

# Usage and Perceptions of Generative AI in Learning among University Students in Bangladesh

K. M. Tahsin Kabir<sup>1,\*</sup>[0009-0009-5060-5060], Koushik Biswas Arko<sup>2</sup>[0009-0006-0479-7397], Arizit Chaki Artha<sup>2</sup>[0009-0001-9643-0667], Md. Fahim Kabir Chowdhury<sup>3</sup>[0009-0001-8912-7395], Md. Mortuza Ahmmed<sup>2</sup>[0000-0002-4735-571X], Md. Ashraful Babu<sup>4</sup>[0000-0003-2144-6610], and M. Mostafizur Rahman<sup>2</sup>[0000-0002-3788-1118]

<sup>1</sup> Asian University of Bangladesh, Bangladesh  
tahsin@aub.ac.bd

<sup>2</sup> American International University-Bangladesh, Dhaka-1229, Bangladesh  
22-49234-3@student.aiub.edu, 23-52303-2@student.aiub.edu,  
mortuza@aiub.edu, mostafiz.math@aiub.edu

<sup>3</sup> Bangladesh Army International University of Science and Technology (BAIUST),  
Comilla, Bangladesh  
fahim.cse@baiust.ac.bd

<sup>4</sup> Independent University, Bangladesh, Dhaka-1229, Bangladesh  
ashraful388@iub.edu.bd

**Abstract.** This study investigates the reported use and perceptions of Generative Artificial Intelligence (GenAI) among students enrolled at selected universities in Bangladesh. A cross-sectional quantitative survey was conducted during the Spring 2025–26 academic session using an online questionnaire administered through Google Forms. A total of 452 undergraduate and graduate students from different academic disciplines participated in the study. Participants responded to Likert-type questionnaire items concerning GenAI usage, perceived benefits, limitations, academic integration, and potential over-reliance. Descriptive statistics, Pearson correlation analysis, and exploratory stepwise multiple linear regression were used to examine associations among the questionnaire indicators. Participants generally reported positive perceptions of GenAI, particularly regarding time saving, perceived digital competence, accessibility, and personalized feedback, while also recognizing concerns related to inaccuracy, bias, and excessive reliance. Exploratory analyses showed that self-reported reliance was more strongly associated with several academic- and perception-related indicators than with the included demographic indicator. Given the cross-sectional, voluntary, and self-report nature of the study, the observed relationships are interpreted as associations rather than causal effects or objectively measured learning outcomes.

**Keywords:** Generative AI, higher education, student perception, learning support, Bangladesh

## 1 Introduction

The acquisition of knowledge, skills, and competencies through learning leads to the development of intellect and a person's professional expertise. However, besides being an avenue through which students gain knowledge, higher education is also concerned with: how well students develop their ability to think critically, solve problems, reflect, and apply knowledge to real-world situations [21,14]. Additionally, with the increasing adoption and use of learner-centred and technology-based educational models, technology plays a major role in helping students engage in academics and succeed in their coursework [11,2].

Learner's perspectives are among the most important psychological components impacting a student's overall learning experience. A learner's perspective consists of their beliefs, attitudes, awareness, and acceptance of the tools available to him or her to enhance their learning experience [27,22]. Therefore, it is vital for educators to assess and understand student perceptions prior to the introduction of any of the many new technologies that will dramatically impact the relationship between teachers and students in today's higher education environment [5].

In Higher Education, many people have started using Generative Artificial Intelligence (GenAI) technology to take advantage of its capabilities in the area of Natural Language Generation, Natural Language Reasoning, creating content in all areas, including the arts, social sciences (psychology), business, and computer science. GenAI systems, including conversational chatbots and large language models, can generate human-like textual responses [3,9]. The systems are capable of explaining different concepts and summarizing content produced by various academics, and providing immediate feedback to users. Unlike traditional educational technologies, GenAI provides interactive, adaptive, and personalized learner support. This allows for new avenues to enhance learning processes [1].

In the last few years, the use of GenAI tools has grown rapidly in learning environments in higher education institutions globally. More and more students are using GenAI tools for assistance in writing documents, brainstorming ideas, coding application logic, summarizing the results of research, preparing for exams, and pursuing self-directed learning activities [7,6]. GenAI provides educators with opportunities to reduce the burden of administering coursework, support the development of assessments and give learner-specific feedback [15]. While there are many advantages of using GenAI tools, there are also concerns regarding factual inaccuracies associated with the information generated, bias in the responses provided by the system, potential ethical implications of the use of AI-generated content, and the possibility of excessive reliance on AI-based content [13,24]. The way that students view GenAI within their learning experiences affects how well they adopt and use the technology effectively when learning. Recent studies show that many students believe that using GenAI as part of their education is beneficial and saves them time during schoolwork; however, other students have seen drawbacks with using this type of tool such as uncertainty regarding how GenAI operates and whether or not it can be relied upon for developing both critical thinking and transferable skills [16,14,5]. This creates

a need to better understand how students' perceptions and reported GenAI-use behaviours are associated with their learning experiences and how these patterns are perceived within university settings.

In Bangladesh, using Generative AI technology is still developing within universities where students are facing barriers to using it. As Bangladesh continues to expand Higher Education and provide increasing access to Digital Technologies, more Bangladeshi students are being introduced to AI Learning Tools; however there exist obstacles associated with Digital Literacies, Institutional Policies, Ethical Awareness, and the Readiness of Infrastructure [18,12]. Thus far, very few primary studies exist that document either the ways in which Bangladeshi University Students use or perceive Generative AI tools and therefore additional research conducted in an experiential manner will help to develop our knowledge of these resources in order aid policymakers and administrators at universities in Bangladesh [23,25].

The objectives of this research include:

- Examining how participating university students report using GenAI tools for academic purposes.
- Assessing students' perceptions of the integration of GenAI into their academic activities.
- Identifying the perceived advantages, limitations, and concerns associated with GenAI use in higher education.
- Examining associations between GenAI-related perceptions, reported usage, and self-reported reliance among students from selected private universities in Bangladesh.

This study contributes context-specific evidence regarding GenAI use and perceptions among students from selected universities in Bangladesh. The findings may help educators, university administrators, and policymakers identify areas in which students perceive GenAI as useful, as well as areas requiring additional guidance concerning accuracy, academic integrity, excessive reliance, and AI literacy. However, the findings are perception-based and should not be interpreted as evidence that GenAI use causes improvements in learning outcomes or that participating students necessarily engage in responsible GenAI use.

## 2 Literature Review

The attitude of learners towards GenAI, has been recognised as an important factor that can help determine the effectiveness of GenAI in educational contexts, as well as the extent to which it is used by learners [20]. The term 'perception' refers to the way students perceive GenAI, including how aware they are of GenAI-based tools; their attitudes and beliefs towards GenAI; their level of trust and acceptance of GenAI-based tools; etc. In many studies conducted to date, students have indicated that they view GenAI as an enhancement to their

understanding, as well as a learning assistant that can help alleviate their academic workload [8]. In addition, a number of studies have indicated that positive student perceptions of GenAI are linked to perceptions of usefulness, ease of use and that GenAI tools provide prompt and constructive feedback and explanations [10]. At the same time, however, students have expressed concerns about the limitations of GenAI, including the potential for GenAI to generate factually inaccurate or biased information. Concerns have also been raised regarding academic misconduct, learning dependent on AI, and how using GenAI may inhibit the development of students' critical thinking skills [26]. The results of all of these studies suggest that while many students find GenAI helpful, they remain cautious when considering the overall reliability of GenAI and its long-term impact on the learning process. Furthermore, the results of these studies emphasise that perceptions are not just positive or negative, but should be viewed as a more complex construct than a simple attitudinal view.

GenAI can be utilized in a variety of areas of academics. Research indicates that students are using generative AI tools for virtually everything related to writing; brainstorming for writing topics; summarizing class materials; coding; problem solving; and preparing for exams [4]. Since these tools can provide real-time, individually tailored support, they are highly regarded as being appropriate for individualized self-paced learning. From the perspective of instruction, GenAI has been examined as an option for automating some of the administrative duties of instructors; as a creator of electronic resources; and as a provider of formative assessment feedback [17]. GenAI-based chatbots incorporated into a blended or fully online learning environment can improve student interactions, through the development of conversationally-based or interactive experiences. However, how and when GenAI will be used depends on the discipline, academic level, and types of institutions using it; thus, GenAI adoption is highly dependent on the context in which it is used.

While the literature on Education & the Use of GenAI continues to grow, several key limitations exist. One limitation is that much of the research currently available has been conducted almost exclusively within developed nations which limits the ability for readers to apply the findings to educational environments located in developing nations such as Bangladesh [19]. A second limitation relates to the fact many of the studies completed in the area of Education & the Use of GenAI tend to consist of small samples and are often based on one specific area of study, i.e., STEM, thus constituting a very small population from which to draw upon when attempting to generalize findings across multiple disciplines. Thirdly, the majority of the existing literature continues to focus on one area of either perception or use as a standalone study, rather than utilizing an empirical model to examine the relationship of both. Furthermore, most studies that have been conducted to date are cross-sectional in nature and do not provide insight into long-term impacts or long-term outcomes related to education. Lastly, the ethical, cultural, and institutional aspects of the use of GenAI, while frequently mentioned and recognized, have yet to be sufficiently operationalized for use in empirical analyses. This further substantiates the need for comprehensive studies

to determine the integrated usage patterns, perceptions, challenges, and benefits of the use of GenAI in specific educational contexts.

To consolidate the reviewed studies, Table 1 presents a structured summary highlighting key focus areas, methods, and identified gaps in the existing literature.

Table 1: Summary of Literature on Generative AI in Learning

| Focus Area                       | Key Findings                                                                | Methodology                        | Identified Gaps                                             |
|----------------------------------|-----------------------------------------------------------------------------|------------------------------------|-------------------------------------------------------------|
| Perception of GenAI in learning  | Generally positive attitudes; concerns about accuracy, bias, and integrity  | Surveys, Likert-scale analysis     | Limited contextual and cultural analysis                    |
| Usages of GenAI in learning      | Writing support, summarization, coding, exam preparation, feedback          | Case studies, surveys              | Overemphasis on student use; limited instructor perspective |
| Usages and perception combined   | Positive correlation between usage and acceptance; ethical concerns persist | Regression, correlation analysis   | Lack of longitudinal and causal analysis                    |
| Context-specific studies         | Higher adoption in tech-related disciplines                                 | Cross-sectional studies            | Underrepresentation of developing countries                 |
| Ethical and pedagogical concerns | Risks of dependency, reduced critical thinking                              | Conceptual and qualitative studies | Limited empirical validation                                |

### 3 Methodology

This study employed a cross-sectional quantitative survey design to examine the reported use of and perceptions toward GenAI among students from selected universities in Bangladesh. The methodology included five components: (1) study design, participants, and sampling; (2) questionnaire variables and measurement; (3) data preparation and missing-data handling; (4) statistical analysis; and (5) ethical considerations and data privacy.

#### 3.1 Study Design, Participants, and Sampling

This study employed a cross-sectional quantitative survey design to examine university students' reported use of and perceptions toward Generative Artificial Intelligence (GenAI). Data were collected during the Spring 2025–26 academic

session from undergraduate and graduate students enrolled at selected universities in Bangladesh, including American International University-Bangladesh (AIUB), North South University (NSU), Independent University, Bangladesh (IUB), Asian University of Bangladesh (AUB), BRAC University, and other universities.

A non-probability voluntary-response sampling approach was used. The questionnaire was administered online using Google Forms and was distributed through public online student groups associated with the selected universities. These university-based student groups served as the primary recruitment channels and enabled the questionnaire to reach students from different academic disciplines and study levels.

The sampling frame therefore consisted of students from the selected universities who had access to the online student groups through which the survey invitation was circulated. Eligible participants were students enrolled at one of the selected universities during the data-collection period who voluntarily chose to complete the questionnaire. A total of  $n = 452$  usable responses were included in the analysis.

Because the questionnaire link was circulated through public online student groups, the exact number of eligible students who viewed or received the survey invitation could not be determined. Consequently, a conventional survey response rate could not be calculated. Furthermore, because participation was voluntary and based on online self-selection rather than probability sampling, the sample should not be considered statistically representative of all university students in Bangladesh.

The questionnaire contained closed-ended Likert-type items, multiple-selection questions, and open-ended questions. Closed-ended perception items were measured using a five-point scale ranging from 1 (strongly disagree) to 5 (strongly agree).

**Dependent Variable** The dependent variable was self-reported *Reliance* on GenAI, operationalized using the Likert-type questionnaire item:

*“may become over-reliant on generative AI technologies.”*

This item reflects participants’ perceived tendency toward potential over-reliance on GenAI for academic activities. Because Reliance was measured using a single questionnaire item, it is interpreted as an individual perception indicator rather than as a validated multi-item psychometric construct.

**Independent Variables** The predictors came from the questionnaire, which featured various questions related to knowledge, willingness, perceived benefits, and perceived concerns associated with using GenAI resources. In order to facilitate analysis and visualization of the survey responses, all survey questions were grouped and given one-word labels to be included into the analysis pipeline.

Key predictors included: *Gender, Usage, Complexity, Inaccuracy, Inappropriateness, Bias, Statistics, Empathy, Integration, Careers, Competence, Timesaving, Insights, Feedback, Availability, Anonymity, Undermining, Socialization, Skills, Reliance, Benefits, Challenges, Perception, Advantages, Disadvantages.*

**Questionnaire Language** The questionnaire was administered in English and was not translated into another language. Therefore, translation and back-translation procedures were not required.

### 3.2 Data Processing and Missing Data

Before analyzing the data, raw responses were exported from Google Forms and were prepared to be analyzed. To prepare the raw responses for analysis, the following steps were completed:

1. **Data cleaning:** The timestamps and emails were removed, and a review was performed for missing data and consistency of responses.
2. **Encoding:** The Likert Scale responses were encoded numerical from 1 to 5 (5 is high agreement).
3. **Variable renaming:** Long response items were renamed to short one word variable names (e.g., *Timesaving, Competence, Reliance*) for improved readability within tables and figures.
4. **Handling categorical variables:** Measures of Gender and how often GenAI was being used were treated as categorical/ordinal variables for correlation and regression.
5. **Multi-select fields:** Multi-select items will be included as descriptive and, when required to calculate summaries, they will be converted to binary variables.

The dataset was screened for missing responses before analysis. No statistical imputation procedure was applied; analyses were conducted using available responses for the variables included in each analysis.

### 3.3 Statistical Analysis

The analytical strategy combined descriptive and exploratory inferential techniques to summarize response patterns and examine associations among questionnaire indicators. Because the study used a cross-sectional self-report design, all inferential relationships were interpreted as associations rather than causal effects.

**Descriptive Statistics** Frequencies and percentages were used to summarize categorical response patterns, while means and standard deviations were used to describe selected Likert-type perception indicators. Descriptive comparisons were also conducted between more frequent and less frequent GenAI users to characterize differences in reported benefits and concerns.

**Correlation Analysis** Pearson correlation coefficients were calculated for selected questionnaire indicators to describe the direction and magnitude of linear associations among reported GenAI perceptions, usage-related indicators, and self-reported Reliance. A correlation heatmap was generated to facilitate interpretation of these relationships, and a scatterplot matrix was used for exploratory visualization. The correlations are interpreted as cross-sectional associations and not as evidence of causal relationships.

**Exploratory Multivariable Regression** An exploratory stepwise multiple linear regression analysis was conducted to examine conditional associations between selected questionnaire indicators and self-reported Reliance. The analysis was exploratory rather than confirmatory and was not intended to test a prespecified structural theory or establish causal relationships. Standardized regression coefficients were used to compare the relative direction and magnitude of associations among the included indicators.

Because predictor selection was data-driven, coefficient magnitudes and predictor rankings should be interpreted as sample-specific exploratory findings rather than stable causal determinants. Partial regression plots were used as exploratory visual diagnostics of conditional relationships after accounting for the other variables included in the model.

### 3.4 Ethical Considerations and Data Privacy

Participation in the survey was voluntary. Before completing the questionnaire, participants were informed about the academic purpose of the study, the voluntary nature of participation, and the intended use of responses for aggregate research analysis.

Personally identifying information was not retained in the analytical dataset. Email-related information and timestamps were removed during data preprocessing, and results were analysed and reported in aggregated form to protect participant privacy.

## 4 Results

Awareness of Generative AI limitations was substantial among participants. More than half of the respondents (51.9%) agreed that Generative AI has difficulty handling complex tasks, while 45.5% agreed that it can generate factually inaccurate outputs. Perceptions of biased or unfair responses were acknowledged by 45.5% of respondents, with 33.8% remaining neutral. Limited emotional intelligence was recognized by 39.5% of participants, while 37.7% expressed neutrality. Heavy reliance on statistical patterns was agreed upon by 50.0% of respondents.

Overall attitudes toward the application of Generative AI in learning was generally positive. Most students agreed that it saves time (64.9%) and is relevant in their future careers (63.7%). Over half of the students appreciated the

fact that it is available 24/7 (57.2%). Despite the high level of appreciation for the application of AI in learning activities (48.1%), a considerable number of students expressed a balanced attitude.

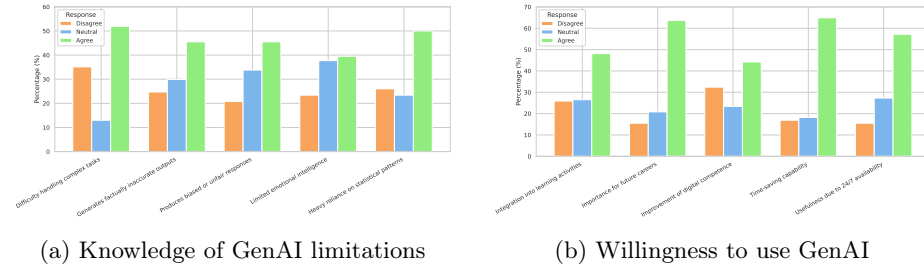


Fig. 1: Knowledge and willingness regarding GenAI

The patterns of use for the Generative AI tool differ by subject. Students from Computer Science and Engineering have the highest level of frequent use (68%), followed by students from the Faculty of Electrical and Electronic Engineering (54%). Students from other faculties have lower frequent use (46%) with more occurrences in the other two categories.

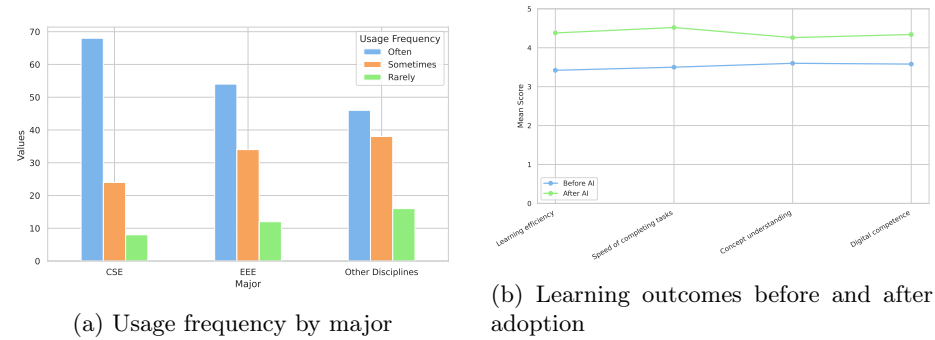


Fig. 2: Usage frequency and learning outcomes

Comparison of the retrospective self-assessed ratings showed higher reported scores after GenAI adoption across several learning-related dimensions, particularly task-completion speed, perceived learning efficiency, and perceived digital competence. Because these measures were self-reported within a cross-sectional questionnaire, the observed differences should not be interpreted as objectively measured learning improvements or causal effects of GenAI use.

Table 2: Perceptions of Ethical and Learning-Related Concerns by Usage Intensity

| Concern                               | Frequent users (mean) | Infrequent users (mean) |
|---------------------------------------|-----------------------|-------------------------|
| Risk of over-reliance                 | 4.20                  | 3.40                    |
| Limits transferable skills            | 3.60                  | 3.20                    |
| Reduces interaction and collaboration | 3.70                  | 3.30                    |
| Undermines educational value          | 3.30                  | 3.10                    |

Table 3 presents a descriptive comparison of user perceptions according to reported GenAI usage frequency together with observed associations among selected learning-related indicators. Frequent users reported higher perceived benefits across several dimensions, particularly time saving, digital competence, and access to personalized feedback, whereas infrequent users reported comparatively moderate perceived benefits. Positive associations were observed between time-saving perceptions and perceived learning efficiency, as well as between personalized feedback and perceived understanding. Relationships between usage frequency and over-reliance or ethical concerns were comparatively weaker. These findings describe patterns of association among self-reported perceptions and should not be interpreted as evidence that greater GenAI usage causes improvements in academic effectiveness.

Table 3: Comparison of User Perceptions and Observed Relationships

| Dimension & Statement        | Frequent Users | Infrequent Users | Related Perception                    | Paired Observed Relationship |
|------------------------------|----------------|------------------|---------------------------------------|------------------------------|
| Improves digital competence  | High           | Moderate         | Usage frequency ↔ Over-reliance       | Moderate positive            |
| Saves time in academic work  | Very high      | Moderate         | Time saving ↔ Learning efficiency     | Strong positive              |
| Provides unique insights     | High           | Moderate         | Usage frequency ↔ Ethical concern     | Weak positive                |
| Offers personalized feedback | High           | Moderate         | Personalized feedback ↔ Understanding | Strong positive              |

Figure 3a presents the Pearson correlation matrix for the selected questionnaire indicators and self-reported Reliance. Several educational and perception-related indicators showed moderate to strong positive associations. For example, Competence and Timesaving showed a strong correlation ( $r = 0.87$ ), while other indicators also demonstrated substantial relationships.

Reliance showed moderate to strong positive correlations with Undermining ( $r = 0.73$ ), Skills ( $r = 0.62$ ), Competence ( $r = 0.62$ ), and Integration ( $r = 0.63$ ).

These results indicate that higher scores on these perception indicators were associated with higher self-reported Reliance scores within the observed sample. In comparison, Gender showed comparatively weak correlations with Reliance and several other questionnaire indicators. These relationships are associative and should not be interpreted as causal effects.

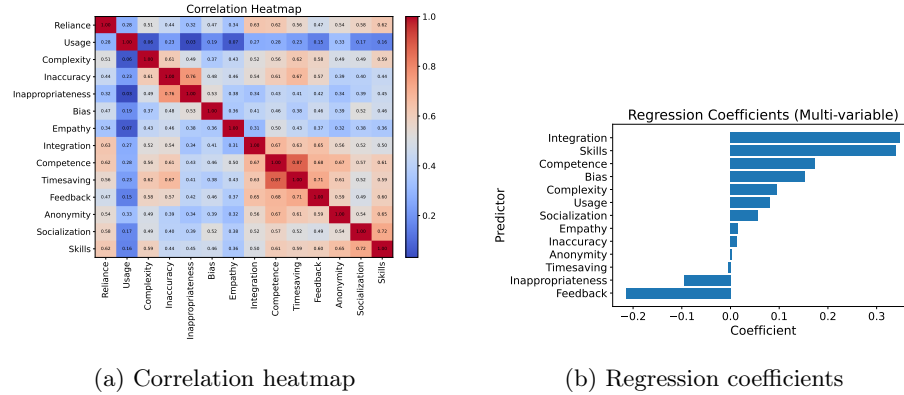


Fig. 3: Correlation and regression analysis

In Figure 3b, the final column of data illustrates which of the predictor variables had the highest standardized regression coefficients according to the multiple linear regression model predicting Reliance, along with the standardized regression coefficients of Undermining, Skills, Integration, and Competence. Each of these four variables had standardized regression coefficients of 0.20 or greater, indicating that these four predictor variables are substantially influencing Reliance. Conversely, predictor variables such as Gender and Inappropriate had standardized regression coefficient values close to 0, thereby demonstrating very low levels of predictive power. Overall, reliance on generative AI is mainly due to the perceived use of generative AI in a student's academic environment rather than demographic differences.

The multiple variable scattergraph shown in Figure 4a depicts the relationships of the variables Gender, User, Complex, Incorrect, Unacceptable, Bias, Stats and Empathy to one another. The histograms on the diagonal show you how the Likert scales are distributed, while the scatterplots (off-diagonal) show the linear relationship between different perceptions of a variable e.g., Complexity vs Inaccuracy (and also Bias vs Stats). These relationships are grouped with clusters showing the existing moderate to high correlation outlined in the previous chart (e.g., Complexity and Inaccuracy are correlated at a  $r = 0.61$ ). This indicates that the relationships are structured rather than randomly spread across the graph.

Figure 4b presents partial regression plots illustrating the conditional relationships between individual questionnaire indicators and Reliance after ac-

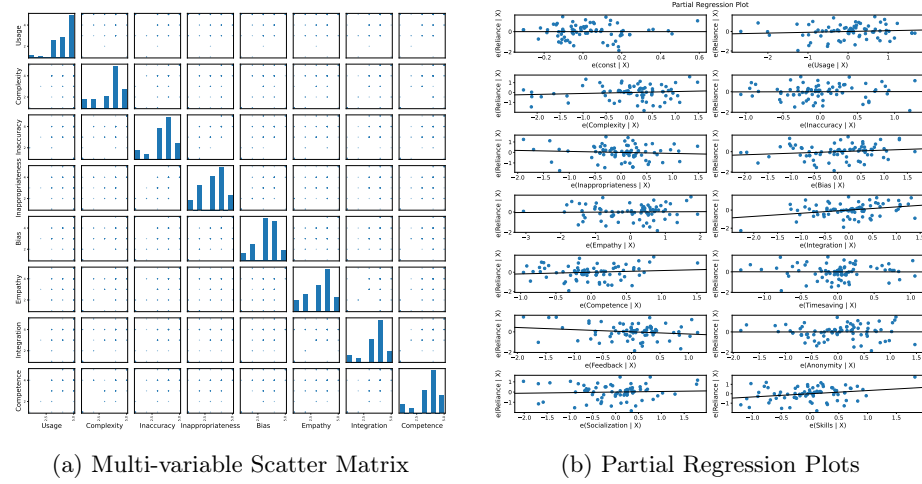


Fig. 4: Scatter matrix and partial regression analysis

counting for the other variables included in the exploratory model. Positive or negative trends can be visually observed for several indicators; however, these plots are presented only as exploratory visual diagnostics. They should not independently be interpreted as evidence of statistical significance, model robustness, or causal relationships.

## 5 Discussion

Overall, students participating from the selected universities reported generally positive perceptions of GenAI as an academic support tool. Time saving, accessibility, perceived digital competence, personalized feedback, and relevance to future academic or professional activities were among the commonly reported benefits. At the same time, participants demonstrated awareness of limitations associated with GenAI, including factual inaccuracies, biased responses, limitations in handling complex tasks, and potential excessive reliance.

The correlation and exploratory regression analyses further showed that self-reported Reliance was more strongly associated with several perception- and academic-context indicators than with the included demographic indicator. Integration, Competence, Skills, and Undermining showed comparatively strong relationships with Reliance within the observed sample. These relationships should be interpreted as cross-sectional associations rather than evidence that these factors cause students to become more dependent on GenAI.

Differences in reported GenAI usage were also observed across broad academic disciplines, with students from technology-oriented disciplines reporting comparatively frequent use. However, these descriptive patterns do not establish that academic discipline itself causes differences in GenAI adoption. They

instead indicate that GenAI usage and perceptions may vary according to academic context and warrant more detailed investigation using larger stratified samples.

Importantly, perceived educational usefulness should be distinguished from responsible GenAI use. The present study assessed students' reported perceptions of usefulness, accessibility, academic integration, skill development, concerns, and potential over-reliance. It did not directly evaluate responsible-use behaviours such as verifying AI-generated information, disclosing AI assistance, complying with academic-integrity requirements, appropriately citing AI-supported work, or protecting confidential information. Accordingly, the findings should not be interpreted as evidence that participants necessarily used GenAI responsibly.

From a practical perspective, the findings may help universities identify areas in which students perceive GenAI as useful and areas requiring additional institutional guidance. Universities may consider strengthening AI-literacy education, information-verification practices, academic-integrity guidance, and awareness of excessive reliance. However, these recommendations should not be interpreted as evidence that increasing GenAI use will necessarily improve learning outcomes. The effectiveness of such interventions should be evaluated in future longitudinal or experimental studies.

### 5.1 Limitations

Several limitations should be considered when interpreting the findings. First, the voluntary online, non-probability sampling of students from selected universities may have introduced self-selection bias and limits the generalizability of the findings to all university students in Bangladesh. Second, predictor and outcome variables were collected through the same self-report questionnaire, which may have introduced common-method effects. Third, the cross-sectional design does not establish temporal ordering or causality; therefore, the observed associations should not be interpreted as evidence of actual learning effects. Fourth, several variables were measured using single questionnaire items rather than validated multi-item constructs, limiting reliability and factor-based validation. Detailed respondent-level information was also insufficient for formal sensitivity analyses across institution, discipline, and study level. Finally, the exploratory stepwise regression was data-driven, and correlations among some predictors may have affected coefficient stability. Future studies should use broader probability-based samples, validated multi-item measures, theory-led models, and longitudinal or experimental designs.

## 6 Conclusion

The results indicate that GenAI is widely perceived as a valuable support tool for students' learning. Consistently, the most frequent users of GenAI recorded higher levels of perceived value related to time savings, increasing digital competence, obtaining personalised feedback, and exposure to diverse academic

sources. Thus, GenAI contributes to the growth of self-accessed, flexible learning experiences especially in technology-supported educational systems.

By means of correlation and regression analyses, results indicate that students' reliance on GenAI is mainly driven by pedagogical and functional factors and not by demographic characteristics. Based on the results, the perceived benefits of GenAI for skill development, academic integration, perceived undermining of traditional education, and perceived digital competence were the strongest predictors of students' reliance on GenAI. Meanwhile, the demographic variable of gender and isolated concerns about inappropriate responses were relatively weak predictors of students' reliance on GenAI. Thus, the results suggest that students are influenced primarily by their perception of learning value and how they incorporate GenAI into their academic practice.

On one hand, the findings support students' increased use of GenAI as an enhancement to their academical support system. On the other hand, the findings also raise concerns about over-reliance and the potential erosion of transferable skills. As a result, it appears that students are aware of the limitations and risks associated with using GenAI. Therefore, a need exists for structured guidance and pedagogical frameworks to support responsible and reflective use of GenAI rather than simply encouraging students to rely on it.

## References

1. Baidoo-Anu, D., Ansah, L.O.: Education in the era of generative artificial intelligence (ai): Understanding the potential benefits of chatgpt in promoting teaching and learning. *Journal of AI* **7**(1), 52–62 (2023)
2. Bozkurt, A., Sharma, R.C., et al.: Speculative futures on chatgpt and generative artificial intelligence (ai): A collective reflection from the educational landscape. *Asian Journal of Distance Education* **18**(1), 53–130 (2023)
3. Brown, A., Green, T.: The rise of generative ai in education. *International Journal of AI in Education* **12**(1), 22–34 (2023)
4. Brown, T., Green, S.: From coding to writing: Comprehensive student usage of genai. *International Journal of EdTech* **19**, 200–215 (2024)
5. Chan, C.K.Y., Hu, W.: Students' voices on generative ai: perceptions, benefits, and challenges in higher education. *International Journal of Educational Technology in Higher Education* **20**(1), 43 (2023)
6. Cotton, D.R.E., Cotton, P.A., Shipway, J.R.: Chatting and cheating: Ensuring academic integrity in the era of chatgpt. *Innovations in Education and Teaching International* **61**(2), 228–239 (2023)
7. Davis, M.: How students are using genai for coursework. *TechTrends* **68**, 101–115 (2024)
8. Doe, J., Lee, M.: Genai as a learning assistant: Enhancing understanding. *Educational Technology Review* **35**, 45–60 (2023)
9. Dwivedi, Y.K., Kshetri, N., Hughes, L., et al.: “so what if chatgpt wrote it?” multidisciplinary perspectives on opportunities, challenges and implications of generative conversational ai for research, practice and policy. *International Journal of Information Management* **71**, 102642 (2023)
10. Gupta, R., Chen, L.: Correlating perception and feedback in genai tools. *Computers & Education* **102**, 104–118 (2024)

11. Johnson, E.: Technology-Based Educational Models. Academic Press (2021)
12. Kong, B., Li, Z., Ratner, S., Hemberg, E., Haque, S.: Artificial intelligence for education in bangladesh: Insights from the first small-scale ai needs assessment. ADB Sustainable Development Working Paper Series 101, Asian Development Bank, Manila, Philippines (2024)
13. Lee, S., Kim, J.: Ethical concerns and bias in ai-generated content. *AI Ethics Journal* **5**, 200–215 (2023)
14. Lindebaum, D., Fleming, P.: Critical thinking in the age of generative ai. *Academy of Management Learning & Education* **23**(1), 1–12 (2024)
15. Michel-Villarreal, R., Vilalta-Perdomo, E., Salinas-Navarro, D.E.: Generative ai in higher education: An overview of administrative and pedagogical applications. *Journal of Applied Learning & Teaching* **6**(2) (2023)
16. Miller, K.: Benefits and drawbacks of genai: Student perspectives. *Journal of Educational Technology* **40**(3), 330–345 (2023)
17. Miller, P.: Automating administration: The instructor's view on genai. *Higher Education Management* **40**(4), 330–345 (2022)
18. Rahman, M., Islam, S.: Digital literacy and ai adoption in bangladeshi universities. *Bangladesh Education Journal* **15**(2), 55–78 (2024)
19. Rahman, S., Ahmed, F.: The digital divide: Ai research gaps in developing nations. *Journal of Global Education* **12**, 88–95 (2023)
20. Smith, A., Johnson, B.: Learner attitudes towards ai: A determinant of effectiveness. *Journal of AI in Education* **14**(2), 112–125 (2023)
21. Smith, J., Doe, J.: Critical thinking in higher education: A review. *Journal of Higher Education* **45**(2), 112–130 (2020)
22. Strzelecki, A.: To use or not to use chatgpt in higher education? a study of students' acceptance and use of generative artificial intelligence. *Interactive Learning Environments* pp. 1–14 (2023)
23. Tanvir, K., Islam, M.S., Sezan, S.B.K.: Impact of chatgpt on academic performance among bangladeshi undergraduate students. *International Journal of Research in Science & Engineering* **3**(5), 18–28 (2023)
24. UNESCO: Guidance for generative ai in education and research. Guidance, UNESCO, Paris, France (2023)
25. UNESCO and a2i: Bangladesh launches national ai readiness assessment report to guide ethical, inclusive and human-centred ai governance. Press Release, UNESCO Dhaka Office (2024), retrieved from UNESCO.org
26. Williams, K.: Critical thinking and dependency: The risks of ai. *Academic Integrity Journal* **8**(1), 22–34 (2023)
27. Williams, R.: Understanding student perceptions of learning tools. *Educational Psychology Review* **31**, 45–60 (2019)