

Generative Artificial Intelligence integration in higher education: A constructivist learning theory approach

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ABSTRACT

The integration of Generative Artificial Intelligence (GAI) in higher education presents transformative opportunities for teaching, learning, and research, particularly in resource-constrained developing countries like Bangladesh. This study investigates the potential of GAI adoption in Bangladeshi universities through the lens of Constructivist Learning Theory (CLT). Employing a mixed-method approach combining surveys ($n = 255$ faculty members) and Focus Group Discussions (FGDs), the research explores factors influencing GAI adoption, including competency, domain relevance, and institutional support. The research employed Structural Equation Modeling (SEM) using SmartPLS to examine the relationships among key constructs. The findings highlight that attitude towards GAI use is a strong predictor of the extent of GAI use ($\beta = 0.556, p < 0.001$), influenced significantly by users' competency, domain-specific technology relevance, and students' technology use provision. Among the predictors of attitude towards GAI use, domain-specific technology relevance exhibited the strongest effect ($\beta = 0.413, t = 6.561, p < 0.001$). However, subjective norms and institutional technology use provision are not found to be significant in the context. While students' technology use provision showed a positive and significant contribution, the findings of thematic analysis indicated the teachers' strong concern regarding technology use. Post hoc analysis revealed that the control variables age, gender, education, and academic role had negligible effects. The study recommends enhancing university capacities through training, integrating GAI into pedagogy, and promoting ethical guidelines and support for both students and teachers. Future research should examine the longitudinal effects of GAI on teaching outcomes and institutional readiness in various contexts.

1. Introduction

Since its introduction, Generative Artificial Intelligence (GAI) has seen a rapid and widespread adoption, especially among students and educators worldwide. With its disruptive nature, it has become a powerful tool that affects the teaching and learning process across disciplines [1–3]. This tool generates content, provides answers to users' queries, and offers an inimitable learning experience using its large language model [3,4]. Most importantly, it facilitates personalized as well as inquiry-based learning experiences and extends students' access to a large knowledge resource [5]. Furthermore, it encourages the development of innovative approaches to curriculum design and teaching methods [6]. However, despite its potential, it has also raised debate over the integration of such technologies in academics. GAI disrupts the traditional teaching-learning process, raising concerns

about academic integrity and the ethical use of technology in education [7,8]. With such a facility, students might heavily depend on technology, imperiling the existing assessment process and conventional classroom teaching. This, in the long run, may cause destruction, disengagement, and a decline in their critical thinking and learning ability.

Following the global trend, GAI has experienced widespread adoption among internet users, particularly university students in Bangladesh. Yet, no national or institutional policy has been introduced to guide its responsible use in academia. Many universities face major challenges, including inadequate digital infrastructure, limited faculty training programs, confusion surrounding academic integrity, and varied perceptions regarding the ethical use of GAI. Furthermore, many faculty members remain unaware of how GAI can be effectively and positively integrated into their teaching and learning processes. This

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lack of clear policies and guidelines leaves educators and institutions uncertain about its implications for academic settings [6,9].

Amid such dilemmas, this study addresses the integration of GAI within higher educational institutions from a developing country perspective, using Bangladesh as a case. It focuses on faculty perspectives, grounded in the theoretical foundations of Constructive Learning Theory (CLT). The specific objectives were to: (i) determine university teachers' attitude and extent of GAI use in their teaching-learning practices, and (ii) explore how GAI could be used in supporting collaborative, inquiry-based, student-centered learning experiences. By achieving these objectives, the study provides a roadmap for leveraging GAI to enhance higher education while addressing the potential risks and challenges.

2. Literature review

2.1. Generative artificial intelligence and its use in higher education

GAI is a transformative force in higher education, enabling innovative approaches to personalized learning, curriculum design, and interdisciplinary applications. It is built upon deep learning models and defines a class of top-tier AI assistants—such as ChatGPT, Bard, and Claude—that generate human-like content and perform complex, thought-provoking tasks. These tasks include tutoring, writing assistance (academic, comedic, commercial, etc.), performance evaluation, and various other user-driven functions [3,10]. Unlike traditional search engines we are familiar with, GAI models' advanced reasoning engine permits dynamic, interactive, and immersive experiences between user and bot; adapting to individual learning styles and quirks, hence their existence is invaluable in the modern educational landscape [11]. These tools, as mentioned, are designed to adapt to users and their learning needs so they can produce immediate and understandable yet professional feedback. They also enable data-driven curriculum adjustments that accommodate diverse learning preferences [2,12].

In fields that require critical thinking, such as engineering, medicine, and agriculture, by processing real-time data, GAI can generate relevant content within seconds and offer the simulations, assumptions, reasoning, and solutions required for the issues given [13,14]. GAI redefines how educators design materials for students and allows for a more adaptive, learner-centered educational ecosystem. However, integrating GAI into higher education raises critical concerns. Academic integrity is put at risk as the content can easily mimic human words, leaving a strong dilemma of whether human effort was part of the work. Hence, we require robust detection tools and a series of ethical guidelines [15,16], yet these can be faulty.

Additionally, there are ethical and social implications of GAI integration into education. The key challenges include ensuring data privacy, addressing potential information bias, bridging the digital divide, and managing unequal access to technology and the internet, exacerbating existing disparities and inequalities, and limiting the benefits of GAI for underprivileged and marginalized communities [17] and potentially skewing its outcomes. Over-reliance may hamper critical thinking, creativity, and independent problem-solving skills, as students may skip meaningful cognitive engagement with problems and rely on AI to complete their work, gaining little to no learning experience in the process [18,19]. Moreover, concerns about job displacement and declining job security among educators and other information-handling services necessitate a strategic integration of AI that preserves their essential roles while leveraging the technology to enhance outcomes and avoid human replacement [7].

Addressing these challenges is vital to ensure the equitable, ethical, and pedagogically sound use of GAI in higher education. Institutions must also prioritize data privacy and security to prevent the misuse of sensitive information for harmful purposes [7]. To ensure responsible use, higher education institutions should implement clear, transparent, and well-considered ethical policies and usage guidelines. However, our

research did not identify any relevant policies or initiatives addressing these concerns within Bangladesh's education sector. This study aims to fill that gap by examining the current use of GAI among faculty members and institutions across Bangladesh. The following section discusses the theoretical foundation of this study.

2.2. Constructivist learning theory

Constructivist Learning Theory (CLT) was founded by Jean Piaget (1896–1980) and was later developed by Vygotsky [20]. CLT, or constructivism, is a learning theory postulating that learners develop understanding by incorporating new knowledge with their prior beliefs and experiences. The root of CLT is on the same ground as many cognitive theories, yet CLT emphasizes the 'social context' principle in the learning process. Unlike theories that consider human learning as their internal or mental process, CLT theorists argue that learning is not entirely a process of learners' cognitive reasoning, but it combines their social, environmental, and cultural settings, while context plays a significant role in constructing new knowledge or understanding.

CLT challenges the traditional learning process, like repeating content or 'rote learning'. Rather, it believes in the active engagement of learners in real-world activities like workshops or role-playing. Since learning is a dynamic process, learners' understanding must come from making meaningful connections between new and prior knowledge and the learning process [21]. CLT emphasized developing an 'autonomous learner' who can learn independently. Therefore, learners should play the most active roles in the learning process by constructing new knowledge based on their experiences and prior knowledge, while educators are more like facilitators who should encourage learners to interact, exchange thoughts, and co-construct new knowledge [22]. CLT recognizes the importance of discovery-based learning, where learners develop shared understanding through a collaborative process.

Vygotsky [20] and others applied CLT principles in child educational settings. However, recent evidence highlights the significance of the CLT approach for more advanced types of knowledge acquisition [23]. As university students prepare for potential real-world job markets or construct new knowledge through research, implementing CLT principles may be the right choice for educators.

Students in higher studies can obtain several benefits from the CLT approach. First, it offers them better engagement through active participation, questioning, inquiry-based learning, and opinion formulation, thus enhancing their critical thinking ability. Second, this approach presents a more interactive classroom experience than a passive lecture-based learning experience. It further tailors the curriculum to align with students' interests and leverage their prior knowledge and experiences to make lessons more relevant and engaging. More interaction among students and teachers allows for diverse perspectives and the development of essential social and interpersonal skills. Overall, this approach empowers university students to take ownership of their learning and develop a deeper understanding and critical thinking.

2.2.1. Connectivist learning theory

Contrasting constructivist learning theory, one may argue for connectivism, particularly given that this study explores digital technology in educational settings. Connectivism, developed by Siemens [24], recognizes that technology is integral to learning. It focuses more on creating connections between knowledge resources and artifacts than on the idea that learning solely involves human mental processes. Based on the understanding that learning may reside in non-human appliances such as databases or machine algorithms, learners' ability to learn is determined by their ability to find and use those resources. This enables them to exchange knowledge over technology platforms like learning management systems and Web 2.0. blogs, or collaborative platforms.

Connectivism was mostly developed in the context of MOOCs, where learners experience a vast array of digital learning content like pre-recorded videos, online quizzes, and experiments, including live

sessions. In such educational settings, collaboration between peers not only encourages individual learning but also constructs and shares knowledge collectively, facilitating further learning opportunities. Despite Siemens' claim that connectivism is distinct from other cognitive theories, even separate from social constructivism, they share some common features, such as autonomous learners, collaboration, and inquiry-based learning.

Nevertheless, the key difference between these two theories is that constructivism centers on the individual's personal construction of knowledge, while connectivism focuses on the collaborative nature of knowledge. In constructivism, the teacher is a facilitator, guiding students in their learning process. In connectivism, the teacher's role is more of a connector, helping students link to others using various digital resources and networks.

Despite these two theories not being mutually exclusive, their shared elements—especially collaborative and inquiry-based learning practices—offer a comprehensive approach that leverages the strengths of each. Constructivist learning processes help explain how learners engage prior knowledge and are motivated to acquire new knowledge through personalized and meaningful learning experiences. On the other hand, the connectivist approach equips teachers to present a wide array of digitally-enabled tools and resources, thereby creating more opportunities for learners to access and construct new knowledge than in traditional educational settings.

2.3. Technology in education and the value of constructivism and connectivism

The use of technology in education has been a common practice, from traditional tools like overhead projectors and multimedia projectors to Internet-based technologies such as computers, mobile phones, Web 2.0, and apps, transforming both classroom and home learning experiences. Augmented and virtual reality further enhance flexibility and pervasiveness in learning, enabling students to engage actively with information. Studies (for example, [22,25,26]) highlighted the positive impact of technology, with a constructivist approach, in order to develop personalized and interactive learning environments that foster deeper understanding and improved student learning experience.

Despite many universities initially refraining from allowing their students and faculty to use GAI for education, some of them later relaxed their restrictions with certain limitations. In the past year, notably in 2023, several studies have emerged discussing the opportunities and risks associated with GAI in education. GAI in education has presented a paradox, as highlighted by Lim et al. [27], particularly for educators, as it brings both opportunities and threats. While some scholars perceive it as a potentially destructive tool for learners, possibly diminishing motivation and critical thinking skills, others view it as a revolutionary means of accessing information that can empower educators to develop personalized learning opportunities. These conflicting perspectives among educators and learners have sparked a debate regarding the potential use of GAI in education.

In a resource-constrained context like Bangladesh, GAI platforms hold immense potential. They can bridge educational gaps by connecting students to global knowledge networks and developing peer-to-peer learning in virtual environments. Platforms like ChatGPT facilitate Socratic questioning, guiding learners through thought-provoking dialogue to discover solutions and clarify concepts [28]. Connectivism, introduced by Siemens [24], highlights the importance of networks and digital technologies in learning. It argues that knowledge is distributed across various connections, with learners gaining insights by interacting with different nodes in a network. By integrating GAI within constructivist and connectivist frameworks, Bangladeshi institutions can empower students to engage actively with learning materials and build meaningful connections in a globalized academic landscape. Very recently, a study conducted by Jin et al. [29] provides insight into

teachers, students, and institutional roles in promoting AI in education, while we need further investigation. We believe our research is going to add further insight to the existing body of research.

Therefore, given this context, it is imperative for educational institutions, particularly universities in Bangladesh, to swiftly devise strategies for integrating GAI into education, especially in higher studies. Understanding the attitudes, beliefs, usage, and intentions of university faculty regarding the adoption of GAI can provide valuable insights for developing effective GAI utilization strategies in Bangladeshi universities.

2.4. Personal-Social-Environmental-Cultural (P-S-E-C) framework

Grounded on the constructivist principles, this study adopted the Personal-Social-Environmental-Cultural (P-S-E-C) framework (Fig. 1) to empirically test the theoretical model developed for this study (Fig. 2). This framework facilitates a multidimensional analysis of the factors that influence university faculty's attitudes, readiness, and use of GAI. The personal dimension encompasses individual characteristics, including age, gender, educational qualifications, teaching experience, academic role, technological competency, attitudes toward GAI, and the extent of GAI usage. These factors directly shape how educators perceive and engage with GAI tools in their teaching methods.

As a social dimension, subjective norm refers to the perceived expectations from colleagues, professional networks, and institutional culture concerning GAI adoption. This acknowledges that individuals' decisions are often influenced by the attitudes and behaviors of their immediate academic community. The environmental dimension examines institutional and infrastructural conditions, including the availability of GAI-related technological resources, administrative support, and access to such technology platforms. These factors play a significant role in determining the feasibility and ease of integrating GAI into instructional settings. Lastly, the cultural dimension addresses the relevance of technology in specific academic domains, reflecting the values, traditions, and expectations within various disciplines that influence how GAI is perceived and applied. For instance, GAI may be regarded as more appropriate or beneficial in technical fields compared to others due to disciplinary norms.

2.5. Conceptual framework and hypothesis

GAI integration in higher education has gained momentum globally as academic institutions seek to leverage its potential for personalized learning, academic productivity, and enhanced student engagement. Referring to CLT, this study views learning as an active, contextual process wherein individuals construct knowledge through interaction with their environment, prior experiences, and social context [20]. Technology, including GAI, can serve as a powerful cognitive tool when it aligns with learners' needs, disciplinary goals, and institutional ecosystems [30,31]. From this theoretical perspective, a conceptual framework was developed incorporating six antecedent variables hypothesized to influence the attitude toward GAI use, which affects the extent of GAI use of such technologies in academic environments.

The conceptual framework (Fig. 2) illustrates a causal linkage in which individual-level variables, such as competency, domain-specific technology relevance, and subjective norm, interact with institutional technology use provisions and technology use provisions for students. These elements affect attitudes, which subsequently influence the extent of GAI use. This model provides a comprehensive perspective based on constructivist theory and current research in educational technology.

2.5.1. Hypothesis development

Competency refers to the knowledge and skills an individual has gained through participation in specific activities such as professional work, academic learning, or personal efforts. Digital literacy and familiarity with AI-related tools significantly shape perceptions and

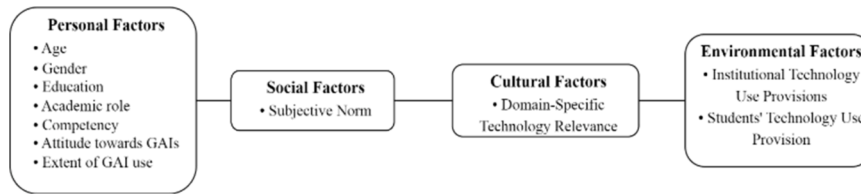


Fig. 1. Personal-Social-Environmental-Cultural (P-S-E-C) Framework.

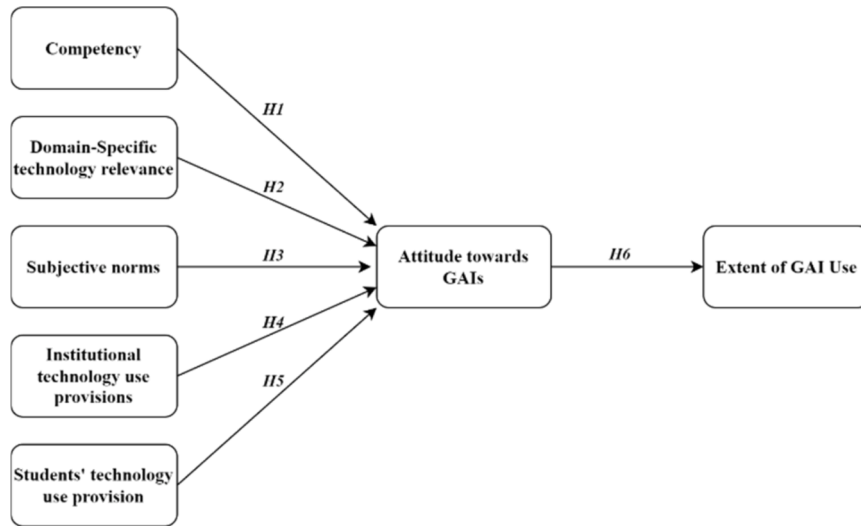


Fig. 2. Conceptual framework.

attitudes toward technology integration [32]. Those with higher competency are more likely to perceive GAI as useful and adopt it confidently. Therefore, we argue:

H1. Competency positively influences attitude towards GAI use.

Domain-specific technology relevance is the degree to which a user believes that technology supports tasks and skills relevant to their subject domain. GAI's alignment with academic tasks and cognitive processes in a specific discipline significantly impacts user acceptance. Constructivist theory suggests that integrating technology is most effective when it directly supports domain-specific teaching and learning processes.

H2. Domain-specific technology relevance positively influences attitude towards GAI use.

Subjective norm is defined as the degree to which a user's behavior is influenced by significant others such as family, friends, colleagues, or society at large. The influence of peers, colleagues, and social groups on an individual's behavioral intentions is significant [33]. In educational settings, the beliefs and behaviors of respected individuals can shape one's willingness to use GAI. However, the extent of this influence may vary depending on the context.

H3. Subjective norm positively influences attitude towards GAI use.

Institutional technology use provisions refer to the degree to which a user receives support, guidelines, and resources from their institution for the responsible use of technology, such as GAIs, within educational settings. Institutional support, which includes policy guidelines, technical infrastructure, and administrative encouragement, is crucial for technology adoption [34]. Measures that ensure ethical and effective use of GAI can significantly influence users' confidence and attitudes.

H4. Institutional technology use provision positively influences attitude toward GAI use.

Technology use provision for students emphasizes the degree to which an educator believes that students may use GAIs to enhance their learning experience and academic performance. Constructivism emphasizes learner-centered approaches, and educators who believe in empowering students through emerging technologies may be more inclined to support GAI use. Student-focused provision reflects the educator's belief that students should engage with GAI to improve academic performance and learning outcomes [24]. Therefore, we hypothesized.

H5. Students' technology use provision positively influences attitude towards GAI use.

Attitude toward GAI use is defined as the degree to which a user holds positive feelings toward using a technology for both personal and professional purposes [33]. The extent of GAI use refers to the degree to which a user uses a technology or system to perform certain activities [35]. According to these models and supported by constructivist principles, a positive attitude toward technology significantly predicts actual use.

H6. Attitude towards GAI use positively influences the extent of GAI use.

Therefore, it can be concluded that individuals who hold favorable attitudes toward GAIs are significantly more likely to actively engage with and utilize these technologies in their academic and professional activities.

3. Methodology

3.1. Research design

This study used a triangulation research Fig. 3 method to provide a comprehensive understanding of the integration of GAI in higher education. Three distinct but complementary approaches were employed:

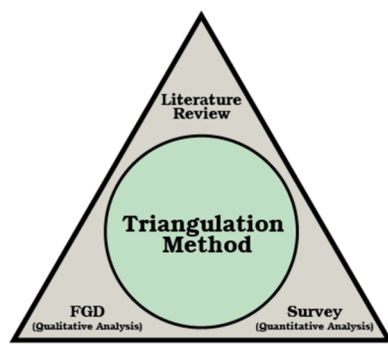


Fig. 3. Triangulation method.

(1) a literature review to establish the conceptual and theoretical foundation; (2) quantitative data collection through a structured survey of faculty members; and (3) qualitative insights gathered from focus group discussions (FGDs). The integration of these sources allowed the research to validate and cross-verify findings, enhancing both the depth and credibility of the research outcomes.

For the quantitative aspect, a cross-sectional survey was conducted using a structured questionnaire to collect data from university faculty members. To enhance the quantitative findings, Focus Group Discussions (FGDs) were also held to provide contextual insights. FGDs and survey data were collected simultaneously.

Data were analyzed using Partial Least Square-based Structural Equation Modeling (PLS-SEM) via SmartPLS software. This method was selected for its ability to handle complex models with multiple latent variables and its suitability for studies emphasizing prediction and theory development.

3.2. Locale of the study

The study was conducted in four Bangladeshi universities, representing diverse institutional categories: Sher-e-Bangla Agricultural University (SAU) – Agricultural University, Shahjalal University of Science and Technology (SUST) – Science and Technology University, University of Dhaka (DU) – the largest general Public University, and North South University (NSU) – the first Private University in Bangladesh. These institutions were purposively selected to ensure representation from public and private sectors, as well as from science, agriculture, and general education disciplines.

3.3. Population and sample of the study

The population of this study is the faculty members in higher education institutions in Bangladesh. Initially, we chose four universities, and the faculties of the selected universities were considered the population. The sample included academic professionals at various ranks—Lecturer, Assistant Professor, Associate Professor, and Professor—engaged in teaching, research, and administrative responsibilities.

Using a 95% confidence level and a 6% margin of error for a total faculty population of 3423 across the four universities, a sample size of 248 faculty members was determined. Sampling was conducted based on proportional stratification across ranks and institutions. However, considering the non-response rate for the online survey, the electronic survey link was circulated through teachers' social media groups across different universities for the last week of the data collection. As a result of these efforts, we collected a total of 268 responses, of which 255 were considered valid and included in the final dataset. The distribution of the respondents is presented in Table 1.

Table 1
Population and sample of the study.

University	Population	Target sample size	Revised sample size
Sher-e-Bangla Agricultural University	340	25 (10.08%)	30 (11.76%)
Shahjalal University of Science and Technology	566	41 (16.53%)	42 (16.47%)
Dhaka University	1992	144 (58.06%)	100 (39.22%)
North South University	526	38 (15.33%)	41 (16.08%)
Other Universities	n/a	n/a	42 (16.47%)
Total	3423	248 (100%)	255 (100%)

3.4. Development of the research instrument

The research began with an extensive literature review Fig. 4 to identify potential variables and measurement items. This desk research came up with different journal articles and reports relevant to the use of GAI in education. Based on these findings, items were selected to develop the initial research instrument, a questionnaire. This preliminary version was sent to two scholars familiar with survey data collection for content validity. Their feedback and suggestions informed revisions to the questionnaire. The revised version was then subjected to a two-round card-sorting exercise to ensure reliability and validity, following the guidelines proposed by Moore and Benbasat [36].

3.5. Card sorting and initial validation

A total of 33 questions were developed to represent seven (7) constructs (Q1–Q7), drawing on theoretical frameworks and prior research. Each item was designed to measure a specific construct, ensuring comprehensive representation. Four groups of participants, each consisting of 2 persons (for a total of eight raters), were invited to participate in the 1st round of the card sorting exercise after the instrument was revised based on experts' suggestions.

The participants were informed about the research objectives, and all constructs, along with operational definitions and items, were presented. Each group was asked to place all 33 items under each relevant construct. The groups independently sorted the cards into categories representing the seven constructs. The output of the two-stage card sorting exercises is presented in Table 2 and Table 3. The placement ratio or hit ratio was calculated using Cohen's Kappa's formula for inter-rater reliability. The overall hit ratio was calculated as:

$$\text{Hit Ratio} = \frac{\text{Number of Agreements}}{\text{Total number of Items}}$$

In the first round, there were 132 (i.e., $33 \times 4 = 132$ items) item placements, with 128 items correctly placed into their intended categories, achieving an overall hit ratio of 96.97%, indicating high agreement among participants. However, certain questions were identified as problematic. These questions were restructured based on qualitative feedback and statistical analysis to enhance clarity and relevance.

In the second round, after removing and refining problematic questions, the hit ratio improved to 100%, signifying complete agreement among the participants. This demonstrated the effectiveness of the iterative refinement process in achieving content validity and reliability.

3.6. Data collection methods and tools

The finalized questionnaire was developed using KoBoToolbox, a versatile platform for designing and deploying data collection tools. KoBoToolbox facilitated both online and offline data collection, ensuring inclusivity and accessibility for all participants.

Both open and closed-ended questions were included in the survey. The questionnaire was specifically designed for university teachers, the target respondents of the study, and a mixed-mode approach was

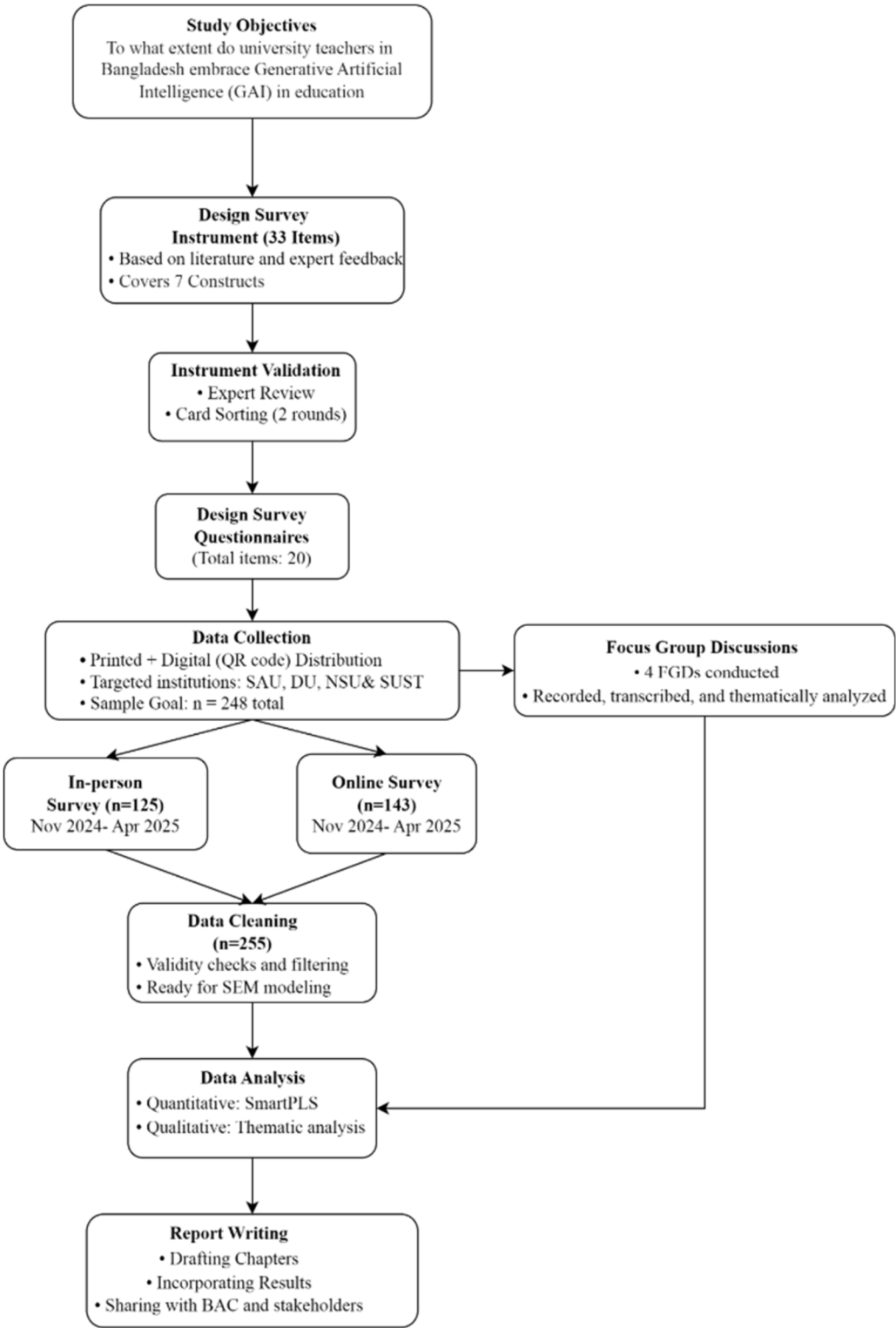


Fig. 4. Study workflow.

adopted to maximize participation. Printed hard copies were distributed in envelopes, which included a small token of appreciation—a pen and a notepad. The completed hard-copy questionnaires were manually collected and entered into the KoBoToolbox database by the researchers. This approach offered participants flexibility, enabling them to choose their preferred response method. Combining digital and traditional methods enhanced response rates and ensured convenience, developing inclusivity for respondents with varying levels of access to digital tools

[37].

For the qualitative component of the study, four Focus Group Discussions (FGDs) were conducted across four selected universities. Each group comprised six faculty members, chosen through stratified sampling to ensure gender diversity. The discussions were recorded with the participants' consent, and subsequently transcribed for thematic analysis.

Table 2

First card sorting round.

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	N/A	Total	TGT%
Q1	18	0	0	0	0	0	0	0	18	100
Q2	0	16	0	0	0	0	0	0	16	100
Q3	1	0	16	0	0	0	0	0	17	94.12
Q4	0	0	0	24	0	0	0	0	24	100
Q5	0	0	0	0	20	2	0	0	22	90.91
Q6	0	0	0	0	0	18	0	0	18	100
Q7	1	0	0	0	0	0	16	0	17	94.12
Total Item Placements: 132			Hits: 128			Hits Ratio: 96.97				

Bold indicates that items were placed correctly under each respective construct.

Table 3

Second card sorting round.

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	N/A	Total	TGT%
Q1	16	0	0	0	0	0	0	0	16	100
Q2	0	16	0	0	0	0	0	0	16	100
Q3	0	0	16	0	0	0	0	0	16	100
Q4	0	0	0	24	0	0	0	0	24	100
Q5	0	0	0	0	20	0	0	0	20	100
Q6	0	0	0	0	0	16	0	0	16	100
Q7	0	0	0	0	0	0	16	0	16	100
Total Item Placements: 124			Hits: 124			Hits Ratio: 100%				

Bold indicates that the items were placed correctly under each respective construct.

3.7. Data processing and analysis

3.7.1. Data cleaning

To omit errors, the raw data were reviewed properly. A careful scrutiny was made by the researcher when completing an interview for better facilitation of coding and tabulation of all data.

3.7.2. Categorization of data

In contrast to traditional methods that categorize respondents based on their answers, this study employed a distinctive approach. Scale variables were evaluated by respondents' ratings on a 5-point modified Likert scale for each item. Subsequently, each construct was categorized according to the frequency of responses from the respondents. For demographic variables (age, education, gender, etc.), respondents were categorized according to their characteristics.

3.8. Data analysis techniques

This study employed a mixed-method data analysis strategy, integrating both quantitative and qualitative techniques to explore the integration of GAI in higher education through the lens of CLT.

3.8.1. Quantitative data analysis

The PLS-SEM-based technique consists of two essential models, i.e., the measurement model for reliability and validity and the structural model. For the sake of the measurement model, four tests are conducted: internal consistency (composite reliability), convergent validity (average variance extracted), discriminant validity, and indicator reliability [38]. Internal consistency, represented by Cronbach's alpha, assumes equal outer loading of all indicators on the relative constructs, with an expected outer loading above 0.7 for each indicator. Additionally, internal consistency can be gauged by the composite reliability value (0.60–0.70) of a latent variable. Convergent validity determines if an indicator can converge or share a high portion of construct variation. The widely used measure for convergent validity, Average Variance Extracted (AVE), should surpass 0.50, indicating that the construct explains over half of the variance of its indicators.

Distinctiveness among constructs is assessed through discriminant validity, examining cross-loadings of indicators. Adequate discriminant

validity is confirmed if an indicator's outer loadings on its respective construct are higher than on other constructs. Conversely, for indicator reliability assessment, a bootstrapping method (5000 sub-samples, two-tailed, at 5% level of significance) is employed to eliminate insignificantly weighted indicators.

A significance level of 5% was set to evaluate the hypotheses. Support for a hypothesis was determined if the computed (β) value equaled or exceeded the significance level, indicating a significant contribution of independent variables to the dependent variable. Conversely, if the computed (β) value was below the significance level, the hypothesis was not supported, suggesting no significant contribution of the independent variables to the dependent variable.

3.8.2. Qualitative data analysis

To complement the quantitative findings, qualitative data were collected through Focus Group Discussions (FGDs) conducted at four universities. The FGDs aimed to capture participants' deeper perspectives on GAI use, including perceived benefits, concerns, and institutional readiness. In this regard, a thematic analysis approach was applied. First, all FGD responses were transcribed from the local language (Bangla) to English. Transcripts were read iteratively to identify emergent codes and subsequent themes using a platform named napkin. ai. Themes were cross-checked with quantitative findings to ensure consistency and enrich interpretation. This triangulation approach enabled a comprehensive understanding of the research problem, allowing the study to move beyond surface-level trends and uncover deeper contextual factors influencing the adoption of GAI in Bangladesh higher education.

4. Results

4.1. Demographic distribution

The gender distribution among respondents shows, nearly two-thirds of respondents were male (64%, $n = 162$), and just over one-third were female (36%, $n = 93$), reflecting national trends in higher education employment where male faculty dominate [39]. This disparity may influence access to AI training and participation, highlighting the need for gender-sensitive approaches to GAI integration [40,41]. Nearly a quarter of the faculty members (Male = 51, Female = 18) are classified as mid-career faculty, aged between 31 and 42. While early- to mid-career faculty (ages 19–42) represent over 58% of the sample, females are most concentrated in the early-career group.

This youthful composition of the faculty is encouraging, as younger educators are often more adaptable and likely to experiment with technologies such as Generative Artificial Intelligence (GAI) for content creation and learner engagement [42].

Regarding qualifications, over half of the respondents (59.61%) held postgraduate degrees (Male = 86, Female = 66), while approximately one-third (34.12%) had completed doctoral studies. Male faculty members outnumbered female faculty members in every qualification category, including among PhD holders (63 males compared to 24 females). Since faculty members with higher degrees typically lead curriculum development, this gender gap could lead to unequal involvement in the integration of GAI at the institutional level [41].

On the other hand, over one-third of the respondents (34.90%) came from science disciplines, followed closely by Commerce at 34.51% and Arts at 30.59%. While males were predominant across all disciplines, the gender gap was narrower in the Arts (Fig. 5). The integration of GAI is likely to vary across disciplines; Science and Commerce are expected to focus more on data-driven applications, while the Arts may benefit from generative tools in writing and analysis [28].

Among the respondents, Lecturers/Senior Lecturers represent the largest group within the academic roles, making up 46.70% (Male = 63, Female = 56) of the sample (Fig. 6). This is followed by Assistant Professors at 22.70%. Associate Professors account for 11.8%, while

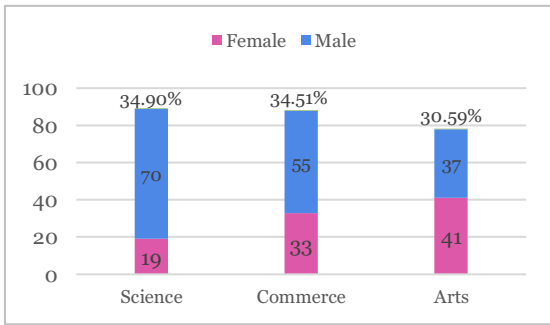


Fig. 5. Discipline-wise gender distribution.

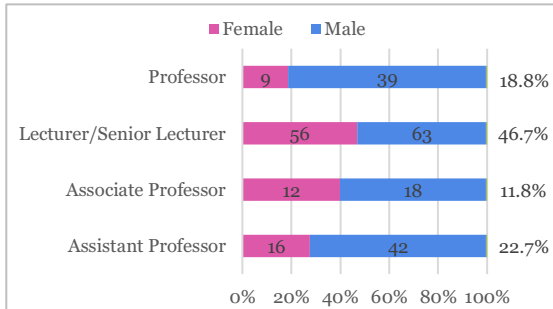


Fig. 6. Gender distribution based on academic role.

Professors make up only 5.88% of the sample. Male respondents are more prevalent at all academic ranks, particularly in senior positions. Since senior faculty play a significant role in shaping academic policy and making curricular decisions, these disparities may hamper equitable input in reforms related to GAI, unless inclusivity is deliberately prioritized [40].

Based on the length of service in higher education, one-third of faculty (37.25%) had <5 years of experience, and another 23.14% had served between 5 and 9 years (Fig. 7). This predominance of early-career educators aligns well with the demands of GAI integration, as this group tends to be digitally fluent and pedagogically flexible [5]. However, without structured institutional guidance, their interest in GAI may not translate into effective, ethical, and equitable classroom use [41].

Fig. 8 examines faculty engagement with GAI tools. A significant portion of respondents, 68.24%, reported active experimentation with GAI in their academic tasks for more than six months. Meanwhile, 18.04% of the faculty reported moderate use of GAI (between three to six months), and 3.53% have utilized GAI for a shorter period (less than three months). Notably, only 0.20% of faculty members have stopped

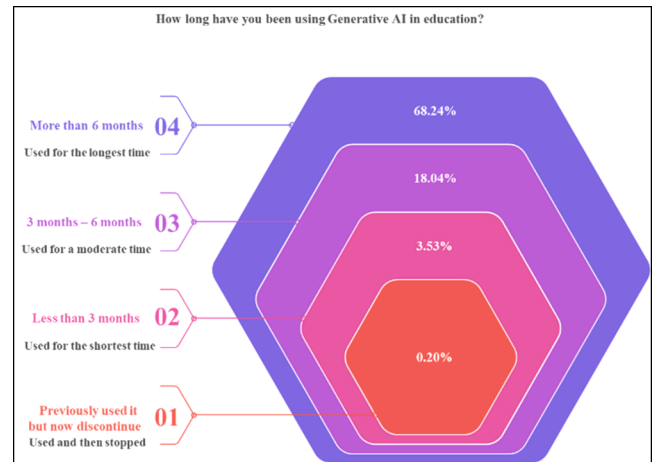


Fig. 8. Generative AI usage in education.

using GAI after having previously used it. Males reported slightly higher levels of usage, although the gender differences were less pronounced compared to other areas. Increasing exposure to tools like ChatGPT and Grammarly has started to shift perceptions of GAI from being seen as a

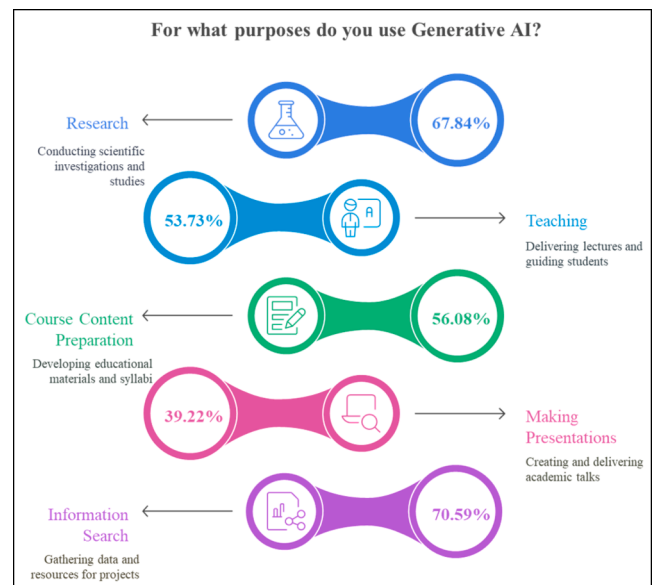


Fig. 9. Purpose of using Generative AI in education.

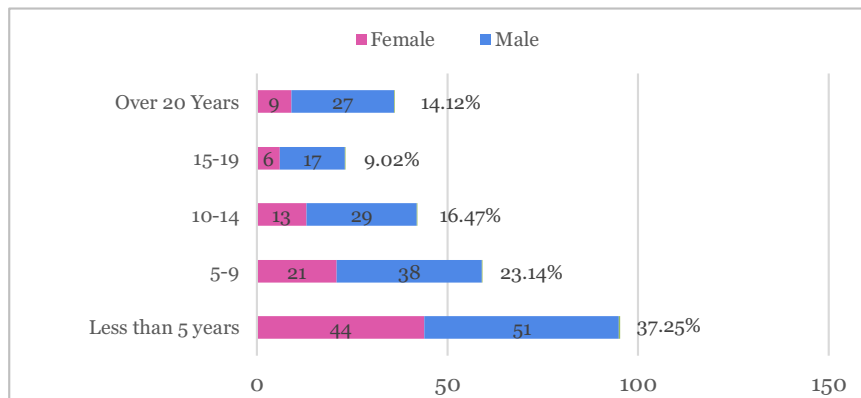


Fig. 7. Gender and length of service in higher education.

novelty to becoming a necessity in academic workflows [42].

Fig. 9 shows that faculties primarily use GAI for information searches (70.59%), followed by research activities, including scientific investigations and studies (67.84%). Teaching-related tasks, such as lecture preparation, account for 57.73%. Additionally, 56.08% of faculty use GAI for preparing course content, and 39.22% utilize it for creating presentations for academic talks. These suggest that faculty view GAI as a tool to enhance their work rather than as a replacement for traditional teaching methods. Faculty are using GAI to manage workloads, brainstorm teaching ideas, and personalize materials, practices that reflect a shift toward human-AI instructional models [40]. However, the lack of formal training may result in inconsistent practices, highlighting the need for capacity-building initiatives across departments [41].

4.2. Assessment of common method bias (CMB)

To ensure the reliability and validity of the collected data and reduce potential bias, several procedural and statistical methods were implemented. After completing the survey, Harman's one-factor test was conducted to detect common method bias (CMB). The analysis was performed using SPSS v.27 software. The result showed that the primary factor accounted for 28.30% of the variance, which is below the commonly accepted threshold of 40% ([43], p.2534). In addition, the variance inflation factor (VIF) values for all measurement items were <3, except for one item, which had a VIF slightly over 3 (Table 4), suggesting the absence of multicollinearity and potential method bias. Therefore, these findings suggest this study does not suffer from serious effects of common method bias [44].

Table 4
Validation of the measurement model.

Construct	Items	Measurement Items	Outer Loading	VIF	AVE	CR	Cronbach's α	rho_a
Attitude towards GAIs (ATT)	ATT_Q1	I believe using GAI is beneficial in higher education.	0.852	2.101	0.686	0.847	0.847	0.850
	ATT_Q2	I am open to incorporating new technological tools, like GAIs, in education.	0.809	1.801				
	ATT_Q3	I feel that GAIs can improve the quality of education.	0.860	2.301				
	ATT_Q4	I believe that GAIs are transforming higher education in positive ways.	0.789	1.835				
Competency (Comp)	Comp_Q1	My experience with the functions and features of GAI is necessary for my job	0.844	2.199	0.739	0.882	0.882	0.887
	Comp_Q2	I possess the necessary skills to use GAI tools proficiently in my work	0.905	3.044				
	Comp_Q3	I am capable of overcoming any challenges I might face while using GAI in my work	0.846	2.388				
	Comp_Q4	I feel competent using GAI tools to improve the quality of my work output	0.840	2.109				
Extent of Use of Technology (USE)	USE_Q1	I use GAIs for teaching, research, and administration purposes	0.886	1.652	0.649	0.733	0.733	0.794
	USE_Q2	I use GAIs to search for information both for academic and non-academic reasons	0.842	1.610				
	USE_Q3	I use GAIs for language editing services	0.673	1.286				
	USE_Q4*	I use GAI tools for in-depth reading of books, journals, and articles	-	-				
	USE_Q5*	I use GAIs to find solutions for coding, computation, or related problems	-	-				
Technology Use Provision for Students (TUPS)	TUPS_Q1	I believe students should use technology like GAIs at any stage of their learning	0.845	1.763	0.678	0.763	0.763	0.792
	TUPS_Q2	I encourage my students to use GAIs for class preparation	0.884	1.446				
	TUPS_Q3	I allow my students to use GAIs ethically for writing essays, reports, or theses	0.735	1.469				
	TUPS_Q4*	I believe students can use GAI under certain provisions	-	-				
Domain-Specific Technology Relevance (DSTR)	DSTR_Q1	GAIs have potential applications in my academic subject domain	0.818	2.080	0.745	0.886	0.886	0.900
	DSTR_Q2	GAI tools are well-suited for enhancing teaching and learning in my subject domain	0.899	2.887				
	DSTR_Q3	My subject domain may benefit from the use of advanced technologies like GAIs	0.896	2.593				
	DSTR_Q4	I believe that GAIs can address the unique challenges of my subject domain	0.836	2.179				
Subjective Norms (Peer Influence) (SN)	SN_Q1	My colleagues encourage me to use GAIs in my work.	0.802	1.866	0.601	0.834	0.834	0.838
	SN_Q2	I see many of my peers adopting GAIs in their teaching.	0.749	1.583				
	SN_Q3	There is pressure within my academic community to embrace GAI technology.	0.764	1.654				
	SN_Q4	Faculty discussions often involve how GAI can improve education.	0.738	1.643				
Technology Use Provisions (ITUP)	SN_Q5	Peer support influences my decision to use GAI.	0.819	2.051	0.645	0.748	0.748	0.940
	ITUP_Q1*	My university has clear guidelines for the use of GAI in teaching.	-	-				
	ITUP_Q2	There are established policies regarding the ethical use of GAIs	0.798	1.763				
	ITUP_Q3	I am aware of the rules and restrictions governing the use of GAIs at my institution	0.695	1.446				
	ITUP_Q4	The university provides resources and support for integrating GAIs into my work.	0.903	1.469				

Note:.

* Factor loadings below 0.65 were removed from the analysis.

4.3. Reliability and validity of the measurement model

The Structural Equation Modeling (SEM) analysis was conducted using SmartPLS to examine the proposed relationships in the conceptual framework regarding the GAI in higher education in Bangladesh. The model demonstrated strong reliability and validity. All constructs met the thresholds for internal consistency reliability, with composite reliability (CR) values ranging from 0.733 to 0.886. Additionally, the average variance extracted (AVE) values for all constructs exceeded the recommended minimum of 0.50, confirming convergent validity. The values of Cronbach's alpha (α), and rho_a were all greater than 0.7, indicating adequate internal reliability of the measurement model. The indicator loadings were above 0.70, and factor loadings below 0.65 were removed from the analysis to improve the measurement quality. The outer loadings of two indicators, USE_Q3 and ITUP_Q3, fall slightly below the threshold (≥ 0.7), yet they are retained in the model, as removing or retaining them does not change the relationships among variables ([44], p. 142, Exhibit 4.5).

On the other hand, discriminant validity was also established through the Fornell–Larcker criterion [45], as the square root of each construct's AVE was greater than its correlations with other constructs. The cross-loading analysis showed that the factor loadings for each construct were higher than those for other constructs (Table 5).

The Heterotrait–Monotrait Ratio (HTMT) values were below the recommended threshold of 0.90 (Table 6), further confirming discriminant validity. Overall, these results demonstrate that the measurement model exhibits strong reliability and satisfactory convergent and discriminant validity.

4.4. Results of the structural model

The theoretical model and hypothesized relationships were analyzed using SmartPLS. The model's explanatory power was evaluated through the R^2 value of the dependent variable. Hypothesis testing involved calculating the t-statistics for the standardized path coefficients at a 5% significance level.

As shown in Fig. 10, the structural model explained 47.9% of the variance in attitude towards GAI use and 30.9% in the extent of use. The path from attitude to extent of use of GAI was both positive and significant ($\beta = 0.556$, $t = 10.439$, $p < 0.001$), indicating that a more favorable attitude toward GAI strongly predicts higher GAI usage in academic contexts. Among the predictors of attitude toward GAI use, domain-specific technology relevance exhibited the strongest effect ($\beta = 0.413$, $t = 6.561$, $p < 0.001$), followed by competency ($\beta = 0.261$, $t = 4.217$, $p < 0.001$), and technology use provision for students ($\beta = 0.168$, $t = 3.020$, $p = 0.003$). These findings highlight the critical roles of subject relevance, user competence, and belief in student benefits in shaping positive attitudes toward GAI.

In contrast, subjective norm and technology use provision by institutions did not have significant effects on attitude, with path coefficients of $\beta = 0.092$ ($p = 0.102$) and $\beta = 0.030$ ($p = 0.576$), respectively Table 7. These nonsignificant paths suggest that social influence and institutional support alone may not be sufficient to develop

Table 5
Validation of the measurement model and bivariate correlations.

	ATT	Comp	USE	TUPS	DSTR	SN	ITUP
ATT	0.828						
Comp	0.490	0.860					
USE	0.564	0.408	0.891				
TUPS	0.403	0.267	0.313	0.823			
DSTR	0.601	0.378	0.441	0.342	0.863		
SN	0.337	0.297	0.222	0.215	0.303	0.775	
ITUP	0.132	0.002	0.035	0.148	0.109	0.193	0.870

Note: Diagonal elements are the square root of AVE, and off-diagonal elements are correlations.

Table 6

Assessment of discriminant validity using HTMT.

	ATT	Comp	USE	TUPS	DSTR	SN	ITUP
ATT							
Comp	0.564						
USE	0.676	0.526					
TUPS	0.493	0.316	0.421				
DSTR	0.687	0.429	0.542	0.419			
SN	0.398	0.345	0.310	0.283	0.350		
ITUP	0.147	0.101	0.057	0.153	0.143	0.257	

positive attitudes toward GAI integration without individual competency and perceived relevance.

Overall, the findings support the hypothesis that individual and contextual factors influence attitudes, which in turn significantly drive the extent of GAI use in higher education settings (Table 8), which also reports the effect size (f^2) and variance inflation factor (VIF) values. The findings confirm that H1, H2, H5, and H6 are supported, as their corresponding relationships are statistically significant. In contrast, H3 and H4 are not supported, since subjective norm and technology use provision do not significantly influence attitude toward GAI. The effect size results indicate that domain-specific technology relevance ($f^2 = 0.251$) and attitude toward GAI ($f^2 = 0.447$) have relatively strong effects within the model, while competency and student-focused provision demonstrate moderate effects. Furthermore, all VIF values are below the threshold of 5, indicating that multicollinearity is not a concern in the structural model.

4.5. Mediation analysis

The mediating role of attitude was examined using the bootstrapping procedure, and the results are summarized in Table 9. The findings reveal that attitude significantly mediates the relationships between Competency (Comp) and Extent of Use of Technology (USE) ($\beta = 0.145$, $t = 3.683$, $p < 0.001$), Technology Use Provision for Students (TUPS) and Use of Technology (USE) ($\beta = 0.094$, $t = 2.976$, $p = 0.003$), and domain-specific technology relevance and extent of use ($\beta = 0.230$, $t = 5.193$, $p < 0.001$). These results indicate that these factors influence the extent of GAI use indirectly through shaping users' attitudes toward the technology. However, the mediating effects of attitude between subjective norm and Extent of Use of Technology ($\beta = 0.051$, $p = 0.109$) and between technology use provision and Extent of Use of Technology ($\beta = 0.017$, $p = 0.577$) are not statistically significant. Therefore, the mediation hypotheses associated with these relationships are not supported.

Overall, the results suggest that individual competencies and contextual technological relevance play an important role in shaping attitudes toward generative AI, which subsequently drive its extent of use in higher education settings.

A post-hoc analysis Fig. 11 was also run to see the effect of control variables on the theoretical model of this study. Out of the five control variables, no variable showed a significant contribution to the extent of GAI use.

Age ($\beta = -0.028$), gender ($\beta = 0.064$), education ($\beta = -0.015$), and academic role ($\beta = -0.005$) did not show a significant contribution to the extent of GAI use. These results indicate that demographic factors such as age or education are less predictive of GAI utilization compared to one's academic position. This highlights the potential impact of institutional roles and responsibilities on the adoption of emerging technologies in higher education contexts.

4.6. Strategies for GAI use in education

The other main objective was to identify how GAI could be used in supporting a collaborative, inquiry-based, student-centered learning environment. This objective is satisfied using open-ended responses from the survey and four FGDs conducted at different universities across

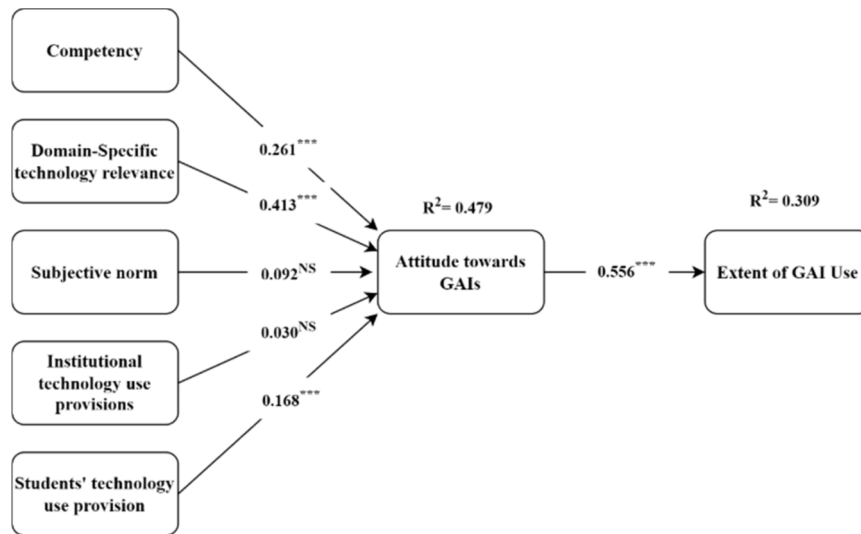


Fig. 10. Results of the study model showing the coefficient and variance.

Table 7

Results of the structural model of path coefficients.

Relationship	Path Coefficients	t values	Sig. values	p values
ATT → USE	0.556	10.439	***	0.000
Comp → ATT	0.261	4.217	***	0.000
TUPS → ATT	0.168	3.020	**	0.003
DSTR → ATT	0.413	6.561	***	0.000
SN → ATT	0.092	1.635	NS	0.102
ITUP → ATT	0.030	0.559	NS	0.576

NS=Not significant; *p < 0.05; **p < 0.01; ***p < 0.001.

Bangladesh.

In this section, we develop a thematic map Fig. 12 from responses to open-ended survey questions. First, all raw responses to open-ended survey questions were extracted using NotebookLM, a Google-supported platform for text analysis, to generate initial codes. These codes were carefully read for overlapping themes and concepts. After initial cleaning and sensitizing, those codes were uploaded to the Napkin.ai platform to develop a thematic map, which generated ten (10) overarching themes for GAI use areas in education.

Key themes identified include the importance of Monitoring and Evaluation, which was frequently highlighted as a concern. Respondents emphasized the need for institutions to use AI-detection tools such as Turnitin to identify potential misuse of Generative AI (GAI) in student submissions. Evaluating the originality and authenticity of student work emerged as a priority. One respondent stressed that “copy-pasting from ChatGPT is not allowed at all,” and recommended that “AI-generated plagiarism should be prevented,” advocating for limits on AI-generated content, suggesting a maximum of 25% usage in any academic submission.

Curriculum Development was identified as essential for long-term

integration of GAI. It was suggested that GAI-related content be incorporated into the existing curriculum, ensuring that all students, regardless of their backgrounds, have equal access to these tools. A significant focus was placed on designing course materials that “encourage, motivate, or require students to learn the core concepts of a subject, whether or not they use GAI.”

Collaborative and Interactive Learning also emerged as a key theme. Survey participants proposed using GAI to facilitate team projects and problem-solving exercises that encourage peer learning. Several emphasized the need for “teaching-learning approaches to be more interactive and analytical,” suggesting that teamwork and applied tasks help reduce overreliance on AI tools.

The theme of Ethical and Responsible Use featured prominently. Many responses stressed the importance of setting clear ethical guidelines around AI use, encouraging student disclosure, and cultivating moral accountability. As one quote highlighted, “effective guidelines

Table 9

Results of mediating effects.

Relationship	Path Coefficients	t values	p values	Sig. values	Results
Comp → ATT → USE	0.145	3.683	0.000	***	Supported
TUPS → ATT → USE	0.094	2.976	0.003	**	Supported
DSTR → ATT → USE	0.230	5.193	0.000	***	Supported
SN → ATT → USE	0.051	1.603	0.109	NS	Not Supported
ITUP → ATT → USE	0.017	0.557	0.577	NS	Not Supported

Note: NS=Not significant; *p < 0.05; **p < 0.01; ***p < 0.001.

Table 8

Results of direct relations with the proposed hypotheses.

Hypothesis	Relationship	β values	t values	p values	f²	VIF	Sig. values
H1 Competency positively influences Attitude toward the use of GAI	Comp → ATT	0.261	4.217	0.000	0.105	1.247	***
H2 Domain-Specific Technology Relevance positively influences Attitude toward the use of GAI	DSTR → ATT	0.413	6.561	0.000	0.251	1.306	***
H3 Subjective Norm positively influences Attitude toward the use of GAI	SN → ATT	0.092	1.635	0.102	0.014	1.191	NS
H4 Technology Use Provision positively influences Attitude toward the use of GAI	ITUP → ATT	0.030	0.559	0.576	0.002	1.306	NS
H5 Student-Focused Provision positively influences Attitude toward the use of GAI	TUPS → ATT	0.168	3.020	0.003	0.046	1.053	**
H6 Attitude positively influences the Extent of Use of GAI	ATT → USE	0.556	10.439	0.000	0.447	1.000	***

Note: NS=Not significant; *p < 0.05; **p < 0.01; ***p < 0.001.

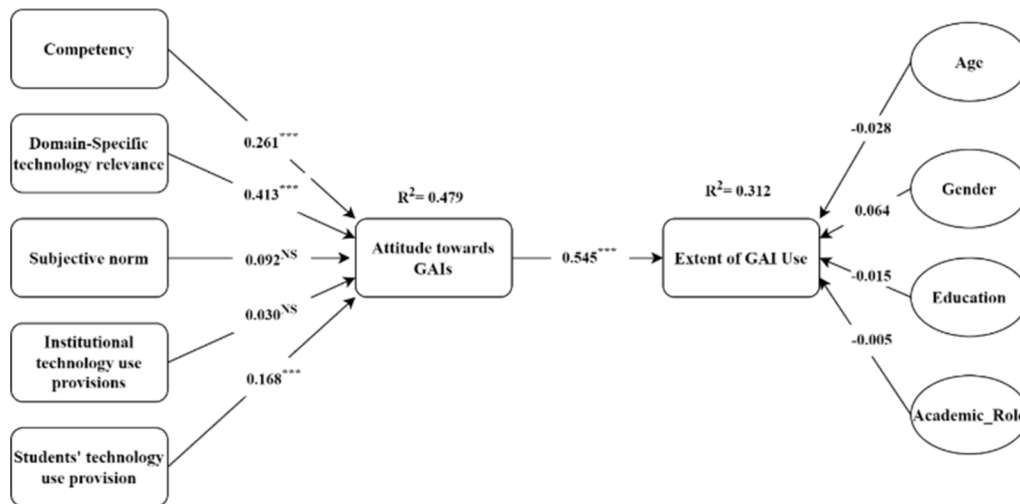


Fig. 11. Results of the study with the control variable.

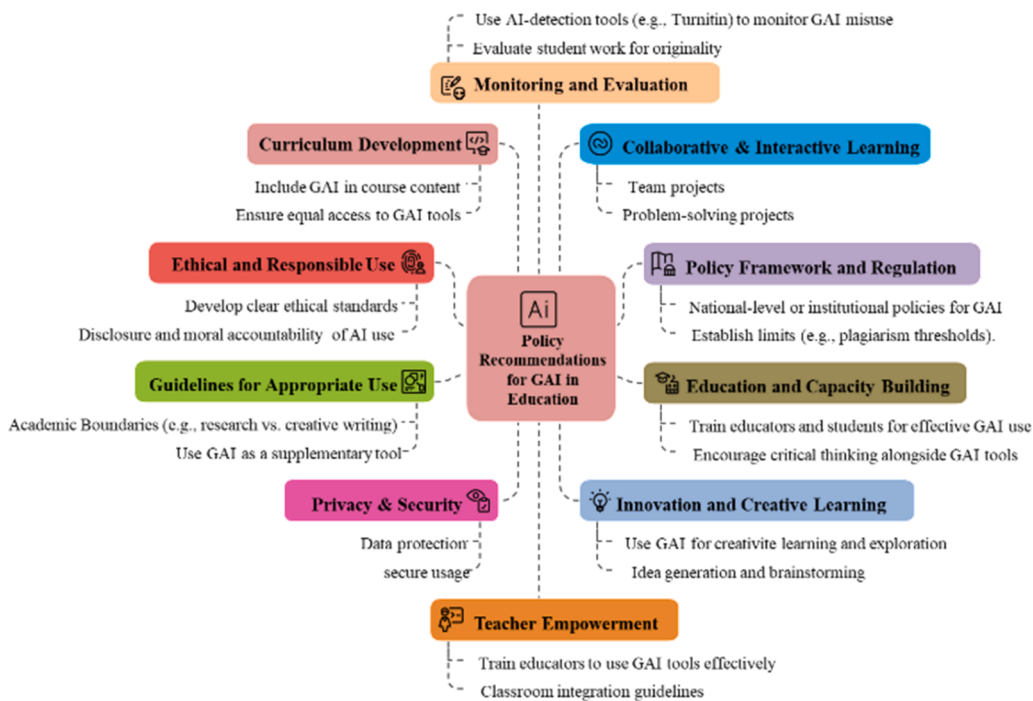


Fig. 12. The thematic outcomes were derived from open-ended survey questions.

should be developed for safe and proper utilization of GAI in higher education in Bangladesh.” GAI should be seen as a “supportive tool, not a replacement,” with ethical usage boundaries and clear expectations for students and educators alike.

Policy Framework and Regulation was suggested to address institutional ambiguity. Respondents advocated for university-level and national policies that define appropriate boundaries for GAI use, including “acceptable percentage and extent for using GAI,” especially in assessment. There was strong support for “setting ethical policies regarding AI use at institutional levels.”

Guidelines for Appropriate Use reflected a desire to distinguish between contexts where GAI adds value and where it may undermine learning. Tools like Grammarly or ChatGPT can support learning, particularly in ideation and proofreading, but should not be used to replace student thinking. Respondents noted that “AI should be used as a tool to learn rather than replacing human experience and knowledge.”

Education and Capacity Building emerged as a widely supported theme. Participants expressed a strong need for structured training programs for both teachers and students. “Training on GAI and education should be incorporated for both the students and faculty members across all departments,” said one respondent. This would promote “digital literacy, critical thinking, and responsible integration of AI tools within curriculum design.”

Concerns regarding privacy and security were raised by several respondents. They emphasized the importance of data protection and the need for secure platforms when using AI tools. Additionally, the absence of institutional oversight was identified as a potential risk that could compromise user safety and academic integrity.

On a more positive note, the potential for innovation and creative learning emerged as a significant theme. GAI was recognized as a valuable resource for “idea generation and brainstorming”, particularly beneficial for students seeking conceptual support. However, some

respondents expressed concerns about the overuse of GAI, suggesting that “extensive reliance on GAI could hamper students’ creativity—they need to think critically and establish special policies to use these tools responsibly.”

Finally, Teacher Empowerment was cited as essential for successful classroom integration. Respondents called for professional development opportunities and clear usage frameworks that enable teachers to use GAI meaningfully in instruction. There were calls for “classroom integration guidelines” that allow educators to align AI use with broader learning goals.

Overall, the ten themes derived from survey respondents highlight a balanced perspective on GAI—one that combines caution with creativity and regulation with innovation. The insights highlight the importance of proactive policies, ethical guidance, and human-centered pedagogy in shaping the future of higher education in the age of artificial intelligence.

4.7. Findings from the FGDs on GAI integration in higher education

The findings from the four FGDs conducted across North South University (NSU), Sher-e-Bangla Agricultural University (SAU), Shahjalal University of Science and Technology (SUST), and Dhaka University (DU) between December 2024 and April 2025 highlight the increasing prevalence of Generative Artificial Intelligence (GAI) in academic environments, as well as the significant implications it has for pedagogy, assessment, and institutional policy in Bangladesh’s higher education sector.

Faculty members across all institutions agreed that the use of GAI tools, especially ChatGPT and Grammarly, has become widespread among students. The discussions revealed a shared concern that overdependence on these tools is gradually diminishing students’ fundamental learning abilities. One DU respondent noted that students “copy and paste the question into ChatGPT but don’t even understand the answer,” underscoring both linguistic and cognitive barriers. Teachers pointed out that students’ attention spans are shrinking, and their ability to write independently is diminishing. “Confidence in freehand writing is declining,” observed one faculty member from SAU, a sentiment that echoed across institutions.

The most immediate challenge reported was the decline in critical thinking, creativity, and academic originality. Respondents cited cases of students submitting assignments generated entirely through AI tools without attempting to understand the material. An NSU faculty member reported, “they (students) rely on these tools instead of engaging their minds. It creates a kind of handicap.” Another faculty member from SAU noted that “while conducting class, I observed that students preferred asking ChatGPT about topics they didn’t understand instead of approaching me directly, which shifted their attention and hindered their understanding of core concepts.” However, several educators also acknowledged the positive dimension of GAI, particularly in empowering less confident or previously underperforming students. GAI tools, when used appropriately, have enabled students to write better applications, conduct initial research, and prepare visually compelling presentations.

In terms of assessment, there is a visible gap between existing evaluation criteria and the realities of AI-assisted learning. University teachers repeatedly emphasized the inadequacy of current assessment systems, which are heavily summative in nature and rely on long-standing practices of written submissions. As one DU participant explained, “ninety percent of marks go to exams, so students don’t think critically; they just memorize.” Several teachers at NSU and DU no longer collect written reports due to their susceptibility to AI generation. Instead, they now prefer oral presentations and reflective discussions, where students must defend their understanding face-to-face. “Even if they make a beautiful slide with AI, I can assess their comprehension by talking to them,” said an NSU teacher.

Concerns over the lack of institutional support were repeatedly

highlighted. Faculty members expressed the need for structured training on AI usage for both teachers and students. One SUST respondent stated, “there is no comprehensive training. Everything is self-initiated.” Teachers also reported significant disparities in digital literacy among their peers. Younger faculty were often more digitally while many senior teachers had only a superficial understanding of generative AI tools. The absence of policy-level intervention has further widened this gap. Faculty members stressed that they are left to develop personal strategies in the absence of standardized institutional guidelines. “We don’t have a policy to block AI use. We just rely on our own methods,” said a SAU participant.

Assessment integrity emerged as a major theme. Most faculty have started using plagiarism detection software, but few tools are capable of detecting AI-generated content. Respondents called for the development of AI-specific detection frameworks and suggested that universities adopt content threshold models, similar to plagiarism policies, where a certain percentage of AI-generated input (e.g., 30%) might be deemed acceptable. “There should be a ceiling for AI usage just like plagiarism,” suggested one SAU respondent.

Another salient issue was the infrastructural and technological divide among institutions. Some teachers mentioned using free versions of GAI tools, which often produced superficial or incorrect results. Faculty noted that if universities could provide paid premium software, both accuracy and ethical usage would likely improve. Several respondents emphasized the need for a university’s central digital repository and Learning Management System (LMS) integration for monitoring student work.

Teachers across institutions also highlighted the increased risk of inequality in digital access, particularly for students from rural areas and female students, who may not have the same exposure to new technologies. “Women are often left behind in tech adaptation,” noted a SAU faculty member. Consequently, the inclusion of GAI in higher education must consider both technological access and digital literacy to avoid reinforcing educational disparities.

The FGDs also shed light on future directions for policy. Almost unanimously, respondents agreed that GAI is not a temporary trend but a transformative force that must be embraced thoughtfully. The emphasis was on constructive adoption—integrating GAI as a complement to learning, not a replacement for it. Faculty from NSU recommended a phased model: first, train teachers; second, empower students; and third, align curriculum and evaluation with GAI realities. Echoing this sentiment, a DU speaker said, “We need to revise the curriculum, not resist the technology.”

In conclusion, the FGDs provided robust evidence that while GAI presents clear risks to academic integrity, it also offers significant opportunities for enhancing creativity, inclusivity, and personalized learning. The key lies in proactive, institution-wide policies that include capacity building, ethical education, technological investment, and curricular reform. Without these, higher education in Bangladesh risks falling behind in adapting to one of the most transformative educational technologies of the 21st century.

5. Discussion

One of the most notable demographic features of this study was the predominance of early- and mid-career faculty members. Nearly 60% of the respondents were between the 19–42 age group, indicating a youthful and potentially digitally literate academic workforce. These results align well with global trends where younger faculty exhibit higher openness towards technology-assisted learning environments and are more likely to integrate advanced tools like GAI into their teaching-learning practices [5]. Like the other trend, young professors are often found to be the key adopters and influencers of technology use in education [46].

Gender has shown significant disparities. Male faculty dominated all categories across age, academic qualifications, institutional affiliations,

and academic disciplines. While this mirrors national patterns in academic staffing, it also raises concerns regarding equitable access to GAI training, leadership roles, and pedagogical influence. Without targeted support, female faculty may be underrepresented in GAI-related curriculum reforms and professional development initiatives [47]. This reinforces the need for gender-sensitive strategies in faculty training and institutional planning to ensure that GAI integration does not inadvertently perpetuate existing inequalities in higher education [40].

Educational qualifications among respondents were strong, with nearly 60% holding postgraduate degrees and over one-third possessing doctoral degrees. Such academic grounding is promising for GAI integration, as faculty with higher qualifications often have greater autonomy in curriculum development and assessment design [28]. However, male faculty held higher numbers across all qualification levels, including PhDs. To fully harness the potential of GAI in education, institutional policies must also focus on empowering all qualified faculty, regardless of gender, to engage with and lead technological innovation in pedagogy.

Institutionally, faculty were drawn from a wide range of public and private universities, though notable disparities in gender representation and GAI engagement were found across institutions. Universities like NSU demonstrated relatively balanced gender representation, whereas others like SAU and SUST were male-dominated. These variations may reflect differing institutional cultures, access to technological infrastructure, or administrative support for digital teaching tools. It is therefore imperative that GAI implementation strategies be tailored not only to individuals but also to institutional contexts [48].

The disciplinary spread, primarily in Science and Commerce, with fewer from the Arts, suggests diverse potential applications for GAI. In Science, faculty may use GAI for data modeling, simulation, or coding support, while in the Arts and Commerce, generative tools can assist with writing, synthesis, and instructional content development [28]. Faculty across all disciplines indicated use of GAI for content creation, assessment generation, and administrative tasks, reinforcing GAI's role as an augmentative tool rather than a replacement for human educators [46]. This is consistent with global findings that GAI is most effective when used to enhance instructional design and reduce administrative burden, rather than to automate teaching itself [41].

While overall engagement with GAI tools was encouraging, the findings also suggest a need for structured institutional guidance and formal training. Without clear pedagogical frameworks and ethical guidelines, this ad hoc usage may lead to inconsistent teaching practices and possible academic integrity concerns [47]. To move beyond experimentation, higher education institutions must invest in faculty development programs that focus on ethical, inclusive, and pedagogically grounded uses of GAI.

The findings of this study provide strong empirical support for the theory, particularly regarding how individual attitudes and contextual elements interact to drive technology adoption in educational settings. A key finding is the significant positive influence of attitude towards GAI on the extent of GAI use ($\beta = 0.556, p < 0.001$). This result reinforces the constructivist view that learners (and educators) are more likely to integrate new tools when they perceive them as meaningful and relevant to their personal and professional contexts. Positive attitudes may reflect the recognition of GAI's potential to enhance teaching strategies, personalize learning, and support constructivist practices such as exploration, creativity, and critical thinking.

Among the antecedents of attitude toward GAI use, domain-specific technology relevance emerged as the most powerful predictor ($\beta = 0.413, p < 0.001$), suggesting that the perceived alignment of GAI with subject-specific tasks and goals significantly shapes users' disposition toward its use. This aligns with prior research that emphasizes the importance of domain-specific technology integration for deep, contextual learning [30]. Educators are more likely to adopt GAI tools when they perceive them as beneficial for the particular cognitive tasks and content areas they teach.

Competency also showed a strong and significant influence on attitude ($\beta = 0.261, p < 0.001$), confirming that the knowledge and skills gained through professional or academic experiences enhance users' confidence and openness toward new technologies. From a constructivist standpoint, this highlights the role of prior knowledge and experiential learning in shaping behavior. As users become more competent in digital environments, they develop more positive attitudes, which in turn facilitate meaningful use.

Interestingly, technology use provisions for students, or the belief that students should use GAI for academic growth, also positively influenced attitude ($\beta = 0.168, p = 0.003$). This reflects an awareness of learners' evolving needs and resonates with the constructivist emphasis on learner-centered approaches. Educators who value GAI's potential to empower student inquiry and autonomy are more likely to support its adoption.

However, subjective norm and institutional technology use provisions were not significant predictors of attitude. While social norms often influence behavior in educational settings, their weak effect in this study suggests that peer or institutional pressure alone does not suffice to cultivate positive attitudes toward GAI. Similarly, the lack of significance for institutional technology use provisions (institutional guidelines and support) indicates that policy and infrastructure must be paired with training and pedagogical relevance to make a meaningful impact. While we do not discount the importance of institutional support for technology acceptance as such reported by Wang et al. [49], the corresponding path ITUP→ATT was found to be insignificant. In fact, our study finds that current use of GAI is largely informal and driven by individual initiative rather than coordinated policy. Although university faculties have access to GAIs, the extent of their use is inconsistent. While all sampled universities provided access to platforms such as Turnitin, none offered premium accounts for tools like ChatGPT, and only one granted access to Bard. Moreover, no institution had established formal guidelines for using these platforms. This likely explains why institutional provisions for technology use were found to be insignificant in this study.

On the other hand, the post hoc analysis revealed that among the control variables, including age, gender, education, and academic role, there was no meaningful predictive power. This indicates that while demographic characteristics may inform attitudes, they do not strongly determine actual usage behavior. The findings highlight the importance of role-based engagement strategies in promoting effective GAI integration.

Overall, the study emphasizes the importance of academic domains in shaping educators' attitudes and behaviors toward emerging technologies like GAI. The relatively young and academically qualified faculty base, with rising experimentation with GAI tools, presents a favorable landscape for innovation. Institutions must promote inclusive training, invest in digital infrastructure, and implement supportive policies that empower all faculty to use GAI responsibly and effectively in teaching and learning.

6. Conclusion

Using the lens of Constructivist Learning Theory (CLT), this study offers ways of integrating GAI in higher education settings. The objectives were to explore how faculty members' perceptions, individual competencies, domain-specific technology relevance, and institutional support influenced their use of GAIs in the teaching-learning process.

The study confirms that GAI usage is highly linked with users' psychological and need-based factors, like domain-specific technology relevance and competency, rather than external pressures or institutional facilities. However, we did not discount the need to develop institutional capacities to promote technology use in education.

Since a favorable attitude is a prerequisite for actual technology adoption, faculty members' positive disposition in favor of GAI use for their teaching-learning process was the central construct. The study

reported that such positive disposition was significantly influenced by an individual's perceived competency, the relevance of GAI within their academic discipline, which in turn leads to actual GAI use.

As opposed to the initial hypotheses, subject norms and institutional provision of technology use were not found to be significantly affect attitude towards GAI and the extent of use. This suggests that while external factors like peer influence and organizational support mechanisms are important, they may not be as influential as individual beliefs and professional relevance in favor of GAI use.

Furthermore, this understanding is aligned with the constructivist principles that highlight the importance of learners' autonomy, self-paced learning, and technology exploration in educational settings. Despite teachers raised concerns regarding students' use of GAI, viewing it as a threat to the development of their critical thinking ability and a challenge to fair assessment practices, they broadly spoke for developing a formal institutional framework to guide the ethical use of technology in education. Overall, this research captures a contextualized understanding of GAI use in higher education institutions and offers multifaceted insights for fostering student-centric learning environments in the age of GAI.

This research is not beyond limitations. The first limitation was that we did not include a student sample in this research, so future studies could examine both faculty and student samples for a comprehensive understanding of GAI adoption and learning outcomes. Second, respondents participated in the study mostly voluntarily, not chosen through random sampling. Subsequently, there is a possibility that respondents with prior exposure to and interest in technology are over-represented in the sample of the study. Third, the cross-sectional survey design captured only a snapshot in time and therefore cannot account for changes in faculty attitudes or GAI usage behaviors over time, nor how CLT principles may gradually foster learner autonomy. Instead, the study examined antecedents grounded in CLT principles as well as related factors shaping GAI use. Therefore, a longitudinal study is recommended to explore these dynamics. Fourth, an uneven representation of male and female faculty participants could lead to biased interpretations regarding perceptions and behaviors related to GAI integration. A more balanced demographic distribution would have allowed for deeper comparative analysis and more inclusive conclusions. Fifth, the research was conducted and validated in Bangladesh, though it has the potential for replication in other developing countries.

Despite such limitations, focusing on faculty members, the study

provides insights from those who are directly involved in curriculum design, pedagogical decisions, and assessment practices, which remain comparatively underexplored. Second, the study contributes methodologically by rigorous development and validation of measurement scales for key variables, enabling a more systematic and reliable assessment. Third, guided by a constructivist lens, the study moves beyond perception to examine the extent to which teachers consider GAI as a tool that supports learner autonomy, transforms knowledge acquisition processes, and influences the evolving nature of pedagogy. Finally, the mixed-method design, combining SmartPLS-SEM with thematic analysis, offers both empirical robustness and contextual depth, particularly in understanding emerging changes in assessment rubrics, teaching strategies, ethical concerns, and institutional policy readiness. Taken together, these contributions offer meaningful theoretical, methodological, and practical implications for educators and policymakers seeking to more effectively integrate GAI in higher education.

7. Recommendations

Despite the several limitations, the following policies and practical recommendations Fig. 13 are proposed to support the effective and ethical integration of GAI in higher education:

Professional development training should be a continuous part of higher education institutions. Faculty members should be informed and updated through tailored GAI training for their professional needs. Since technology-induced changes are inevitable, universities should integrate GAI into both curriculum design and pedagogy. This may foster an interactive and autonomous learning environment that aligns with constructivist principles, emphasizing students' active engagement and agency.

While we did not dismiss the risks or potential overuse of technologies like Generative AI in education, most teacher-respondents strongly echoed the need for clear institutional guidelines to support its responsible use, particularly concerning data privacy and academic integrity. Instead of limiting access to GAI tools, they emphasized the importance of building technical infrastructure and establishing support centers to promote effective adoption. One promising strategy is the creation of communities of practice through inter-university collaboration. At a broader level, a comprehensive national policy framework addressing issues such as intellectual property rights and academic integrity in the context of GAI is urgently needed. In this regard, fostering partnerships



Fig. 13. Schematic presentation of the policy recommendations of this study.

with international organizations such as UNESCO and other education-focused agencies is seen as essential for promoting best practices. Finally, scholars and policymakers are encouraged to invest sustained effort and resources in ongoing research and monitoring to better understand the impact of GAI on education and to refine strategies as the technology continues to evolve.

CRedit authorship contribution statement

Md Mahbubul Alam: Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Sakib Farhaz:** Writing – original draft, Visualization, Formal analysis, Data curation. **Shah Md Atiqul Haq:** Writing – review & editing, Methodology, Investigation. **Minhaj Ferdous:** Writing – review & editing, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

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