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Impact of Generative AI on Undergraduate Students: A case study of Kyungdong University Global

Bikram Singh Bhat, Nirjala Machamasi, Mohammed Abdulhakim Al-Absi, Khadak Singh Bhandari*

Department of Smart Computing,
Kyungdong University Global, 46 4 gil, Bongpo, Gosung, Gangwon-do 24764, Republic of Korea

bikramsbhat46@gmail.com ; nirjalamachamasi1234@gmail.com ; mohammed@kduniv.ac.kr
*Corresponding author: mekhadak@kduniv.ac.kr
Tel: +82-10-5726-5598

Abstract

This study identifies how generative AI tools influence undergraduate students' learning behavior and problem-solving skills in the Smart Computing department at Kyungdong University Global, South Korea. To identify the frequency, purposes, and impact, a quantitative cross-sectional survey of 160 students was conducted. The findings illustrate that such tools enhance the quality of assignments, efficiency, and understanding of the programming concepts. Nonetheless, overreliance on AI tools may shrink problem-solving skills and critical thinking, with occasional errors in AI outputs. The research highlights the importance of ethical and responsible integration of GenAI tools in education, while safeguarding self-learning capacity.

Keywords: Generative AI; Undergraduate Students; Learning Behavior; AI Tools

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1.0 Introduction

The growing development of artificial intelligence (AI), Internet of Things (IoT), and Cloud Computing has created significant demand across various sectors (Bhandari et al., 2020). In recent years, generative AI tools such as ChatGPT and similar platforms have become widely accessible, allowing students to support their academic activities in new and innovative ways (Wu et al., 2025). These tools are commonly used for tasks such as understanding complex topics, completing assignments, and assisting with programming and writing.

The increasing use of generative AI among students has raised crucial questions regarding its influence on learning behavior. While these tools offer benefits such as improved efficiency and accessibility of information, there are growing concerns about overdependence, reduced critical thinking, and issues related to academic integrity (Wiredu et al., 2024; Abbas et al., 2024). As a result, understanding how students interact with AI tools in their learning process has become an important area of research.

Although earlier studies have analyzed the role of generative AI in education, limited attention has been given to its impact within specific academic disciplines and student groups. There is a need to explore how students in computing-related fields use these tools and how such usage influences their learning behavior. Therefore, this study aims to investigate the impact of generative AI on the learning behavior of undergraduate students in the Smart Computing department at Kyungdong University Global.

2.0 Literature Review

2.1 Educational Benefits of Generative AI

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Recent advancements in generative artificial intelligence (GenAI) have significantly changed teaching methods and learning practices in higher education. Maila Rahiem (2026) reported that students use AI tools for tasks such as summarizing information, improving writing quality, and organizing study activities, leading to enhanced learning effectiveness. Hmoud et al. (2024) similarly reported that AI tools positively influence students' motivation by enhancing engagement, interaction, and perceived relevance of learning tasks. Research by Qianli Wu et al. (2025) indicates that factors such as performance expectations, social influence, and effort expectancy significantly affect students' intention to use AI tools. These findings align with the Technology Acceptance Model (TAM; Davis, 1989), which suggests that perceived usefulness and ease of use are the primary determinants of technology adoption. Accordingly, students who perceive GenAI as reducing cognitive burden and improving output quality are more likely to integrate it into their learning routines.

2.2 Risks and Challenges of Generative AI

Despite evident benefits, several studies highlight critical challenges related to the use of GenAI in education. Muhammad Abbas et al. (2024) found that increased use of AI tools is associated with negative outcomes, including procrastination, memory loss, and reduced academic performance. Japheth Kodua Wiredu et al. (2024) revealed that while AI tools improve comprehension, they also raise serious concerns regarding academic integrity and overreliance. Islam and Sahi (2025) further observed that when students depend on GenAI tools as a primary source to get answers rather than a supportive tool, the depth of learning declines. These concerns are consistent with Cognitive Load Theory (Sweller, 1988), which warns that offloading cognitive tasks to external tools may reduce the fundamental processing necessary for deep learning and knowledge consolidation.

2.3 Generative AI in Computing Education

Within computing disciplines, GenAI tools are particularly relevant due to their capabilities in coding, debugging, and technical explanation. Chengliang Wang et al. (2024) found that students' attitudes and AI literacy strongly influence their behavioral intention to adopt generative AI technologies. Lee et al. (2024) examined educators' perspectives and found uncertainty regarding assessment design, institutional readiness, and the risk of students bypassing authentic problem-solving. Wood and Moss (2024) similarly noted that while student comfort with AI is growing, ethical awareness and self-regulatory practices remain underdeveloped. This issue is particularly relevant in programming courses where AI can generate complete solutions.

2.4 Research Gap

Despite the growing body of evidence, most studies focus on general higher education samples and do not explore GenAI's impact within specific disciplinary contexts. In particular, how computing students who encounter AI as both a study aid and a core subject interact with GenAI tools remains underexplored. Ben Otman et al. (2025) acknowledged that the impact of AI on learning varies depending on digital literacy and usage patterns, suggesting that context-specific investigations are needed. This study addresses that gap by examining GenAI use among Smart Computing undergraduates at Kyungdong University Global, providing discipline-specific insights into usage patterns, perceived benefits, and behavioral effects.

3.0 Methodology

This study uses a quantitative research approach to evaluate the impact of generative AI on the learning behavior of undergraduate students in the Smart Computing Department at Kyungdong University Global. A quantitative cross-sectional survey method was used to collect data, enabling the identification of students' usage patterns, perceptions, and behavioral tendencies at a single point in time.

The study is guided by the following research questions:

RQ1. To what extent do undergraduate students use generative AI tools for academic purposes?
RQ2. How does the use of generative AI influence students' learning behavior and study practices?
RQ3. What are students' perceptions of the benefits and challenges of generative AI in learning?
RQ4. How does the use of generative AI affect students' independent thinking and problem-solving abilities?
RQ5. What are the perceptions and potential impact of generative AI among students who do not currently use these tools?

3.1 Participants and Sampling

The target population of this study consists of undergraduate students from the Smart Computing Department at Kyungdong University Global. A total of 160 students (n = 160) participated in the survey using a convenience sampling method, as they were easily accessible. While convenience sampling limits generalizability, it is a widely accepted approach in exploratory and descriptive educational research when the goal is to capture initial patterns within a bounded institutional context (Etikan et al., 2016). The study aimed to capture diverse perspectives by including both users and non-users of generative AI tools. This allowed for a more comprehensive understanding of AI usage patterns and their impact on student learning behavior.

3.2 Instrument Development and Validation

A structured questionnaire was designed in Google Forms to collect data. The survey questionnaire was split into four main sections:

- Participant Information: including year of study
- Usage of GenAI Tools: screening questions determined whether participants were familiar with AI tools and used them for academic purposes (Yes/No)

- GenAI Usage and Learning Behavior: participants who responded "Yes" were directed to questions related to the frequency of AI usage, the purpose of using AI tools, and their impact on study habits and learning behavior
- Non-Users' Awareness and Perceptions of GenAI Tools: participants who responded "No" were directed to questions focusing on reasons for not using AI tools and their perceptions of such technologies

Items were drawn from related instruments in the GenAI in education literature, including scales used by Abbas et al. (2024) and Wu et al. (2025), and adapted to reflect the Smart Computing disciplinary context. Likert-scale items (5-point scale: 1 = Strongly Agree to 5 = Strongly Disagree) were used for attitudinal and perceptual questions. Responses were grouped into three reporting categories: Agree (Strongly Agree + Agree), Neutral, and Disagree (Strongly Disagree + Disagree). The questionnaire was reviewed for content validity by faculty members in the Smart Computing department prior to deployment. Formal reliability testing (e.g., Cronbach's Alpha) and a structured pilot study were not conducted, which is acknowledged as a methodological limitation of this preliminary investigation. Future replications of this study should incorporate formal psychometric validation procedures.

3.3 Data Analysis and Justification

Descriptive statistics, including frequency distributions and percentages, were used to analyze the data. This approach is appropriate for the study's exploratory objectives, which aim to identify usage patterns, behavioral tendencies, and perceptions rather than to test causal relationships or group differences. Descriptive analysis provides accessible and interpretable summaries consistent with the scope of a preliminary investigation (Creswell, 2017). Future studies could extend this work using inferential statistics to examine group comparisons or predictive relationships.

4.0 Findings

4.1 Overview of the Data

A total of 160 undergraduate students from the Smart Computing program at Kyungdong University participated in this study. The data were collected through a structured questionnaire and analyzed using descriptive statistics, including frequency distributions and percentages. The findings are presented to highlight patterns in the impact of generative AI tools such as ChatGPT on students' learning behaviors.

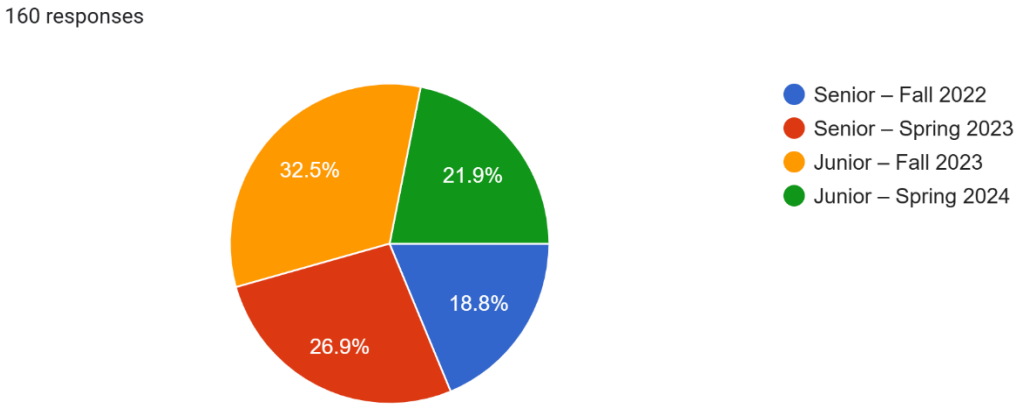

Fig. 1: Participants' Academic Level
(Source:) Prepared by the authors

4.2 Usage of Generative AI Tools

The findings indicate that generative AI tools are widely recognized and used among undergraduate students. A majority of respondents (95%) reported using generative AI tools, while 5% reported not using them.

Among users, varying levels of usage frequency were observed: 65.8% reported daily use, 19.1% weekly use, 11.8% occasional use, and 3.3% rare use. Regarding tool preference, most students identified ChatGPT as the most frequently used tool, followed by Claude AI, Google Gemini, and Microsoft Copilot. These results suggest that generative AI tools have become an integral part of students' academic activities.

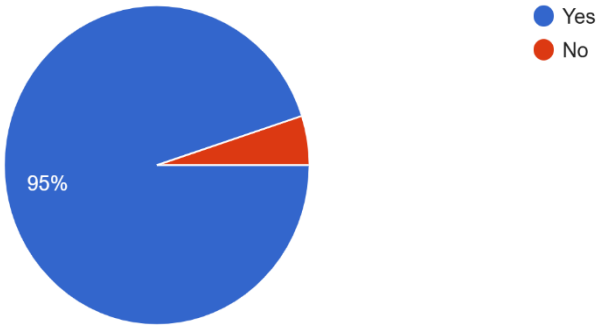

Fig. 2: Usage of Generative AI Tools

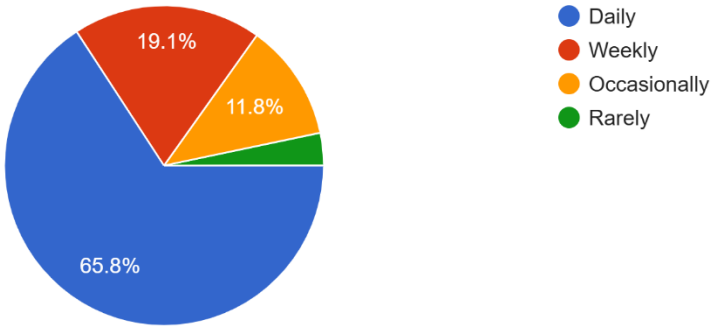

Fig. 3: Frequency of AI Usage
(Source:) Prepared by the authors

4.3 Influence on Learning Behavior and Study Practices

The results demonstrate that generative AI tools significantly influence students' learning behaviors and study practices. A substantial proportion of respondents (92.76%) agreed that generative AI tools help them understand academic concepts more easily.

Additionally, 82.23% of students indicated that they use AI tools to assist with assignments or homework, while 87.5% agreed that AI tools improve their overall study efficiency. A considerable number of respondents (80.92%) also reported relying on AI tools when encountering difficult academic problems. Furthermore, 80.26% of students agreed that AI tools support self-directed learning, and 86.18% indicated that generative AI has a positive impact on their overall learning experience. These findings highlight the role of generative AI in enhancing academic efficiency and supporting modern learning practices.

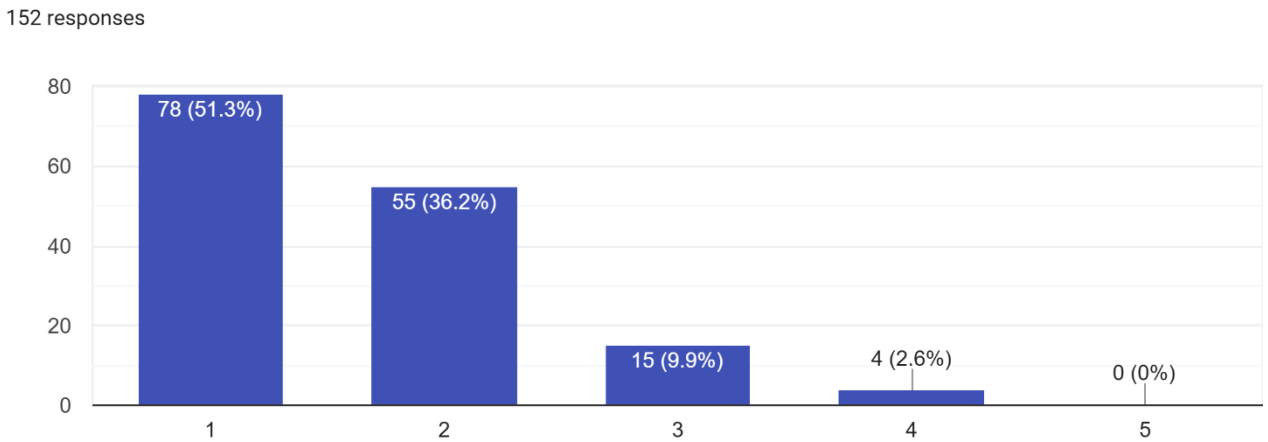

Fig. 4. Impact of AI on Study Efficiency
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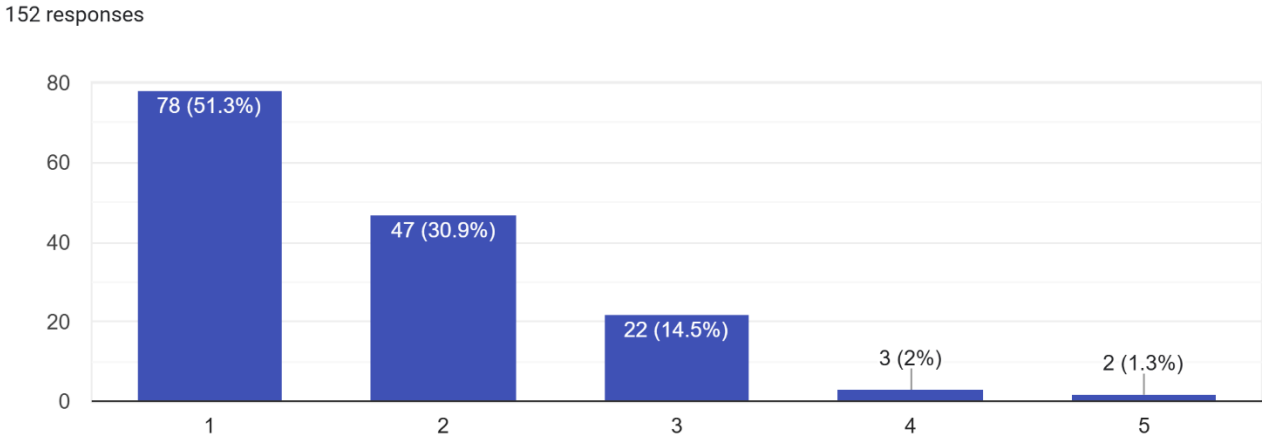

Fig. 5: AI Support in Assignments or Homework
(Source:) Prepared by the authors

4.4 Perceived Benefits and Challenges of Generative AI

Students reported both advantages and challenges associated with the use of generative AI tools.

The most identified benefits include:

- Assistance in coding, debugging, and problem-solving tasks (46.1%)
- Enhanced understanding of programming and technical concepts (23.7%)
- Improved quality of assignments, reports, or project work (17.1%)
- Increased efficiency in completing academic tasks (13.2%)

However, several challenges were also reported:

- Overreliance on AI tools (36.8%)
- Reduced development of independent problem-solving skills (27.6%)
- Inaccuracy or inconsistency in AI-generated responses (23%)
- Difficulty in evaluating and verifying AI outputs (12.5%)

Regarding integration, 66.5% of respondents supported the inclusion of generative AI tools in university learning environments, while 2.6% opposed it and 30.9% remained uncertain. These findings indicate that while the use of generative AI tools provides several benefits, it also presents challenges that need to be addressed.

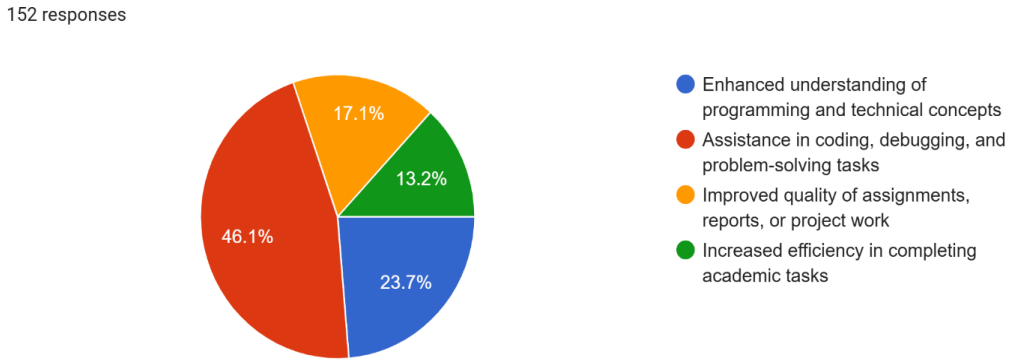

Fig. 6: Perceived Benefits of Generative AI
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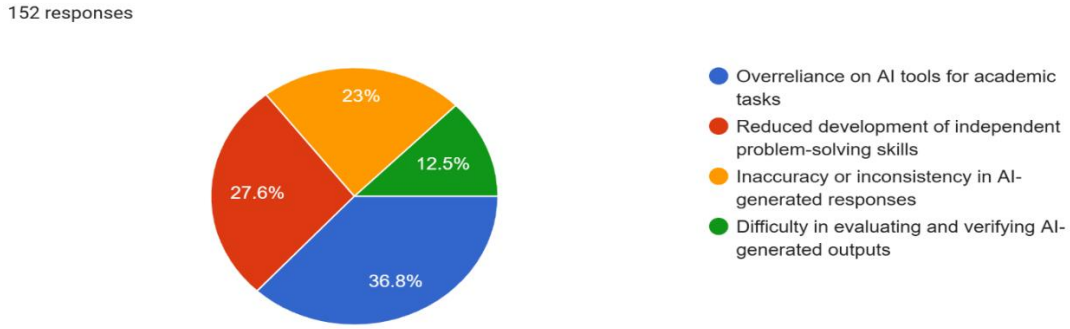

Fig. 7: Challenges of Generative AI Usage
(Source:) Prepared by the authors

4.5 Impact on Independent Thinking and Problem-Solving

The findings reveal mixed perspectives regarding the impact of generative AI on students' independent thinking and problem-solving abilities. A portion of respondents (58.55%) agreed that the use of AI tools may reduce their independent thinking ability, while 41.45% disagreed. At the same time, 80.92% of students reported that AI tools assist them in solving complex academic problems, indicating both supportive and potentially limiting effects. These results suggest that while generative AI can enhance problem-solving capabilities, excessive reliance may negatively impact independent cognitive processes.

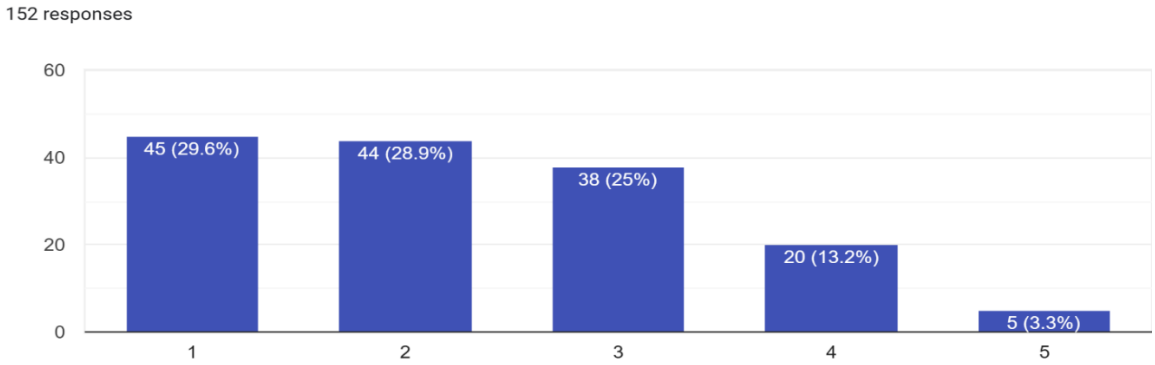

Fig. 8: Impact of AI on Independent Thinking
(Source:) Prepared by the authors

4.6 Perceptions of Non-Users

A tiny fraction of respondents reported not using generative AI tools for academic purposes. The main reasons include:

- Not perceiving AI tools as useful for coursework (37.5%)
- Concerns about the accuracy and reliability of AI-generated content (37.5%)
- Limited familiarity with AI tools (12.5%)
- Preference for traditional learning methods (12.5%)

Despite not using these tools, many non-users still recognized their potential value. Approximately 37.5% considered generative AI moderately useful, 37.5% slightly useful, and 25% not useful. None of the respondents rated them as highly useful.

These findings indicate that even among non-users, there is awareness of the potential role of generative AI in education.

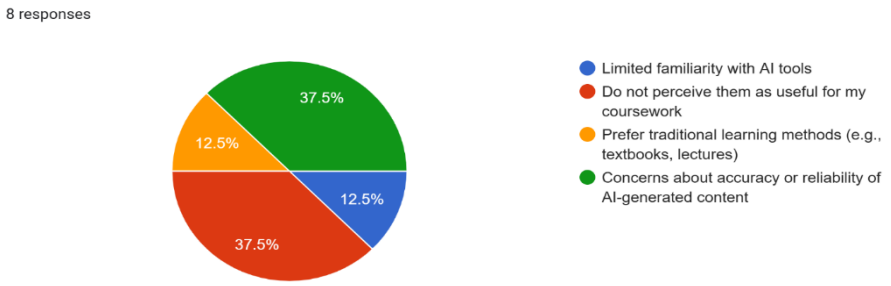

Fig. 9: Reasons for Not Using Generative AI Tools
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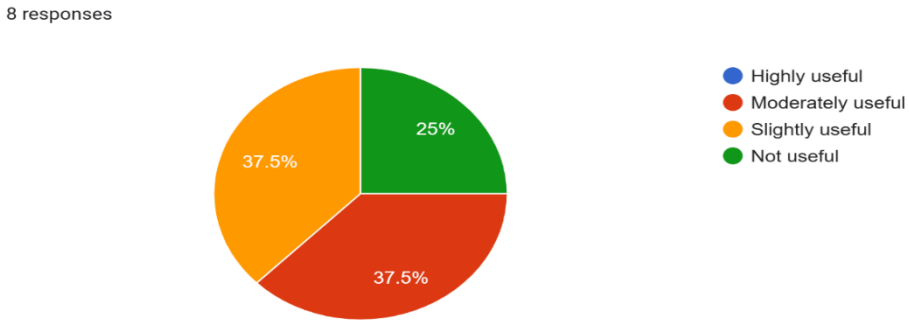

Fig. 10: Perception of Usefulness in Computing-Related Courses
(Source:) Prepared by the authors

5.0 Discussion

5.1 Adoption and Integration of Generative AI Tools

The near-universal adoption of GenAI tools (95%) and the high proportion of daily users (65.8%) in this study exceed comparable figures reported in broader higher education surveys (Wu et al., 2025), suggesting that computing students may be particularly receptive to AI-assisted workflows. This finding aligns with TAM (Davis, 1989), as students in technically oriented programs are likely to perceive high utility in tools that directly support coding, debugging, and problem formulation tasks. The prevalence of ChatGPT as the preferred tool reflects its accessibility, language capability, and code-generation functionality features uniquely relevant to Smart Computing coursework.

5.2 Learning Behavior and Self-Regulation

The strong positive perceptions reported by students, including improved efficiency (87.5%), better conceptual understanding (92.76%), and support for self-directed learning (80.26%), suggest that GenAI tools are functioning as cognitive scaffolds. This is consistent with Self-Regulated Learning Theory (Zimmerman, 2000), which posits that learners who actively monitor and adjust their strategies benefit more from external resources. When students use GenAI to obtain explanations, verify understanding, or iterate on code, they may be engaging in productive metacognitive practices. Ben Otman et al. (2025) similarly found positive correlations between AI usage and self-directed learning, though outcomes varied by digital literacy level.

5.3 Cognitive Risks and Critical Thinking

The finding that 58.55% of students believe GenAI may reduce their independent thinking ability, despite 80.92% relying on it for complex problem-solving, reflects an important tension in AI-assisted learning. From a Cognitive Load Theory perspective (Sweller, 1988), offloading cognitively demanding tasks such as algorithm design or debugging to AI tools may reduce the processing required for skill development and conceptual schema formation. Abbas et al. (2024) documented similar concerns, associating excessive AI use with procrastination and reduced academic performance. These findings suggest that the educational value of GenAI does not depend simply on its use, but on how students interact with its outputs. The key is whether they question, check, and build on AI-generated content or just accept it without thinking.

5.4 Benefits in a Computing Context

The high reported utility for coding and debugging (46.1%) is particularly meaningful in a Smart Computing context, where technical problem-solving is central to the curriculum. Unlike students in many other subjects, computing students engage with AI tools that can generate functional code, identify errors, and offer technical explanations, creating both significant learning support and risks of skill substitution. Lee et al. (2024) found that educators share these concerns and are unsure how to create assessments that accurately measure students' real technical abilities in environments where AI is widely used. The results suggest that educators need subject-specific teaching strategies and guidelines for using GenAI effectively in courses such as Smart Computing.

5.5 Non-User Perspectives and Adoption Barriers

Non-users' primary concerns: low perceived usefulness and accuracy concerns reflect a rational cost-benefit assessment consistent with TAM's perceived usefulness construct. Interestingly, non-users did not reject the potential value of GenAI; many acknowledged its moderate utility. This suggests that targeted digital literacy interventions and structured demonstrations could help bridge the adoption gap, particularly for students who may benefit from AI-assisted learning but lack confidence in evaluating AI outputs (Wood & Moss, 2024).

6.0 Limitations of the Study

Several limitations should be considered when interpreting this study's findings. First, the study was conducted at a single institution (Kyungdong University Global) within one department (Smart Computing), which limits the generalizability of findings to other universities, disciplines, or national contexts. Second, convenience sampling was used due to practical accessibility constraints, which may introduce selection bias and reduce the representativeness of the sample. Third, cross-sectional design captures attitudes and behaviors at a single point in time, precluding causal inferences and the observation of longitudinal change in learning behavior. Fourth, reliance on self-reported data may introduce social desirability bias, as students may overestimate or underestimate their AI use or its perceived effects. Fifth, formal reliability testing of the survey instrument (e.g., Cronbach's Alpha) and a structured pilot study were not conducted, which limits the psychometric rigor of the instrument. Finally, the exclusive use of descriptive statistics limits the analytical depth; relationships between variables such as frequency of AI use and academic performance could not be tested for statistical significance. These limitations underscore the preliminary and exploratory nature of this investigation.

7.0 Future Research Directions

This study opens several avenues for future investigation. Studies that follow the same group of students over several semesters would help researchers understand whether using GenAI improves or weakens students' critical thinking and problem-solving skills over time. Multi-university studies across different disciplines and national contexts would enhance external validity and enable comparative

analysis of adoption patterns. Mixed-method approaches incorporating qualitative interviews or focus groups would provide richer explanations for the attitudinal and behavioral findings reported here. Experimental or quasi-experimental designs could isolate the causal effects of specific AI usage patterns on learning outcomes. Additionally, cross-disciplinary comparisons between computing and non-computing students would clarify whether the benefits and risks identified in this study are discipline-specific or reflect broader patterns in higher education. Finally, research examining the role of AI literacy, self-regulation, and instructional scaffolding as moderating variables would advance understanding of when and how GenAI use promotes or undermines learning.

8.0 Conclusion& Recommendations

This study reviewed the impact of generative AI tools on undergraduate students' learning behaviors at Kyungdong University Global. The findings show that generative AI tools have become an important part of students' academic activities. A higher number of students stated that these tools enhance their study efficiency, their understanding of concepts, and their ability to complete assignments. The study also identified students' concerns about the accuracy and reliability of AI-generated content.

In this study, generative AI tools showed a positive impact on students' learning; however, their effectiveness depends on proper guidance and practice. Based on the findings, universities should integrate AI tools into their learning practices. However, students should be provided with proper guidance, training, and clear policies for ethical use, as suggested by Wood & Moss (2024). Additionally, to preserve problem-solving skills and independent thinking, generative AI tools should be used as a supportive resource rather than relied on completely (Wiredu et al., 2024; Abbas et al., 2024).

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Paper Contribution to the Related Field of Study

This study makes three contributions to the emerging literature on generative AI in education. Theoretically, it extends TAM and Cognitive Load Theory to the context of GenAI use among computing undergraduates, providing a theoretically grounded interpretation of adoption and cognitive risk patterns. Methodologically, it demonstrates the utility of structured questionnaire surveys in capturing discipline-specific GenAI usage behaviors and provides a replicable instrument framework for future comparative studies. In practice, the findings offer actionable insights for educators, curriculum designers, and institutional policymakers seeking to integrate GenAI tools responsibly into computing programs. By focusing on a specific disciplinary and institutional context, this study provides context-sensitive evidence that complements the broader, generalist findings that dominate the current literature.

References

Abbas, M., Jam, F. A., & Khan, T. I. (2024). Is it harmful or helpful? Examining the causes and consequences of generative AI usage among university students. *International Journal of Educational Technology in Higher Education, 21*, 10. https://doi.org/10.1186/s41239-024-00444-7

Ben Otman, S., Ben Otman, S., & Adalı, G. K. (2025). The impact of generative AI on university students' learning experience: A study on cognitive and affective outcomes. *Journal of Information and Organizational Sciences, 49*(2), 329–344. https://doi.org/10.31341/jios.49.2.10

Bhandari, K. S., Seo, C., & Cho, G. H. (2020). Towards sensor-cloud based efficient smart healthcare monitoring framework using machine learning. In *Proceedings of the 9th International Conference on Smart Media and Applications* (pp. 380–383). https://doi.org/10.1145/3426020.3426138

Creswell, J. W., & Creswell, J. D. (2017). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). SAGE Publications.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008

Etikan, I., Musa, S. A., & Alkassim, R. S. (2016). Comparison of convenience sampling and purposive sampling. *American Journal of Theoretical and Applied Statistics, 5*(1), 1–4. https://doi.org/10.11648/j.ajtas.20160501.11

Hmoud, M., Swaity, H., Hamad, N., Karram, O., & Daher, W. (2024). Higher education students' task motivation in the generative artificial intelligence context: The case of ChatGPT. *Information, 15*(1), 33. https://doi.org/10.3390/info15010033

Islam, S., & Sahi, S. A. (2025). Impact of generative AI on student learning behavior: Evidence, patterns, and educational implications. *Journal of Emerging Technology and Digital Transformation, 4*(4), 103–114.

Lee, D., Arnold, M., Srivastava, A., Plastow, K., Strelan, P., Ploeckl, F., & Palmer, E. (2024). The impact of generative AI on higher education learning and teaching: A study of educators' perspectives. *Computers and Education: Artificial Intelligence, 6*, 100221. https://doi.org/10.1016/j.caeai.2024.100221

Rahiem, M. D. (2026). Generative AI in higher education in Indonesia: Patterns of use and learning impact. *Social Sciences & Humanities Open, 13*, 102672. https://doi.org/10.1016/j.ssaho.2026.102672

Sweller, J. (1988). *Cognitive load during problem solving: Effects on learning*. *Cognitive Science, 12*(2), 257–285. https://doi.org/10.1207/s15516709cog1202_4

Wang, C., Wang, H., Li, Y., Dai, J., Gu, X., & Yu, T. (2024). Factors influencing university students' behavioral intention to use generative artificial intelligence: Integrating the theory of planned behavior and AI literacy. *International Journal of Human–Computer Interaction, 41*(11), 6649–6671. https://doi.org/10.1080/10447318.2024.2383033

Wiredu, J. K., Abuba, N. S., & Zakaria, H. (2024). Impact of generative AI in academic integrity and learning outcomes: A case study in the Upper East Region. *Asian Journal of Research in Computer Science, 17*(8), 70–88. https://doi.org/10.9734/ajrcos/2024/v17i7491

Wood, D., & Moss, S. H. (2024). Evaluating the impact of students' generative AI use in educational contexts. *Journal of Research in Innovative Teaching & Learning, 17*(2), 152–167. https://doi.org/10.1108/JRIT-06-2024-0151

Wu, F., Dang, Y., & Li, M. (2025). A systematic review of responses, attitudes, and utilization behaviors on generative AI for teaching and learning in higher education. *Behavioral Sciences, 15*(4), 467. https://doi.org/10.3390/bs15040467

Wu, Q., Tian, J., & Liu, Z. (2025). Exploring the usage behavior of generative artificial intelligence: A case study of ChatGPT with insights into the moderating effects of habit and personal innovativeness. *Current Psychology, 44*(9), 8190–8203. https://doi.org/10.1007/s12144-024-07193-w

Zimmerman, B. J. (2000). Self-efficacy: An essential motive to learn. *Contemporary Educational Psychology, 25*(1), 82–91. https://doi.org/10.1006/ceps.1999.1016