Prithvi Journal of Research and Innovation
[A Peer-Reviewed, Open Access Multidisciplinary Bilingual Journal; Indexed in NepJOL]
ISSN 2705-4888 [Print]; ISSN 2705-4896 [Online]; JPPS Star-Rated Journal
Volume 6; 15 December 2024; pp. 1-21
eJournal Site: http://ejournals.pncampus.edu.np/ejournals/pjri/

Impact of Behavioural Intention to Use Generative Artificial Intelligence on Academic Performance of Students in Higher Education Institutions

Resam Lal Poudel, Chandra Kanta Bastakoti
Faculty of Management, Prithvi Narayan Campus, Pokhara, Nepal

Article History:
Submitted 28 September 2024
Reviewed 17 October 2024
Revised 27 October 2024
Accepted 10 December 2024

Corresponding Author:
Resam Lal Poudel
Email: resampoudel@pncampus.edu.np

Article DOI:
https://doi.org/10.3126/pjri.v6i1.72853

Publisher:
Centre for Research and Innovation
Prithvi Narayan Campus
Tribhuvan University, Pokhara, Nepal
[Accredited by UGC, Nepal]

Tel.: +977-61-576837
Email: research@pncampus.edu.np
URL: www.pncampus.edu.np

ABSTRACT

The rapid advancement of Generative Artificial Intelligence (GAI) technologies has significantly impacted various sectors, including higher education. This study investigates the behavioral intention of students in higher education institutions to adopt GAI and its effect on their academic performance mediating the intention to use GAI. This study uses an analytical cross-sectional design to assess the current relationships among behavioral intention factors, intention to use GAI, and academic performance. Data were collected using a quantitative approach from 279 online and 105 student self-administered responses through purposive sampling. Purposive sampling was employed to target students with GAI experience, ensuring relevant insights aligned with the study's objective of examining adoption patterns among the active users in higher education settings. The students represent seven higher education institutions that are accredited by the University Grants Commission, Nepal. A seven-point Likert scale measured variables like performance expectancy, effort expectancy, social influence, facilitating conditions, intention to use GAI and academic performance. The final sample size was 384, and pilot testing ensured instrument validity. Data analysis was conducted using SMART Partial Least Square (PLS). SmartPLS was chosen for its capacity to handle complex models, making it suitable for analyzing predictive relationships without requiring the normal data distribution. The results show that all the factors of behavioural intentions significantly influence the intention to use GAI; however, the effort expectancy and social influence did not influence academic performance. The mediating role of intention to use GAI was also ensured. The findings highlight the need for educational institutions to provide targeted training and clear ethical guidelines for responsible GAI use, emphasizing its integration into curricula to enhance academic performance.

KEYWORDS: Academic performance, behavioral intention, generative artificial intelligence, higher education

INTRODUCTION

Artificial Intelligence (AI) technologies, particularly Generative Artificial Intelligence (GAI), have rapidly grown and attracted various sectors, including higher education. GAI comprises diverse artificial intelligence models and techniques specially focused on creating content like humans (Cooper, 2023). These models generate the content based on complex commands and questions (Lim et al., 2023). Some common examples of GAI are Chat Generative Pre-Trained Transformer (ChatGPT), Bard, Jenni AI, and Quillbot, which have been used for different workplace, personal and academic activities (Cortez et al., 2024). GAI, a branch of AI, holds immense promise for transforming human-AI collaborations and addressing intricate educational challenges (Russell & Norvig, 2016). Recent data reveals that the market for GAI will reach $207 billion by 2030, a significant increase from $5.67 billion in 2020 and $23.17 billion in 2023 (Uspenskyi, 2024).

The education sector has seen substantial use of GAI compared to other industries. A recent study showed that more than 50 percent of students are already using GAI tools, with the adoption rate increasing exponentially. Students often use these tools for summarizing text, submitting assignments, and paraphrasing content. Notably, 75 percent of students intend to continue using GAI tools in the future (Coffey, 2023). This trend, despite its advantages and support for academic practices, raises concerns for both educators and policymakers. Generative AI is equally applicable in the context of Higher Education institutions (HEIs). It has the potential impact on teaching-learning, instructions, assignments and sources of educational resources (Chan & Hu, 2023; Neumann et al., 2023). However, there are concerns in the academic sector regarding the excessive use of GAI tools. There are issues regarding plagiarism, privacy, biased content and pedagogical challenges (Abd-Alrazaq et al., 2023; Chan & Lee, 2023). However, Chan and Hu (2023) acknowledge that students' perception of GAI tools will facilitate understanding the adoption of those tools, which will be incorporated into the teaching-learning process. It can therefore be inferred that GAI poses both challenges and opportunities to HEIs.

Nepal has seen a significant increase in the use of ChatGPT, ranking second globally in Google searches. The country's tech-savvy population drives this surge, expanded internet access, and growing interest in artificial intelligence (AI) (Nepalitelecom, 2023). The Nepalese people have embraced this cutting-edge technology, eager to explore its capabilities and potential applications. This indicates the increasing use of GAI in the Nepalese context. Research conducted by Ghimire et al. (2024) through qualitative study identified a positive perception towards ChatGPT, a GAI tool. However, the research also raises concern on the misuse of this technology.

Additionally, there are concerns about students' creativity and research ability of students in higher education institutions. It also reflects the use of GAI in the education sector. However, the impact of GAI on students' academic performance is an area that remains unexplored. The present research aims to fill this gap.

Behavioral intention relates to an individual's preparedness to use specific technology for various tasks. Behavioral intention is commonly used to assess attitudes, beliefs, and behaviours (Almahri et al., 2020). Venkatesh et al. (2003) developed a theory to identify the important behavioural factors affecting the usage intention and adoption of new technology. The model is popularly known as UTAUT (Unified Theory of Acceptance and Use of Technology). The major dimensions are performance expectancy, effort expectancy, social influence and facilitating condition. Performance Expectancy (PE) covers different aspects like usefulness characteristics, relative advantage and motivation (Davis, 1989; Davis et al., 1992). It is the perceived belief of the users to improve performance due to the adoption of technology. Effort Expectancy (EE) is defined as the simplicity and user-friendly characteristics of the technology (Venkatesh et al., 2003). Social Influence (SI) factors is related to the benefits of using technology as recommended by others (Venkatesh et al., 2003). Lastly, the Facilitating Conditions (FC) factors include the infrastructural support available to use the new technology (Thompson et al., 1991). Intention to use is a personal desire to continue adopting technology (Venkatesh et al., 2012). It is the tendency to adopt new technology and predict the continuity of usage. It is the tendency of students to adopt GAI in their learning activities. The attitude and belief of a person that drives individual to perform a specific behavior is regarded as the intention to use. It is the practical application of technology in work settings (Salifu et al., 2024). There is a direct connection between behavioural intention factors on the actual use of technology.

Academic performance assesses students' abilities and reflects what they gained during learning. It suggests that students can respond to educational stimuli. Academic performance is influenced by various internal and external elements, including aptitude and motivation (Garcia-Martinez et al., 2023). It reflects and that aptitude and motivation also affect students' academic performance or achievement. Academic performance is measured generally by the grades the students have obtained. However, there are other tools for assessing students' performance.

Only limited studies to date have explored the behavioural intention of the use of GAI in the Nepalese context (Budhathoki et al., 2024; Yadav & Pokhrel, 2023). This indicates the need for academic literature on GAI in the Nepalese context. Prior studies have explored factors influencing behavioral intentions toward GAI adoption (Almahri et al., 2020; Budhathoki et al., 2024; Huang & Cheh, 2022; Yadav & Pokhrel, 2023). However, there is inconclusive evidence regarding students' behavioral intentions to use GAI. While some research has addressed behavioral intention (Budhathoki et al., 2024; Yadav & Pokhrel, 2023), the impact of GAI usage on academic performance remains underexplored, particularly in the Nepalese higher education context. Additionally, other studies have analyzed the mediating role of intention to use GAI on the relationship between behavioral intention and academic performance (Abbas et al., 2024; Dahri et al., 2024; Ifedayo et al., 2021). However, there are inconsistencies in the findings, as some focused on the mediating role of behavioral intention, while others examined GAI use as a mediator. Additionally, these studies show variations in how they present direct and indirect relationships between the variables, leaving the mediating role of intention to use GAI inconclusive. Despite a growing body of literature, a gap remains in understanding how behavioral factors impact Generative AI (GAI) adoption in Nepal, where cultural and institutional dynamics differ. This study seeks to fill that gap, offering localized insights to inform educational policy and enhance GAI integration.

This study seeks to address the impact of generative AI (GAI) on students' academic performance by posing several central research questions. The primary question centers on whether the adoption of GAI influences academic outcomes and, if so, whether this impact is positive or negative. In addition to examining this overarching effect, the study aims to identify specific factors that contribute to students' academic performance. Recognizing the role of behavioral aspects in educational settings, this research investigates which behavioral factors are most influential in shaping students' academic achievements. Moreover, the study explores the potential mediating effect of students' intention to use GAI in the relationship between these behavioral factors and academic outcomes. By addressing these questions, the study intends to provide a comprehensive understanding of the connections between GAI adoption, key behavioral influences, and academic performance, as well as the role of students' intentions in these interactions.

This study faces several limitations that may influence the generalizability of its findings. First, it utilizes the UTAUT model rather than the extended UTAUT-2, thereby limiting the inclusion of factors such as hedonic motivation and price value. Additionally, the research focuses only on higher educational institutions in Pokhara, Nepal with UGC accreditation, which may restrict the applicability of the findings to other regions or non-accredited institutions. The study also relies on cross-sectional data gathered from students in a semester-based system who have experience using GAI, potentially narrowing the scope of insights across different academic settings. Furthermore, the use of an analytical research design restricts the study from capturing in-depth qualitative aspects of students' interactions with GAI.

The present study is expected to provide information to HEI stakeholders to frame policies to make students ethically use GAI for academic purposes. The study is also expected to bridge the existing gaps in academic literature regarding the adoption and impact of GAI on students' academic performance. By employing the UTAUT theory, the study is also expected to advance the theoretical model in the context of a developing economy. The study will also provide practical insights to the academician to integrate the behavioural intention factors to improve the academic performance of students. The mediating role of intention to use GAI will significantly contribute to worldwide literature which has been less explored.

LITERATURE REVIEW

Davis (1989) developed the Technology Acceptance Model (TAM), focusing on perceived usefulness and ease of use. However, TAM fails to account for social influences and facilitating conditions, as well as their link to academic performance. To address these gaps, the present study employs the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Theory of Planned Behavior (TPB). Venkatesh et al. (2003) developed UTAUT, categorizing behavioral intention to use technology into four dimensions as explained above. The UTAUT model predicted that users' behavioral intentions factors would influence their actual acceptance and use of technology. The present study assumes that these four factors directly influence students' intention to use Generative AI (GAI) and it will have a direct impact on the academic performance of students. TPB (Ajzen, 1991) posits that intention predicts behavior, with attitudes, subjective norms, and perceived behavioral control as key factors. Sutter and Paulson (2017) found that TPB aids students in achieving academic performance. In this study, social influence and facilitating conditions, shared with UTAUT, are seen as motivators for better academic results. Behavioral intention to use GAI enhances self-efficacy, leading to improved academic performance. The study proposes that if the four UTAUT factors impact academic performance through the mediator (intention to use), TPB is validated.

Behavioural Intention Factors and Intention to Use GAI

Performance expectancy significantly influences behavioral intention toward GAI, as shown by Almahri et al. (2020) and Huang & Cheh (2022), though its effect varies by context. Prior quantitative studies, including those by Rahim et al. (2022), found that effort expectancy influences users' intentions to adopt AI tools like ChatGPT. However, Strzelecki (2023) emphasized habit over performance and effort expectancy. This study also explores these factors' influence on academic performance. Grassini et al. (2024) used the UTAUT2 model to study ChatGPT acceptance among Norwegian students, finding that performance expectancy strongly influenced behavioral intention, while effort expectancy, social influence, and facilitating conditions did not. This aligns with the findings of Strzelecki (2023) and Venkatesh et al. (2012). Similar results regarding performance expectancy dominance were reported by Edumadze et al. (2022). Menon and Shilpa (2023) also highlighted the importance of performance and effort expectancy in technology use. Additionally, social influence plays a significant role in adoption (Al-Emran et al. 2023; Jo, 2023). Facilitating conditions, such as internet access and technical support, are crucial for ChatGPT adoption (Menon & Shilpa, 2023). Romero-Rodriguez et al. (2023) found that only performance expectancy predicted the intention to use ChatGPT among Spanish students, while effort expectancy and social influence did not. Conversely, Wen et al. (2024) showed that social influence strongly predicted technology adoption among high school students, aligning with findings by Hao et al. (2024) and Budhathoki et al. (2024) conducted a cross-cultural study between Nepal and the UK, showing that performance expectancy, effort expectancy, and social influence GAI use, but anxiety levels varied between the countries, warranting further localized research. Based on the information, the following hypotheses have also been proposed.

H_{1a}. Performance expectancy positively impacts behavioral intention to use GAI.
H_{1b}. Effort expectancy positively impacts the usage intention of GAI
H_{1c}. Social influence positively impacts the usage intention of GAI.
H_{1d}. Facilitating conditions positively impacts the usage intention of GAI.

Behavioural Intention Factors and Academic Performance

Wecks et al. (2024) explored the role of GAI usage in academic performance and found that frequent use of GAI negatively influenced students' academic scores, while non-users demonstrated better performance. This suggests that GAI usage may not necessarily enhance academic outcomes and raises questions about its effectiveness in higher education. These findings align with recent studies by Crawford (2023) and Rasul et al. (2023), which also questioned the positive impact of GAI tools on student performance. Contrarily, other research emphasizes the critical role of behavioral factors in improving academic performance. Ali et al. (2023) identified factors such as study motivation, which positively impacts students' academic achievements. These findings contrast with Vollmer's (1986) earlier research, which focused solely on the influence of effort expectancy on academic performance. Vollmer's study suggested that students' expectations, particularly in the form of self-confidence, play a pivotal role in driving better academic outcomes. Ukut and Krairit (2019), utilizing the UTAUT model among 430 students and 55 IT experts, revealed that social influence and facilitating conditions significantly contribute to academic performance. This study highlighted the importance of guidance from ICT instructors in helping students improve academically, findings that align with earlier studies (Boateng et al., 2016; Thompson et al.1991) research emphasizes that when students effectively handle technology and receive proper mentorship, their academic results improve.

H_{2a}.Performance expectancy positively impacts the academic performance of students
H_{2b} Effort expectancy positively impacts the academic performance of students
H_{2c} Social influence positively impacts the academic performance of students
H_{2d} Facilitating conditions positively impact the academic performance of students
H_3. The intention to use GAI positively impacts the academic performance of students

Mediating Role of Intention to Use GAI

Several studies have examined the mediating role of various factors in technology adoption. Abbas et al. (2024) explored ChatGPT's mediating role between time pressure, sensitivity to rewards, and memory loss among university students. Their findings supported ChatGPT's mediating role in these relationships. Similarly, Dahri et al. (2024) found that the intention to use AI tools mediated the relationship between behavioral intention factors and academic performance, emphasizing the influence of AI on student outcomes. In a different context, Ifedayo et al. (2021) studied the mediating effect of behavioral intention factors on podcast acceptance in Nigeria, confirming their mediation role between beliefs (social, political, cultural) and use behavior. Al-Rahmi et al. (2022) used the UTAUT model to show that behavioral intention partially mediated the relationship between performance expectancy, effort expectancy, social influence, and facilitating conditions on performance, though this was not explicitly mentioned in the study. Abbas et al. (2024) also examined ChatGPT's potential mediation between workload, time pressure, and academic performance. However, neither direct nor indirect relationships were significant, suggesting that ChatGPT use did not mediate these factors, raising questions about the tool's effectiveness in enhancing academic outcomes. Based on the given empirical research, the following hypotheses have been proposed.

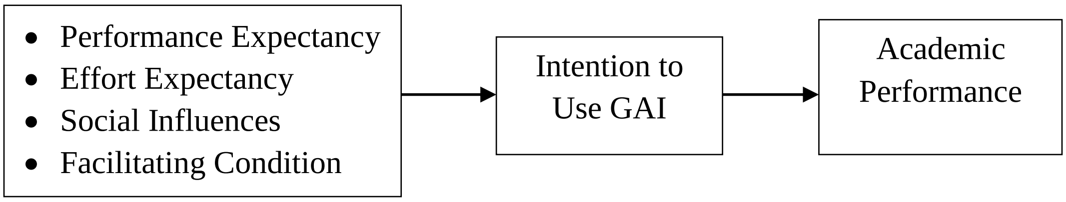
H_{4a}. The intention to use GAI mediates the relationship between performance expectancy and the academic performance of students
H_{4b}. The intention to use GAI mediates the relationship between effort expectancy and the academic performance of students

H_{4c}. The intention to use GAI mediates the relationship between social influence and the academic performance of students

H_{4d}. The usage intention of GAI mediates the relationship between facilitating the condition and academic performance of students. The theoretical underpinning of UTAUT and TPB, review of past studies and the hypotheses clearly indicate the following research framework for the research.

Figure 1

Research Framework



RESEARCH METHODS

The research aimed to examine the impact of behavioral intention factors on the intention to use generative AI (GAI) and academic performance of students, along with the mediating role of intention to use GAI. The analytical cross-sectional research design was employed to analyze the impact of behavioural intention factors on intention to use and academic performance through questionnaire to collect data from students using GAIThe major limitation of this design is that it relies on the assumption that relationships between variables are stable, potentially neglecting variations across time or different settings (Bryman, 2016). An analytical research design is ideal despite its limitations for examining the impact of behavioral factors on academic performance, as it enables a systematic investigation of relationships between variables, facilitating precise (Kothari, 2004), data-driven insights (Creswell & Creswell, 2017) and testing hypotheses (Bryman, 2016).

Data were collected through online and self-administered questionnaires, employing quantitative analysis methods using descriptive and inferential statistics. The study targeted higher education institutions in Pokhara accredited by the University Grants Commission (University Grants Commission, Nepal, 2024), selecting seven institutions offering semester-based programs. The sample included students enrolled in bachelor, master, and higher-level programs under the semester system. Purposive sampling was used to select respondents who used GAI for academic purposes. A final sample size of 384 was determined based on Krejcie and Morgan (1970), with 279 online responses and 105 self-administered questionnaires. Purposive sampling is justified in studies targeting specific respondents as it allows researchers to intentionally select individuals who possess the relevant characteristics or expertise needed to address specific research objectives (Etikan et al., 2016). While purposive sampling is appropriate for identifying respondents with specialized knowledge, it can introduce selection bias. To address this, efforts were made to include a diverse range of students across various academic levels (bachelor's, master's, and higher-level programs) and fields of study, ensuring a broader spectrum of perspectives that reduces the likelihood of overrepresentation from any single group. Although this sampling method prioritizes targeted insights over broad population generalizability, the study is designed with analytical generalization in mind, focusing on understanding patterns in GAI usage that can be applicable in similar academic contexts.

A structured questionnaire, including nominal, ordinal, and interval scales, was used for data collection. A 7-point Likert scale (1=Strongly Disagree, 7=Strongly Agree) was employed, based on recommendations from Alwin and Krosnick (1991) and Cohen et al. (2002), to enhance reliability. The measurement of performance expectancy, effort expectancy, social influence, and facilitating conditions was adapted from Venkatesh et al. (2003, 2012), and academic performance was measured using constructs from Dahri et al. (2024). Pilot testing with 39 respondents confirmed the instrument's validity. Data analysis was conducted through PLS-SEM utilizing SmartPLS 3.0 for inferential analysis (Ringle et al., 2015). The PLS-SEM was used due to its capacity to handle complex models and large data sets (Hair et al., 2014; Wong, 2013). Smart PLS has been utilized in the study as it is a comprehensive software with multiple features (Henseler, 2017). Additionally, it has been utilized in different disciplines (Hair et al., 2017). Likewise, it is a widely accepted technique for analyzing complex models and does not require the assumption of data normality (Gudergan et al., 2008).

The analysis followed two stages: First, the measurement model was evaluated for composite reliability, convergent and discriminant validity (Kock & Lynn, 2012; Podsakoff & Organ, 1986). The use of self-reported data introduces common method bias which will have a direct impact on consistency and accuracy (Podsakoff et al., 2003). If the same instrument is utilized to assess both the endogenous and exogenous constructs in cross-sectional research, the common method bias exists. If a large portion of the variance is explained by a single factor, common method bias can be detected (Harman, 1976). If a single factor explains more than 50 percent variance, the common method bias exists. However, in the present research, it was not a problem as a single factor accounts for only 40.18 percent of the variance. Additionally, Kock and Lynn (2012) propose a VIF value of less than 3.3 for determining the common method bias. The constructs employed in the study confirm no problem associated with multicollinearity and common method bias as the value lies between 1.265 and 2.445 only. Second, the structural model comprising path coefficients was assessed using bootstrapping to test hypotheses. In PLS-SEM, bootstrap confidence intervals using 5000 resamples help validate the stability and significance of path coefficients. This process involves repeatedly resampling the original data and calculating path estimates to form a distribution. Confidence intervals are drawn from the 2.5^{th} and 97.5^{th} percentiles, where intervals excluding zero indicate significant paths. This approach strengthens the robustness of the results shown in Figure 2, confirming that observed relationships are stable across different sample variations. The structural model is utilized to evaluate the relationships between latent constructs after confirming the measurement model. This stage allows researchers to examine the hypothesized relationships (path coefficients) and assess the strength, direction, and significance of these relationships among constructs. R-squared values and f-squared effect sizes were reported to determine the strength of the relationships (Hair et al., 2014).

Mediating effects were examined using Preacher and Hayes' (2008) approach, suitable for PLS-SEM. Mediation analysis is crucial in this study as it helps clarify how behavioral intention factors indirectly impact academic performance through the mediating role of intention to use. This approach is particularly valuable in behavioral and technology adoption research, where mediation reveals underlying pathways between predictor and outcome variables (Baron & Kenny, 1986). By focusing on intention to use as a mediator, it is better to understand how behavioural factors translate into academic outcomes, supporting insights from the UTAUT model, which highlights the mediating role of intention in linking user attitudes to performance (Venkatesh et al., 2003). Such analysis provides an important view of the mechanisms driving students' academic success with GAI adoption, aligning with best practices in studying behavioral impacts on educational outcomes.

RESULTS

The results section displays the major outcome of data analysis.

Profile of Respondents

The respondents in this research comprise a balanced gender distribution, with 51% male and 49 percent female participants. The majority, 69.3 percent are aged between 21-25 years, followed by 14.6 percent aged 26-30, 11.5 percent aged 20 and below, and 4.7 percent aged above 30. In terms of academic background, most respondents are from the management faculty (42.71%), followed by engineering and technology (31.77%), humanities and education (17.97%), and forestry (7.55%). Regarding qualifications, 67.7% hold a bachelor's degree, while 32.3% have a master's degree or higher.

Impact of Behavioural Intention Factors on Intention to Use GAI and Students' Academic Performance

To examine the impact of behavioural intention factors on the intention to use GAI and the academic performance of students, two approaches are used as proposed by Hair et al. (2014). In the first stage, the outer model assessment is used with the help of the measurement model. The measurement model assesses validity, reliability, and indicator factor loading significance. Likewise, the structural model which is also referred to as the inner model is utilized to examine the impact of exogenous variables, behavioural intention factors on endogenous variables namely intention to use GAI and academic performance.

Measurement Model. As given above, the measurement model is generally utilized to assess the fit of the outer model. It is also helpful to analyze the validity and reliability of the measures. The measurement model for reliability and convergent validity has been presented in Table 2.

Table 2

Measurement Model for Reliability and Convergent Validity

Constructs	Items	Loadings	VIF	α value	CR	AVE
Performance Expectancy (PE)	PE1	0.845	1.805	0.761	0.847	0.582
	PE2	0.744	1.556			
	PE3	0.713	1.438			
	PE4	0.742	1.327			

Effort Expectancy (EE)	EE1	0.788	1.629	0.767	0.851	0.591
	EE2	0.609	1.265			
	EE3	0.815	1.707			
	EE4	0.842	1.799			
Social Influence (SI)	SI1	0.820	1.620	0.826	0.896	0.743
	SI2	0.882	2.233			
	SI3	0.882	2.085			
Facilitating Condition (FC)	FC1	0.828	1.803	0.762	0.851	0.594
	FC2	0.836	1.946			
	FC3	0.824	1.714			
	FC4	0.612	1.141			
Intention to Use (IU)	UI1	0.878	2.113	0.870	0.920	0.793
	UI2	0.887	2.382			
	UI3	0.906	2.445			
Academic Performance (AP)	AP1	0.785	1.645	0.831	0.887	0.663
	AP2	0.783	1.721			
	AP3	0.855	2.108			
	AP4	0.833	1.892			

Table 2 displays the measurement model for the outer behavioural intention construct and composite factors of the intention to use and academic performance. The model included four indicators for behavioural intention factors and one indicator with three items for intention to use GAI and one indicator comprising four items for academic performance. All factor loadings exceeded the significant threshold of 0.6, as recommended by Hair et al. (2019), so the decision was taken to retain all the items. Regarding reliability and validity, all latent constructs, surpassed the recommended thresholds for Composite Reliability (*CR) (> 0.7),* all the items were assumed to maintain internal consistency and one aspect of reliability has been fulfilled. Average Variance Extracted (*AVE) (> 0.5*) to assess convergent validity and solve the problem associated with cross-loading. Since the AVE of all constructs was more than 0.5, aligning with prior research (Fornell & Larcker, 1981) indicating acceptable convergent validity under these conditions. Furthermore, Cronbach's alpha values consistently exceeded 0.6, ensuring high inter-item consistency reliability.

Discriminant Validity. Discriminant validity was evaluated using both the Fornell and Larcker criteria as well as the Heterotrait-Monotrait Method (HTMT). To establish discriminant validity, it is crucial that the square roots of Average Variance Extracted (AVE) values, displayed along the diagonal, exceed the inter-construct correlations indicated in the lower off-diagonal cells, in line with the principles outlined by Fornell and Larcker (1981).

Table 3

Discriminant Validity: Fornell-Larcker Criterion

Variables	AP	EE	FC	PE	SI	UI
Academic Performance(AP)	**0.814**					
Effort Expectancy (EE)	0.531	**0.769**				
Facilitating Condition (FC)	0.548	0.608	**0.771**			
Performance Expectancy (PE)	0.645	0.671	0.606	**0.763**		
Social Influence (SI)	0.403	0.342	0.376	0.401	**0.862**	
Usage Intention (UI)	0.652	0.547	0.544	0.631	0.441	**0.890**

Table 3 indicates that the discriminant validity was established as the off-diagonal value as the square root of AVE i.e 0.814, 0.769, 0.771, 0.763, 0.862 and 0.890 are well above the inter-construct correlation.

Table 4

Discriminant validity: Heterotrait-Monotrait Ratio (HTMT)

Variables	AP	EE	FC	PE	SI	UI
Academic Performance (AP)						
Effort Expectancy (EE)	0.645					
Facilitating Condition (FC)	0.686	0.786				
Performance Expectancy (PE)	0.786	0.849	0.791			
Social Influence (SI)	0.488	0.420	0.484	0.493		
Usage Intention (UI)	0.760	0.665	0.662	0.757	0.519	

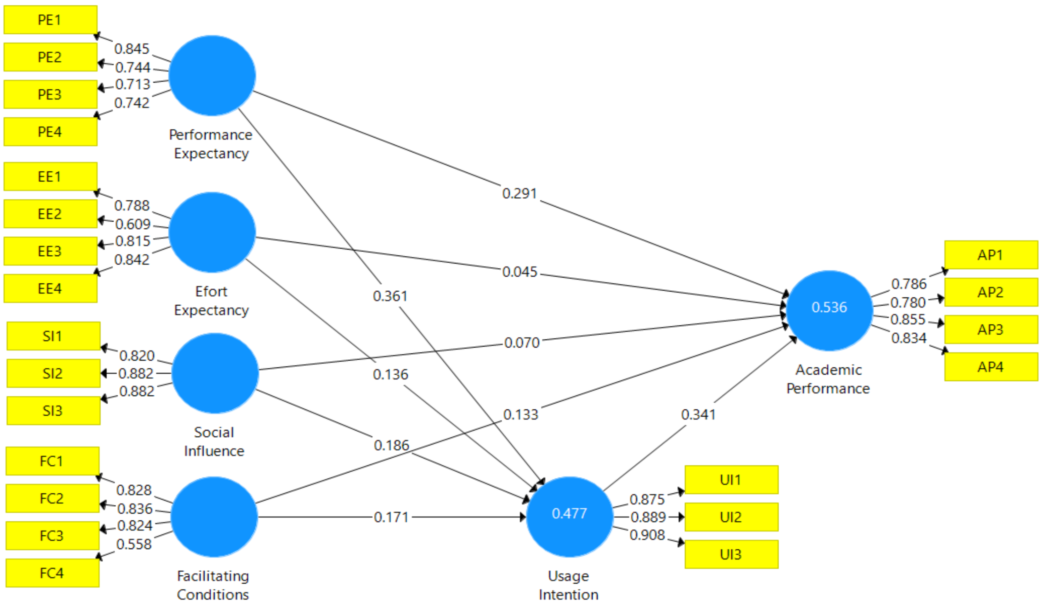
Table 4 presents the HTMT values crucial for establishing discriminant validity in the research. These values range from 0.420 and 0.879, consistently falling below the recommended threshold of 0.85, as stipulated by Henseler et al. (2015). This alignment with the established criterion further strengthens the confidence in the discriminant validity of research constructs.

Structural Model. The structural model is named as inner model The hypotheses are assessed and the path coefficient is validated with this model. The pictorial representation of the model is presented in Figure 2.

The structural model results, as depicted in Figure 2, illustrate the relationships between key constructs, including path coefficients, t-values, bootstrap confidence intervals, and R-square values. The model explains 47.7% of the variance in Usage Intention and 53.6% of the variance in academic performance, underlining its explanatory power. Figure 2 visually supports the findings that performance expectancy has a significant positive impact on academic performance (path coefficient = 0.291), affirming that students' expectations of improved performance through generative AI tools enhance their academic outcomes. While effort expectancy does not significantly affect academic performance directly (path coefficient = 0.045), it positively influences Usage Intention (path coefficient = 0.361), highlighting that ease of use is essential for motivating students to engage with the technology. Similarly, social influence and facilitating conditions significantly contribute to usage intention (path coefficients=0.186

Figure 2

Pictorial Representation of Structural Equation Model



and 0.171, respectively), emphasizing the importance of social support and available resources in promoting AI tool usage. The direct effect of usage intention on academic performance (path coefficient = 0.341) confirms its mediating role in connecting expectancy factors to academic outcomes. These findings suggest that a stronger intention to use generative AI tools positively impacts students' academic performance. Non-significant paths, such as effort expectancy to academic performance, indicate that not all variables directly impact performance, with some operating indirectly through usage intention.

Table 5

Structural Model: Impact of Behavioural Intention Factors on Intention to Use GAI and Academic Performance

Hypotheses	Relationship	*β* (Direct effect)	*SE*	*T*	*LCI* (2.5%)	*UCI* (97.5%)	f^2 Effects Size	Hypotheses
H_{1a}	PE-> UI	0.361	0.063	5.745**	0.233	0.477	0.117	Supported
H_{1b}	EE -> UI	0.136	0.060	2.267*	0.024	0.261	0.017	Supported
H_{1c}	SI-> UI	0.186	0.050	3.717**	0.089	0.286	0.053	Supported
H_{1d}	FC -> UI	0.171	0.056	3.602**	0.062	0.276	0.031	Supported
H_{2a}	PE -> AP	0.291	0.056	5.205**	0.181	0.404	0.077	Supported
H_{2b}	EE-> AP	0.045	0.057	0.795	-0.063	0.161	0.002	Rejected
H_{2c}	SI-> AP	0.070	0.043	1.647	-0.015	0.153	0.008	Rejected

H_{2d}	FC-> AP	0.133	0.057	2.335*	0.020	0.242	0.020	Supported
H_3	UI-> AP	0.341	0.052	6.493**	0.234	0.438	0.130	Supported
R^2 (UI = 0.477, AP = 0.536)								

Note: *n=384. Bootstrap samples=5000, CI (Bias corrected accelerated method)*
*LCI= Lower Confidence Interval, UCI= Upper Confidence Interval, ** p<.01, **p<.05*

Table 5 presents the major output on the impact of behavioural intention factors on the intention to use GAI and the academic performance of students. The model explained 47.7% of the variance in Usage Intention (UI) and 53.6% of the variance in Academic Performance (AP). Both these factors signify moderate variation on the outcome variables. The results show that performance expectancy significantly influences students' intention to use GAI ($\beta = 0.361, p < .01$), supporting H_{1a}, as students expect GAI to improve their performance. Effort expectancy ($\beta = 0.136, p < .05$), social influence ($\beta = 0.186, p < .01$), and facilitating conditions ($\beta = 0.171, p < .01$) also had positive effects on usage intention, supporting H_{1b}, H_{1c}, and H_{1d}, indicating that ease of use, peer support, and resource availability contribute to GAI adoption. For academic performance, performance expectancy ($\beta = 0.291, p < .01$) and facilitating conditions ($\beta = 0.133, p < .05$) had significant effects, supporting H_{2a} and H_{2d}, while effort expectancy ($\beta = 0.045, p > .05$) and social influence ($\beta = 0.070, p > .05$) did not, leading to the rejection of H_{2b} and H_{2c}. Lastly, the intention to use GAI significantly predicted academic performance ($\beta = 0.341, p < .01$), supporting H_3, indicating a strong link between usage intention and academic success. Since the f^2 values lie between 0.02 and 0.15, it explains that the removal of the variable/s from the model will have a medium-term effect on the R2.

Mediating Role of Intention to Use Generative AI

Table 6 exhibits the mediating role of intention to use GAI on the relationship between behavioral intention factors and academic performance.

Table 6

Mediating Model: Mediating role of Intention to Use Generative AI

Hypothesized Relationship	Total effect	Direct effect	Indirect effect	Confidence interval		*T*	Hypotheses	Remarks
				LCI	*UCI*			
H_{4a}: PE->UI-> AP	0.414**	0.291**	0.123**	0.068	0.187	4.048	Supported	Partial mediation
H_{4b}: EE->UI-> AP	0.092	0.045	0.047*	0.008	0.094	2.138	Supported	Full mediation
H_{4c}: SI->UI-> AP	0.134**	0.070	0.064**	0.029	0.102	3.412	Supported	Full mediation
H_{4d}: FC-> UI-> AP	0.191**	0.171**	0.058**	0.020	0.100	2.809	Supported	Partial mediation

Note: *n=384. LCI= Lower Confidence Interval, UCI= Upper Confidence Interval, ** p<.01, *p<.05*

Performance expectancy had a significant indirect effect on academic performance through intention to use ($\beta=0.123, p<.01$), indicating partial mediation and supporting H_{4a}. Effort expectancy also had a significant indirect effect ($\beta=0.047, p<.05$), but with a non-significant direct effect, indicating full mediation and supporting H_{4b}. Social influence showed a significant indirect effect ($\beta=0.064, p<.01$) with non-significant direct effects, confirming full mediation and supporting H_{4c}. Facilitating conditions had a significant indirect effect (*β=0.058, p<.01*), with both direct and indirect effects significant, indicating partial mediation, supporting H_{4d}.

DISCUSSION

The findings indicate that performance expectancy, effort expectancy, social influence, and facilitating conditions significantly influence students' intention to use GAI. Specifically, performance expectancy had a strong positive effect, confirming previous research (Almahri et al., 2020; Budhathoki et al., 2024; Edumadze et al., 2022; Grassini et al., 2024; Menon & Shilpa, 2023; Romero-Rodriguez et al., 2023; Strzelecki, 2023; Venkatesh et al., 2003). Students expecting GAI to enhance academic tasks were more likely to express intent to use it. Effort expectancy displayed a weaker yet significant relationship to use GAI, suggesting it is less pivotal than performance expectancy. This finding supports previous research (Budhathoki et al., 2024; Davis, 1989; Menon & Shilpa, 2023; Venkatesh & Bala, 2008) but contrasts with other studies (Romero-Rodriguez et al., 2023; Strzelecki, 2023; Venkatesh et al., 2012) that found effort expectancy significantly influenced mobile learning adoption, likely due to increased accessibility of technology. Social influence positively impacted the intention to use GAI, aligning with literature on peer recommendations (Al-Emran et al., 2023; Budhathoki et al., 2024; Hao, et al., 2024; Rahim et al., 2022; Wen et al., 2024). However, this effect was modest compared to performance expectancy, indicating varying cultural influences. Facilitating conditions positively influenced intention, supporting the notion that organizational resources are crucial (Almahri et al., 2020; Menon & Shilpa, 2023; Rahim et al., 2022; Ukut & Krairit, 2019). Contrastingly, prior studies found weak effects of facilitating conditions on technology adoption (Strzelecki, 2023; Venkatesh et al., 2012).

Regarding the impact of behavioral intention on academic performance, intention to use GAI significantly correlated with academic outcomes (Ali et al., 2023; Huang & Cheh, 2022; Ukut & Krairit, 2019). However, Boateng et al. (2023) indicated that while intention correlated with performance, its significance varied, suggesting other mediating variables may influence this relationship. The lack of significant effects for effort expectancy and social influence on academic performance contrasts with many studies (Ali et al., 2023; Boateng et al., 2016; Thompson et al., 1991; Vollmer, 1986), indicating that even if students intend to use GAI based on ease and social pressure, these factors may not directly enhance performance. The non-significance of effort expectancy and social influence on academic performance suggests that ease of use and social encouragement alone do not enhance academic outcomes. Academic performance is more likely driven by the perceived usefulness of the technology rather than its accessibility or social approval. Thus, while these factors may boost usage intention, they do not directly impact performance results. The study examined the intention to use GAI as a mediator between behavioral factors and academic performance, revealing partial mediation for performance expectancy and facilitating conditions. This suggests these factors influence academic performance both directly and indirectly through intention, aligning with Al-Rahmi et al. (2022). Full mediation was found for effort expectancy and social influence, where their impact on performance was entirely mediated by the intention to use GAI, reinforcing findings from Dahri et al. (2024) and Abbas et al. (2024).

The results align with the Unified Theory of Acceptance and Use of Technology (UTAUT) model, supporting that performance expectancy, effort expectancy, social influence, and facilitating conditions are key determinants of behavioral intention to use technology (Venkatesh et al., 2003). Additionally, the study's findings validate the Theory of Planned Behavior (TPB), demonstrating that behavioral intentions, shaped by these factors, predict actual behavior (Ajzen, 1991). The acceptance of intention's mediating role strengthens the validation of both UTAUT and TPB in educational contexts.

CONCLUSION

This study investigated the behavioral intention of students toward the adoption of generative AI (GAI) in their academic pursuits and its impact on academic performance, with a particular emphasis on the mediating role of the intention to use GAI. In conclusion, this study highlights the significant impact of key behavioral factors on students' intention to utilize Generative AI (GAI) in academic settings. Notably, performance expectancy emerged as the strongest predictor, reflecting students' beliefs in GAI's potential to enhance their academic tasks. Although effort expectancy and social influence are relevant, their effects are comparatively weaker, emphasizing the critical role of facilitating conditions provided by institutional support. The findings also establish a positive relationship between the intention to use GAI and academic performance, indicating that students with a strong intention to adopt GAI are likely to achieve better outcomes. Specifically, performance expectancy and facilitating conditions exert direct influences on academic performance, while ease of use and social influence do not directly predict success. Additionally, the mediating role of intention reveals that performance expectancy and facilitating conditions partially mediate academic performance, whereas effort expectancy and social influence exhibit full mediation, relying entirely on students' intentions to engage with GAI.

The findings of this study validate the UTAUT and Theory of Planned Behavior (TPB) frameworks in understanding the adoption of Generative AI (GAI) among students, particularly emphasizing performance and effort expectancy, with behavioral intention serving as a key mediator of academic performance. To translate these insights into practice, educational institutions should prioritize ensuring access to GAI tools and providing adequate training for both students and faculty. Collaborations with AI developers can enhance the availability of resources and support. Furthermore, establishing mentoring systems is vital for guiding the ethical integration of GAI into academic work. Given the strong student support for GAI utilization, institutions must develop clear policies outlining acceptable usage and implement comprehensive AI literacy programs. Such frameworks should also address ethical concerns to promote responsible adoption of GAI, ensuring that students understand both the capabilities and limitations of these technologies.

While this study provides valuable insights, it has limitations that warrant consideration. It primarily focuses on the original UTAUT model and the mediating role of intention to use, which may not capture the full complexity of GAI adoption. Investigating other potential mediators like perceived risk, trust, and competence would further validate the UTAUT model. The inclusion of moderating factors like types of educational institutions will help educators to develop GAI use policies as per the nature of the institutions. Future research should expand the investigation to include additional behavioral factors from the UTAUT 2 framework to further validate the theories in higher educational institutions context. Additionally, the research concentrated on limited higher education institutions with a limited sample size within a similar cultural context. Longitudinal studies with diverse samples would further enhance the generalizability of the results and allow for an in-depth analysis of the evolving relationship between GAI usage and academic outcomes. Since the study relies on a quantitative approach, future research should focus on a mixed-method exploration to provide a more comprehensive understanding of the use of GAI in higher education institutions.

CONFLICT OF INTEREST

Both authors declare that they have no conflicts of interest.

ACKNOWLEDGEMENTS

This research is based on the data and information obtained from the Mini Research Grants-2024 (Award No. MRN 04) which was made possible by the Centre for Research and Innovation (CRI) at Prithvi Narayan Campus in Pokhara. The authors would like to extend sincere gratitude to the CRI for their financial support in this research endeavor.

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