

Integrating generative AI in higher education for lifelong learning

Mozaffar Alam Chowdhury^{1,2}, Toong Hai Sam², Md. Sohel Rana¹, Khan Sarfaraz Ali²,
Whee Yen Wong³, Hasanuzzaman Tushar¹

¹IUBAT Business School, International University of Business Agriculture and Technology, Dhaka, Bangladesh

²Business and Management, INTI International University, Nilai, Malaysia

³Department of Computing, Universiti Tunku Abdul Rahman, Kajang, Malaysia

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ABSTRACT

This study investigates the impact of generative artificial intelligence (GenAI) on learning outcomes (LO) and lifelong skills (LLS) within higher education, emphasizing ethical considerations. Employing a quantitative approach, data was collected from 180 students via a questionnaire, examining their AI usage in education. Structural equation modeling (SEM) using SmartPLS 4.1.0.9 was used to analyze the relationship between GenAI use, LO, and LLS. Findings reveal that GenAI can enhance LO, personalize learning experiences, and contribute to developing crucial LLS. However, the study highlights the importance of ethical guidelines to prevent academic dishonesty. This research contributes to the existing literature by exploring the link between GenAI use, LO, and the development of LLS. Practically, it demonstrates that ethical GenAI use promotes both LO and LLS among higher education students, aligning with the sustainable development goals (SDGs) of inclusive and equitable quality education and lifelong learning opportunities.

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Corresponding Author:

Mozaffar Alam Chowdhury

IUBAT Business School, International University of Business Agriculture and Technology

4 Embankment Drive Road, Uttara Model Town-10, Dhaka, Bangladesh

Email: mchowdhury@iubat.edu

1. INTRODUCTION

Education plays a pivotal role in the development of society, and the emergence of artificial intelligence (AI) presents a tremendous opportunity to enhance learning experiences. However, the integration of AI into educational settings brings forth ethical concerns that must be carefully addressed to ensure fairness, transparency, and positive outcomes for students. In this study, we employ the technology acceptance model (TAM) as a theoretical framework to explore the adoption of generative AI (GenAI) in learning analytics within higher education. TAM serves as the foundation for our theoretical analysis, offering insights into users' acceptance or rejection of new technologies. Of particular interest in educational settings is the TAM's ability to forecast and understand how users will embrace and utilize AI tools. This is achieved through two essential components of TAM: perceived use and perceived ease of use. Perceived ease of use captures users' perception of how simple it is to utilize a particular technology, while perceived use reflects users' belief that the technology will enhance their work performance [1].

The integration of AI in education, while holding a tremendous opportunity to enhance learning experience and society development, is hindered by significant ethical concerns that risk undermining its potential. The core statement of the problem is ensuring the development of AI in education is conducted in a manner that guarantees fairness, transparency, and universally positive outcomes for all students.

The research explores key factors influencing the adoption of GenAI, including trust, attitudes, social norms, and cultural factors, which can vary across institutions and demographics. Additionally, we examine the long-term effects of GenAI usage on user acceptability, considering factors such as ease of use, intuitiveness, and the ability to adapt to user demands. This analysis provides valuable insights into how the utilization of GenAI will impact students over time [2]–[4].

Our study aims to investigate the adoption of GenAI in learning analytics for promoting responsible implementation of AI tools in higher education. To accomplish this, we gather insights from both faculty and students participating in a ‘GenAI for learning’ system in Bangladesh. By focusing on the advantages of these tools as learning assistants, we seek to highlight their potential in improving educational experiences. Moreover, we emphasize the importance of distinguishing between AI-assisted and GenAI-complement actions through the use of learning analytics. AI-assisted actions involve machines performing actions while humans make the decisions, whereas AI-complement actions involve collaborative decision-making between humans and machines. This differentiation allows us to address ethical considerations, such as ensuring equitable access to advanced AI tools for all students [5]–[7]. By conducting this study, we intend to contribute to the responsible implementation of GenAI in learning analytics within higher education. Our findings will shed light on the potential benefits of GenAI tools as learning assistants while addressing ethical considerations. Ultimately, this research seeks a solution to ensure that the integration of GenAI in education is conducted in a manner that is equitable, transparent, and beneficial for all students.

The integration of AI in education has been conducted in a way that is not equitable and transparent, but rather beneficial for a particular group. Others were ignored and did not have the same opportunities to learn. Given the importance of ethics, Gen AI is a super helpful tool that can make learning much more engaging, personalize lessons for each student, and boost creativity. However, to achieve these great results, we must ensure that students do not misuse it for cheating or academic dishonesty. By providing the right guidance and teaching students how to use Gen AI responsibly, it becomes a tool that reinforces ethical standards (ES) and promotes original thinking. Ultimately, when we prioritize ethics, the potential for long-term impact is huge. It allows students to develop essential lifelong skills (LLS) that they will need far beyond the classroom. This study subsequently discusses literature review to explain the existing knowledge related to the current field of study. The third section of this study is the research method. The fourth section demonstrates results and discussion to support the analysis of the results. Finally, this study explains conclusion, limitation, and future studies.

2. LITERATURE REVIEW

2.1. Technology acceptance model

TAM is primarily used due to a significant level of perceived usefulness and for the perceived ease of use [8]. The intention to employ GenAI is significantly positively impacted by attitude. The intention to adopt AI is considerably impacted negatively by individual concerns [9].

The perceived usefulness and ease of use of GenAI technology is a crucial determinant of its acceptance in higher education. This is in line with the TAM that shifts toward blended learning contexts and growing emphasis on student motivation and perceived usefulness [10]. Perceived usefulness in the context of AI in education may be linked to the technology’s capacity to improve instruction and learning, whereas ease of use may be connected to the system’s user-friendliness [11]. TAM as the most influential and leading scientific paradigm in investigating the acceptance of educational technology by students, teachers, and other stakeholders.

2.2. GenAI in higher education

With its revolutionary approach to teaching and learning, GenAI has been incorporated into the educational sector more and more [11]. There are four primary categories of GenAI: text generation, picture creation, sound generation, and video production. AI has been applied to improve educational results, increase student engagement, and generate personalized learning experiences [12]. GenAI systems like Chatbots and virtual tutors that have enabled personalized learning pathways, instantaneous feedback, and interactive learning settings [12]. As a result, AI can be used to improve learning outcomes (LO) by facilitating the production of content and data and by leveraging the cognitive development behaviors that come with it [1], [13].

Alzahrani [14] employed a quantitative methodology, gathering data from 350 higher education students using a structured questionnaire. The study developed a conceptual model based on the unified theory of acceptance (UTA) and TAM to analyze how students perceive and behave towards AI technology. One key finding is that perceived risk negatively influences students’ attitudes towards AI in education, whereas perceived performance gains and resource availability play a more significant role than perceived

ease of use. The lesser influence of perceived ease of use contradicts much of the existing literature, suggesting a need for further exploration and validation. Kelly *et al.* [1] conducted a systematic review of studies published between 2019 and 2022, focusing on elements related to AI technology acceptance. Most studies reviewed utilized online questionnaires and surveys, with behavioral intention being the most common measure of acceptance. The expanded TAM was frequently used, highlighting attitudes, trust, and perceived usefulness as key factors. This review underscores the need for further research into trust and perceived usefulness to enhance AI adoption. Educational strategies should focus on building trust and demonstrating the practical benefits of AI technologies.

Kanont *et al.* [12] used the TAM to investigate factors influencing the adoption of GenAI technologies among Thai university students. Using a sample of 911 students, the study employed structural equation modeling (SEM) to analyze data. The findings revealed that expected benefits, perceived usefulness, attitude towards technology, and behavioral intention significantly influence AI adoption. The study's context, being specific to Thai students, might affect its generalizability to other cultural and educational settings. Weng *et al.* [15] concluded that more emphasis should be placed on two LO: career-driven competencies and LLS, as they are becoming increasingly crucial in GenAI-facilitated learning environments. Khodakarami *et al.* [16] found that technology strategy plays a mediating role in the inward export performance of higher education. This suggests that Malaysian higher education institutions (HEIs) should be equipped with the latest education-related technologies to improve their performance. As a result, the use of technology in education is crucial for increasing performance.

The three studies utilize diverse methodologies—quantitative surveys, systematic reviews, and SEM—providing a well-rounded understanding of AI acceptance. This diversity is a strength, offering both breadth and depth of insights. The consistent use of established frameworks like UTA and TAM enhances the credibility of the studies and allows for comparison of findings. These models are crucial for identifying key factors influencing AI acceptance. Future research should incorporate mixed-methods approaches to capture a more holistic understanding of students' attitudes and behaviors towards AI. Comparative studies across different regions and educational settings could provide valuable insights into how cultural and contextual factors influence AI acceptance. By addressing these areas, educational institutions can better leverage AI technology to enhance LO and student engagement. Based on the conceptual framework, as in Figure 1, the study's hypotheses are: i) GenAI has a positive correlation with LO in higher education (H1); ii) ES has a positive correlation with LO in higher education (H2); iii) LO has a positive correlation with LLS in higher education (H3).

Recent studies have explored the integration of AI technologies, such as ChatGPT, in educational settings, focusing on their acceptance, utility, and impact on LO. This review critically examines the findings [17]–[19], highlighting the strengths and limitations of their research. Kizilcec [17] conducted research on the use of the academic resistance model (ARM) and TAM in the context of education. The study highlighted the importance of perceived utility and perceived ease of use of technology in user acceptability. It emphasized the influence of social, psychological, and cultural elements on technology adoption. The study primarily discusses theoretical aspects without providing substantial empirical data to support its claims. Future research should include quantitative and qualitative data to validate the proposed models.

Boubker [18] investigated how ChatGPT, an AI-based tool, may improve LO for students. The study found that perceived utility, ChatGPT usage, and student happiness were influenced by output quality. Social influence also played a significant role in how beneficial people perceived ChatGPT to be and how they utilized it. Perceived ease of use had a substantial impact on students' pleasure and perceived usefulness. The use of convenience sampling may introduce bias, limiting the generalizability of the findings. Future studies should consider more diverse and representative samples.

Nguyen *et al.* [19] studied the integration of ChatGPT at Ho Chi Minh City University of Technology and Education (HCMUTE) and its impact on students' learning practices. The study found that students extensively used ChatGPT for learning and information searches. However, there were also concerns about diminished creativity, academic dishonesty, and ethical issues such as information security and plagiarism. The study's sample size (73 students and 15 faculty members) may not be sufficient to draw broad conclusions. Larger-scale studies are needed to confirm the findings. Hashmi and Bal [20] mentioned valuable insights into the adoption and perception of GenAI in higher education. Their study explores the connection between transparency and responsibility in using GenAI. The findings suggest that HEIs can leverage GenAI to better prepare students for using technology beyond the classroom. The study also highlights the importance of responsible implementation and addresses concerns such as academic integrity. Miller [21] focused on how GenAI is used in university classrooms employing research methodology of focus groups, expert observations, and informal conversations. The study indicates that the usage of GenAI tools in classrooms is acceptable, but educators may have reasons both to use and not to use them. The findings emphasize the need for a balanced approach to integrating GenAI technologies in higher education.

Guillén-Yparrea and Hernández-Rodríguez [22] investigated undergraduate engineering students' understanding of GenAI, its applications, and moral implications. The research adopts a mixed-method approach. The findings reveal that ChatGPT is the most widely used GenAI application among students, but instructors have negative opinions about this technology. The study highlights the importance of considering student perspectives and addressing instructors' concerns in the implementation of GenAI. The purpose of a qualitative study conducted by Summers *et al.* [23] was to investigate nursing students' viewpoints on the use and incorporation of GenAI technologies in their coursework. This study conducted semi-structured interviews with nursing students using a qualitative descriptive methodology. This research was carried out in a rural Australian university in the field of nursing. For this study, interviews with 13 first- and second-year nursing students were conducted. The data analysis produced six separate topics, including the influence of AI tools on education, the creation of an equitable learning environment, the moral implications of using AI, the integration of technology, safe and useful applications, and generational disparities.

- GenAI complement action has a positive correlation with LLS in higher education (H4).
- ES has a positive relation with LLS in higher education (H5).

The conceptual research framework used in this study is presented in Figure 1. Based on the TAM, the framework asserts that the use of GenAI and ethical principles can impact the results of the learning process, which subsequently affects the acquisition of lifelong learning skills. Also, the model considers direct implications of the GenAI and ES on LLS, which gives a detailed framework to use to test the five research hypotheses.

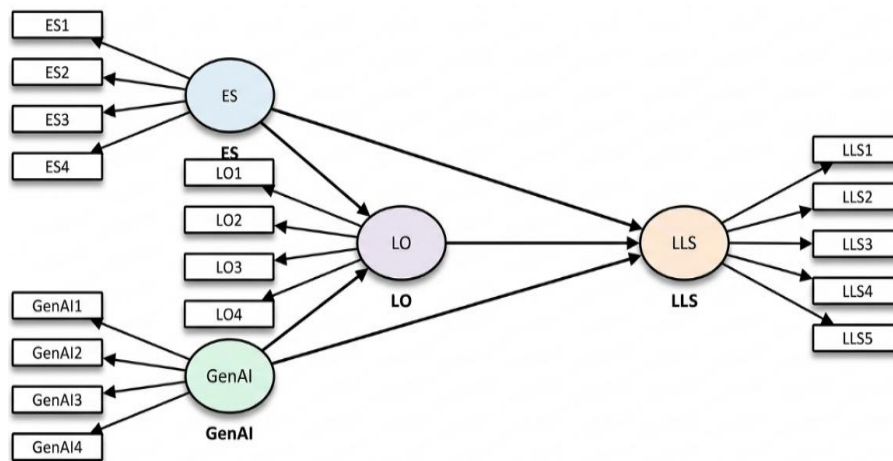


Figure 1. Research framework of the study

3. RESEARCH METHOD

The study employed a quantitative approach to investigate students' AI use towards learning analytics while maintaining ES in higher education. The participants were undergraduate and graduate students enrolled at the International University of Business Agriculture and Technology (IUBAT) Business School, Dhaka, Bangladesh. Data from a sample of 180 students was gathered systematically using a questionnaire, which made it possible to learn about the various aspects impacting students' usage of AI in their education. The study utilized convenience sampling, a form of non-probability sampling. The participants included undergraduate and graduate students enrolled at the IUBAT Business School, Dhaka, Bangladesh. The sample criteria were clearly defined as students in higher education at the aforementioned institution. Participants must be enrolled as undergraduate or graduate students at the IUBAT Business School, and the desired sample size was 180 students.

The survey questionnaire, which served as the research tool, included five sections and was created to collect data for the study. The primary objective of Part 1 was gathering demographic data from the sample, such as year of study, department, gender, age, and level of education. Understanding the characteristics and composition of the responders requires knowledge of this information. The purpose of the second part of the questionnaire was to learn more about usage patterns of GenAI. The trust, attitudes, social norms, and culture around the use of GenAI in educational activities were examined in this part. It is possible to gain information into students' exposure to and familiarity with GenAI by analyzing their current usage habits. The third section of the survey examined GenAI in learning analytics. Learning and teaching may be

enhanced by perceived use in the context of GenAI in education. In order to shed light on how GenAI will impact society over time, the fourth portion of the study looked into the long-term effects of GenAI. The survey's fifth segment looked at the use of GenAI ES. This will offer guidance on avoiding plagiarism, maintaining information security, and eliminating academic dishonesty. Each item was rated by participants on a 5-Likert scale, with each point representing their level of agreement.

The relation between the study's independent and dependent variables was examined by the researchers using the SEM. TAM was used in the study in order to generate theories and validate the conceptual model. In addition, analyze case studies of schools and institutions that have implemented GenAI tools to understand their impact and ethical considerations.

In this study, data analysis was done using SmartPLS 4. To verify convergent validity, the investigation included an examination at factor loadings, composite reliability (CR), and average variance extracted. Prior to starting the SEM study, tests were run to confirm the multicollinearity and normality assumptions. Using SmartPLS software (version 4.0), the SEM analysis intended to investigate connections between latent variables and dive deeper into the proposed model. Confidence intervals were generated using bootstrapping to assess the importance of the correlations in the model [24], [25].

4. RESULTS

4.1. Demographic background

Table 1 shows that 51.4% of the respondents were male and 48.6% were female. Among the sample, 29.3% were aged between 23 and 27, while 65.7% were between 18 and 22 years old. The remaining 3.3% were above 27 years of age. The distribution of year levels was as: 18.2% in their second year, 26% in their third year, 40.9% in their fourth year, and 14.9% in their first year. The majority (85.1%) of the respondents were enrolled in the Bachelor of Business Administration (BBA) program, while the remaining 14.9% were in the Master of Business Administration (MBA) program.

Table 1. Demographic results

Variable	Label	Number	Percentage (%)
Gender	Male	92	51.4
	Female	87	48.6
Age	Less than 18 years	3	1.7
	18-22 years	119	65.7
	23-27 years	53	29.3
	More than 27 years	6	3.3
Current study year	Year 1	27	14.9
	Year 2	33	18.2
	Year 3	47	26.0
	Year 4	74	40.9
Education	Undergrad students	154	85.1
	Master students	27	14.9

4.2. Descriptive analysis

Table 2 shows the mean and standard deviation for the variables investigated in this study. GenAI had the highest mean score of 1.000 out of 5.0, with a standard deviation of 0.0. This suggests that respondents agreed that the use of GenAI enhanced LO when there was a high level of trust that using it had a significant impact. The mean score for LO was 0.845 out of 5.0, with a standard deviation of 0.028. This indicates that using the learner's interactions, such as clicks, navigation patterns, and time spent on GenAI, can improve LO and have a long-term effect on different types of assessment, such as quizzes and assignments. Similarly, the ES had a mean score of 0.291 out of 5.0, with a standard deviation of 0.078. This suggests that the use of GenAI may diminish students' creativity.

4.3. Measurement model

The purpose of this stage was to determine the reliability and validity of the measurement model. Construct reliability, discriminant validity, and convergent validity were used to assess the measurement model. Each variable in the study was evaluated for construct reliability using its unique Cronbach's alpha coefficient. All values exceeded the recommended acceptance criteria of 0.7 [26]. CR of the structure was also examined, and all values were above 0.7, indicating satisfactory reliability [26]. To evaluate the reliability of the indicators, factor loadings were analyzed. According to Summers *et al.* [23], loadings of 0.5 or higher are considered acceptable. The results in Table 2 show that all items met this criterion, except for GenAI2, GenAI3, GenAI4, ES1, ES2, ES3, LO1, LLS4, and LLS5. These items were removed due to their

low loadings. Additionally, the average variance extracted (AVE) was calculated to determine convergent validity, as advised by Summers *et al.* [23]. The AVE values ranged from 0.648 to 1.000, all of which were above 0.50, indicating high convergent validity.

Table 2. Loading, mean, standard deviation, Cronbach's alpha, CR and AVE

Constructs	Indicators	Factor loading (>0.5)	Mean	Standard deviation	Cronbach's alpha (>0.7)	CR (>0.7)	AVE (>0.5)	Q ²
ES	ES1	1.000	0.291	0.078	1.000	1.000	1.000	
GenAI	GenAI1	1.000	1.000	0.000	1.000	1.000	1.000	
LO	LO2	0.784	0.780	0.052	0.729	0.738	0.648	
	LO3	0.786	0.780	0.060				
	LO4	0.845	0.846	0.028				
LLS	LLS1	0.796	0.794	0.050	0.765	0.765	0.681	
	LLS2	0.859	0.859	0.026				
	LLS3	0.819	0.817	0.041				

4.4. Discriminate validity

Three techniques were used to evaluate discriminant validity: cross-loadings, Fornell-Larcker, and the heterotrait-monotrait ratio (HTMT). In order to employ the cross-loadings strategy, the loading of each indicator must be greater than the sum of its cross-loadings. The findings demonstrated that the loading of each indicator in Table 3 exceeds the sum of its cross-loadings.

Table 3. Discriminant validity (cross-loading)

Variable	ES	GenAI	LO	LLS
ES4	1.000	0.184	0.342	0.261
GenAI1	0.184	1.000	0.333	0.440
LO2	0.278	0.327	0.784	0.455
LO3	0.326	0.314	0.786	0.463
LO4	0.233	0.263	0.845	0.628
LLS1	0.256	0.362	0.545	0.796
LLS2	0.258	0.340	0.525	0.859
LLS3	0.133	0.385	0.531	0.819

A statistical method used to evaluate the extent to which a measurement tool accurately reflects the underlying concepts it is intended to measure is known as construct validity. It is a crucial aspect of assessing the reliability and validity of the hypothesis testing in this study. The partial least squares SEM (PLS-SEM) method builds on established methodologies and the Fornell-Larcker criterion facilitates measurement model evaluation [27]. This helps determine if there is a significant difference between the variables, thus validating the outer model's discriminant validity. In other words, if the diagonal components are larger than the other elements in the same row and column, it demonstrates a sufficient level of distinction between the variables. Discriminant validity is essential for this study, as it supports the validity of the hypothesis testing. Table 4 indicates excellent discriminant validity, as the square root of the average variance retrieved for each study variable is higher than the correlation between the other variables [27].

Furthermore, HTMT was used to assess discriminant validity. HTMT is a measure of the mean correlations between different constructs (i.e., heterotrait-heteromethod correlations), rather than the average correlations of indicators within the same construct. According to Hair *et al.* [28], HTMT values above 0.90 can be problematic. Table 5 presents the results of the HTMT analysis, which demonstrated satisfactory discriminant validity as all values were below the threshold of 0.90. Overall, the measurement model used in this study exhibited excellent discriminant validity, as confirmed by the convergent validity and HTMT analysis.

Table 4. Fornell-Larcker criterion for discriminant validity

Variable	ES	GenAI	LO	LLS
ES	1.000			
GenAI	0.184	1.000		
LO	0.342	0.333	0.805	
LLS	0.261	0.440	0.647	0.825

Table 5. HTMT discriminant validity

Variable	ES	GenAI	LO	LLS
ES				
GenAI	0.184			
LO	0.406	0.390		
LLS	0.299	0.502	0.857	

4.5. Structural model

Figure 2 shows the estimated structure model obtained using the PLS-SEM analysis. The relationships between latent constructs GenAI, ES, LO, and LLS that support the hypothesized relationships in the proposed framework are represented by the path coefficients and the level of significance (Table 5). With five main hypotheses in place, the structural model assessment shows the corresponding hypothesis tests, as shown in Table 6 and Figure 2. LO is significantly predicted by GenAI, providing support for H1 with a significance level of $p < 0.01$. Similarly, H2 is also accepted with a significance level of $p < 0.01$, as it is evident that LO is significantly predicted by ES. Additionally, it can be concluded that LO have a major impact on LLS, thus supporting H3 with a significance level of $p < 0.01$. Furthermore, the positive influence of GenAI on LLS is also evident with a significance level of $p < 0.01$, supporting the acceptance of H4. However, the ES is not found to have a significant impact on LLS, as indicated by a significance level of $p > 0.05$, thus not supporting H5.

The direct impact of GenAI on LLS is significantly stronger. This is shown by the standardized path coefficient, which measures the strength of the relationship between exogenous (external) and endogenous (internal) dimensions. Approximately 47.6% of the variation in the LLS can be attributed to GenAI. In contrast, GenAI accounts for only 19.2% of the variation in the LO. Moreover, the direct effect of ES is also significant, accounting for approximately 19.2% of the variation in the LO.

In this study, the effect size (f^2) is an important metric. According to Hair *et al.* [29], f^2 shows the proportionate impact of a predictive construct on an endogenous construct. Cui *et al.* [30] defined f^2 values of 0.02, 0.15, or 0.35 as indicating low, medium, or large impacts, respectively. Therefore, the f^2 results of the study are crucial. Based on the f^2 results, there are low to large impacts observed between GenAI and LO ($f^2 = 0.093$), ES and LO ($f^2 = 0.101$), and LO and LLS ($f^2 = 0.476$). However, the impact size of the link between GenAI and LLS is lower ($f^2 = 0.106$). According to Cui *et al.* [30], multicollinearity must be examined to ensure that the exogenous latent constructs are not significantly interconnected. Table 5 shows that all values for the variance inflation factor were less than 5, as stated by Hair *et al.* [29]. This indicates that multicollinearity is not present in the external latent constructs.

In Table 5, 19.2% of the variation in LO can be explained by GenAI and by ES. However, when considering LO and its impact on LLS, this percentage increases to 47.6%, indicating a greater influence from ES and the GenAI effect combined. Additionally, GenAI accounts for 46.6% of the variation in the long-term effect, which is also a higher percentage. Therefore, it can be concluded that GenAI has a significant impact on LO, and that both GenAI and ES have a greater effect on LO when considered together.

Table 6. Structural path analysis results

Hypotheses	Std. β	Sample mean	Standard deviation	t-statistics	p-values	Decision	R ²	f ²	VIF
H1: GenAI->LO	0.312	0.278	0.086	3.253	0.000	Accepted	0.157	0.115	1.035
H2: ES->LO	0.217	0.291	0.078	3.713	0.004	Accepted	0.157	0.055	1.035
H3: LO->LLS	0.552	0.561	0.080	6.944	0.000	Accepted	0.481	0.476	1.238
H4: GenAI->LLS	0.251	0.245	0.077	3.268	0.001	Accepted	0.481	0.108	1.131
H5: ES->LLS	0.058	0.022	0.082	0.305	0.314	Rejected	0.481	0.006	1.140

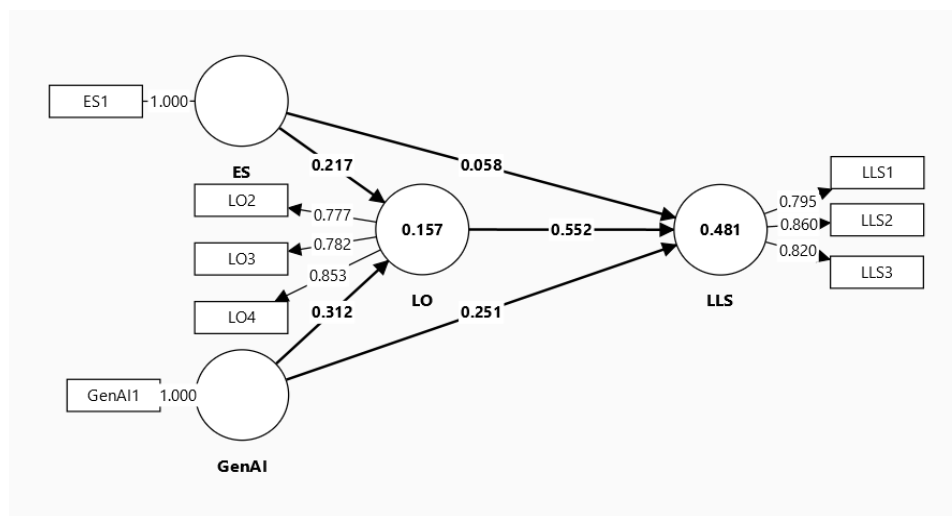


Figure 2. Structural model

5. DISCUSSION

The findings of this study support the relationship between GenAI and LO. This aligns with the results of several previous studies, including those by Lim *et al.* [11]. For instance, Lim *et al.* [11] found that GenAI can help improve teaching and learning. Similarly, Duah and McGivern [31] demonstrated that GenAI can improve educational outcomes through personalized support, though they caution that ethical safeguards are essential to mitigate risks of overreliance and academic misconduct. The results are also consistent with the findings of Kanont *et al.* [12], who discovered that expected benefits, perceived usefulness, attitude towards technology, and behavioral intention significantly influence AI adoption.

Furthermore, Boubker [18] found an AI-based tool improves LO for students. Khodakarami *et al.* [16] found that technology strategy plays a mediating role in the performance of higher education and HEIs should be equipped with the latest education-related technologies to improve their performance. This suggests that students at IUBAT Business School may enhance their learning experience through the use of GenAI. Therefore, the findings of this study support H1.

The results of this study confirm a correlation between ES and LO when utilizing GenAI for learning. It was found that students are highly motivated to exploit plagiarism when using this tool. This aligns with the results of Nguyen *et al.* [19]. For instance, Nguyen *et al.* [19] found that students extensively used ChatGPT for learning. However, there were also concerns about diminished creativity, academic dishonesty, and ethical issues such as information security and plagiarism. This suggests that students at IUBAT Business School may motivate students to enhance their learning experience through the use of GenAI while maintaining ES. Therefore, the findings of this study support H2.

The findings of this study support the relationship between LO and the long-term effects. This aligns with the results of Weng *et al.* [15]. For instance, Weng *et al.* [15] concluded that lifelong learning skills are becoming increasingly crucial in GenAI-facilitated LO. This suggests that students at IUBAT Business School may enhance their LO through the use of GenAI, in order to improve LLS. Therefore, the findings of this study support H3.

Similarly, the findings of this study also support the relationship between GenAI and LLS. This is in line with the results of Weng *et al.* [15], who discovered that the use of GenAI has led to the development of a diverse range of targeted LO, including essential LLS and career-oriented competencies. This indicates that students at IUBAT Business School could enhance their LO through the use of GenAI, ultimately improving their lifelong learning skills. Therefore, the findings of this study support H4.

This study aims to investigate the relationship between LO and the use of GenAI in higher education. Additionally, it aims to explore the impact of GenAI on the development of LLS. These research findings will contribute to the existing body of literature and provide a theoretical contribution to the field. The practical implications of this study suggest that the use of GenAI, when used ethically, can enhance LO for students in higher education. Furthermore, it can aid in the development of LLS. By identifying the influence of GenAI on LO and LLS, this study will provide valuable insights for educators and policymakers. Overall, this research contributes to the understanding of the potential benefits of incorporating GenAI into higher education.

6. CONCLUSION

The findings of this study highlight the significant relationship between GenAI and LO, specifically in the context of IUBAT Business School. The evidence strongly supports the idea that GenAI can enhance teaching and learning experiences, improve student engagement, and encourage personalized learning. In addition, the study emphasizes the importance of ethical considerations when utilizing GenAI, as students may be tempted to misuse these tools for academic dishonesty. However, with proper guidance, GenAI can also promote ES and creativity in learning. Furthermore, the long-term effects of GenAI usage are promising, as it contributes to the development of essential LLS.

The research is based on a specific educational institution, which may limit the generalizability of the findings to other contexts or populations. The ethical implications of GenAI usage, particularly concerning academic integrity, require ongoing examination and discussion. Future research should aim to explore the long-term impacts of GenAI on diverse educational settings beyond IUBAT Business School. Additionally, it would be beneficial to examine the ethical dimensions of GenAI usage in greater detail, focusing on how institutions can foster a culture of integrity while leveraging the benefits of these technologies. Furthermore, investigating the role of faculty perceptions and training in the successful implementation of GenAI tools could further enhance educational outcomes.

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Mozaffar Alam Chowdhury	✓	✓	✓	✓	✓	✓			✓					✓
Toong Hai Sam	✓	✓			✓	✓			✓			✓	✓	✓
Md. Sohel Rana	✓	✓			✓	✓	✓	✓	✓			✓		
Khan Sarfaraz Ali	✓	✓			✓	✓		✓	✓		✓			✓
Whee Yen Wong	✓	✓			✓	✓				✓	✓			
Hasanuzzaman Tushar	✓	✓			✓	✓				✓	✓			

C : Conceptualization

M : Methodology

So : Software

Va : Validation

Fo : Formal analysis

I : Investigation

R : Resources

D : Data Curation

O : Writing - Original Draft

E : Writing - Review & Editing

Vi : Visualization

Su : Supervision

P : Project administration

Fu : Funding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Materials and data availability: upon request, the respective author will provide the data.





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BIOGRAPHIES OF AUTHORS






Mozaffar Alam Chowdhury     is a young economist, professor at IUBAT Business School, Bangladesh and research fellow at INTI International University, Malaysia. He did an MBA from Bedfordshire University, England, and a BBA from Chittagong University. He also did an MA in Economics from Bowling Green State University (USA) and he have a Ph.D. degree from the UPM School of Business and Economics. Dr. Mozaffar is an editorial member of the South Asian Journal of Management (AMDISA, India), the founding associate editor of IUBAT review, editorial member of the Journal of Finance, Business and Management Studies, India and associate editor of SN Business and Economics (Springer Nature), Switzerland. He can be contacted at email: mchowdhury@iubat.edu.






Toong Hai Sam    is an accomplished researcher with expertise in both social science and technology. He wears many hats, serving as a scientist, professor, researcher, entrepreneur, and pilot. With over 20 years of experience in managing businesses globally, he excels at blending his academic work with practical experience. Sam is passionate about fostering international collaboration in scientific research and education. He has been recognized for his contributions to science, including being named a Young Talented Scientist for ASEAN by China. He frequently represents Malaysia at scientific forums and seminars in ASEAN countries and China, playing a crucial role in shaping regional research agendas and partnerships. He can be contacted at email: toonghai.sam@newinti.edu.my.






Md. Sohel Rana    is an associate professor at the College of Business Administration, International University of Business Agriculture and Technology (IUBAT), Dhaka, Bangladesh. He holds a Ph.D. in Business and Management from the University of Malaya (UM), Malaysia, one of Asia's leading research-intensive universities. His academic foundation includes an MBA and a BBA from the University of Rajshahi (RU), Bangladesh, where he developed a strong grounding in business theory and practice. Dr. Rana published several articles and book chapters in the Scopus and Web of Science (WoS) indexed journals. He can be contacted at email: sohelrana.cba@iubat.edu.






Khan Sarfaraz Ali    is an associate professor at INTI International University, Malaysia, and has over 23 years of experience in academia and human resources. He has authored a book titled "A Handbook on HR Solution" and conducts research in qualitative social research. He can be contacted at email: khan.sarfarazali@newinti.edu.my.



Whee Yen Wong    is a professor and an academic researcher from Universiti Tunku Abdul Rahman. The author has contributed to research in topics: quality management system and six sigma. The author has an h-index of 3, co-authored 9 publications. Previous affiliations of Whee Yen Wong include University of Nottingham. She can be contacted at email: wongwy@utar.edu.my.



Hasanuzzaman Tushar    is an associate professor at the International University of Business Agriculture and Technology, Bangladesh. He has a Ph.D. from the Graduate School of Human Resources and Organizational Development, National Institute of Development Administration (NIDA). He also served at Chandigarh University as a visiting professor. His research interest primarily lies in the area of career development, human resource development and management, and social stratification. He can be contacted at email: tushar@iubat.edu.