory GenAI course integrating technical, ethical, and critical perspectives using a pre–post survey design.

2. Research aims and objectives

As the following study aims to examine students' learning achievement and their acceptance of Generative AI through a basic Generative AI course, the following 3 hypotheses have been tested.

H1: Students demonstrate a high level of overall course engagement and learning achievement, as measured by course participation and quiz performance in a university-level Generative AI course.
H2: Students' acceptance of Generative AI will significantly increase from the pre-course to the post-course survey.
H3: Students' prior experience with Generative AI, measured in the pre-course survey, will have a positive effect on their learning achievement in the GenAI course.

3. Methodology

3.1 Research Design

This course contains 5 modules, ranging from the basic principles of GenAI to ethical and privacy perspectives. To facilitate learning assessment, a set of quizzes has been included as a standard evaluation tool for each module. A presurvey had been conducted before enrolling in the course, asking students about their prior experience with Generative AI. Also, a post-survey was administered upon successful completion of the course. The significant changes of pre- and post-surveys examined during this study, also considering the overall quiz performances on each module.

3.1.1 *Course content and structure*

The course aimed to develop students' understanding of generative AI mechanisms, applications, and responsible use. It incorporates five thematic areas from the ChatGPT Literacy Scale (Lee & Park, 2024), aligning the curriculum with established GenAI literacy constructs. Organized into five modules, the course follows First Principles of Instruction, emphasizing problem-centered learning through activation, demonstration, application, and integration. Modules begin with videos presenting problem-centered (authentic academic) scenarios, followed by readings and quizzes that promote evaluative judgment on copyright, ethics, and privacy.

Table 1. Content category and description

Content Category	Description
AI Basics and Points to Note	Basic characteristics and application scenarios of GenAI
AI and Copyright	Handling Copyright, avoiding copyright issues
AI and Critical Thinking	Utilizing GenAI, Deep learning by Critical Thinking
AI and Ethics	Using ethics, Ethical consideration, Data anonymity
AI and Privacy	Privacy concern, Measures to mitigate privacy

3.2 Participants & Data Collection

Students from two universities in Hokkaido participated in the course and surveys, with about 87% completing all five modules. Data were collected via Google Forms, yielding 102 pre-survey and 91 post-survey responses; only matched data were analyzed. The study assessed four dimensions of GenAI acceptance: motivational knowledge (MK), intention to use (IU), hope to use (HU), and privacy awareness (PA). MK reflects understanding of AI's value and limitations, IU indicates planned use, consistent with technology acceptance models (e.g., Fred Davis; Viswanath Venkatesh). HU captures positive expectations, while PA addresses ethical and data protection concerns, central to responsible AI use (Luciano Floridi). These dimensions represent cognitive, behavioral, emotional, and ethical aspects of acceptance

3.2 Data Analysis

For Hypothesis 1, student learning achievement, as indicated by their quiz feedback, was analyzed separately for each module. For each module, descriptive analysis was conducted to determine the mean and standard deviation.

For Hypothesis 2, to analyze the effect of the GenAI Course on Acceptance (Pre–Post Change), pre- and post-survey feedback were compared across constructs such as (MK), (IU), (HU), and (PA). A paired-samples test was conducted to check the mean, standard deviation, t-value, and one-sided p-value.

For Hypothesis 3, prior Generative AI experience had been categorized to conduct the cluster analysis. The cluster dendrogram and cluster plot were checked to identify the cluster profile. For data analysis, IBM SPSS Statistics Version 28.0.1.0 was used.

4. Results

Data relevant to Hypothesis 1 show that the course participation rate was higher in Modules 1 and 5 (Table 2), whereas the feedback percentage was lowest in those modules. When the individual feedback percentage was checked for modules 1 and 5, it was found to be lower than for other modules. Overall, student feedback indicated improved learning achievement, supporting hypothesis 1.

Table 2. Course Participation and Learning Achievement

Module Name	Number of Participants	Quiz Feedback (%)
Generative AI Basics and Points to Note	145	92.55
Generative AI and Copyright	118	97.79
Generative AI and Critical Thinking	119	96.80
Generative AI and Ethics	111	98.37
Generative AI and Privacy	134	93.03

Table 3. *Paired Samples Statistics*

Pair	Variable	Mean	N	Std. Deviation	Std. Error Mean	t value	P value
Pair 1	MK_pre	3.40	67	.80	.09	-2.33	.02
	MK_post	3.60	67	.78	.09		
Pair 2	IU_pre	4.02	67	.62	.07	-1.44	.15
	IU_post	4.13	67	.69	.08		
Pair 3	HU_pre	3.66	67	.74	.09	-1.38	.17
	HU_post	3.77	67	.85	.10		
Pair 4	PA_pre	3.34	67	.79	.098	-9.20	<.001
	PA_post	4.25	67	.52	.06		

Data relevant to Hypothesis 2 show that, after conducting a paired-samples test using pre- and post-survey data, significant improvements were found in two constructs: privacy awareness (PA) and motivational knowledge (MK). For the other two constructs, intention to use (IU) and hope to use (HU), there is no significant improvement (Table 3).

For Hypothesis 3, students' prior GenAI experience was grouped into five clusters using Principal Component Analysis. The clusters represented academic-focused users, idea-generation users, everyday support users, comprehensive power users, and hybrid users combining academic and creative tasks. A series of one-way ANOVA tests showed no significant differences across clusters in quiz performance or GenAI acceptance (motivation, intention, hope, privacy awareness; all $p > .05$). Effect sizes were small, indicating minimal practical differences among groups.

5. Discussion

Hypothesis 1 predicted high engagement and learning achievement. Results showed quiz scores above 90% across modules and about 87% completion, indicating strong engagement and mastery. Problem-centered scenario-based activities and application-focused quizzes supported learning of copyright, ethics, and critical thinking. Lower scores in introductory and privacy modules were linked to complex question phrasing and limited opportunities for knowledge integration, consistent with First Principles of Instruction. Overall, findings suggest that a structured, scenario-based curriculum effectively supports foundational GenAI learning.

Hypothesis 2 predicted increased GenAI acceptance. Analyses showed significant gains in motivational knowledge and privacy awareness, but not in intention or hope to use, partially supporting the hypothesis. This aligns with Technology Acceptance Model, which suggests knowledge does not automatically lead to behavioral intention. Limited opportunities for real-world application may explain this gap, indicating a need for more task-based learning.

Hypothesis 3 proposed that prior GenAI experience would positively influence learning achievement. However, cluster-based ANOVA analyses revealed no significant differences in quiz performance or acceptance measures across usage groups. Effect sizes were small, indicating limited practical separation. Therefore, Hypothesis 3 was not supported. Taken together, these findings suggest that the course functioned effectively across diverse learner profiles including students with differing levels of prior GenAI experience (e.g., novice to advanced users), varied usage purposes (academic, creative, everyday).

6. Limitations and Future Directions

First, this study was situated within a specific institutional setting. Replicating across diverse universities and national systems would enhance the generalizability of the findings and enable comparative insights into how governance cultures shape learning. Second, note the limited observable growth in behavioral intentions. Future iterations could integrate authentic tasks, scenario-based moral challenges, and reflective activities to provide opportunities for knowledge integration. In this way, GenAI curricula can evolve from foundational literacy to education that supports actual and effective utilization.

Acknowledgements

This work was supported by JST SPRING, Grant Number JPMJSP2119

References

Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., ... & Vayena, E. (2018). AI4People—An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. *Minds and machines*, *28*(4), 689-707.

Biggs, J. (1996). Enhancing teaching through constructive alignment. Higher Education, 32(3), 347–364.

Kasneci, E., Seßler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., … Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. Learning and Individual Differences, 103, 102274.

Cavoukian, A. (2011). Privacy by design in law, policy and practice: A white paper for regulators, decision-makers and policy-makers.

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use and User Acceptance of Information Technology. MIS quarterly.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 425-478.

Lee, S., & Park, G. (2024). Development and validation of ChatGPT literacy scale. Current Psychology, 43(21), 18992-19004.

Merrill, M. D. (2002). First principles of instruction. Educational Technology Research and Development, 50(3), 43–59.