

Factors Affecting Behavioral Intention to Use ChatGPT: Mediating Role of Attitude

Sujan Raj Paudel¹, Neelam Acharya²

¹Research Scholar, Tribhuvan University, Kathmandu, Nepal

²BBA Graduate, DAV College, Tribhuvan University, Kathmandu, Nepal

sujanraj2001.srp@gmail.com; acharyaneelam387@gmail.com

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ABSTRACT

ChatGPT, widely recognized generative AI tool, supports diverse academic and non-academic tasks. Despite its growing use, determinants affecting students' behavioral intents to adopt and utilize ChatGPT effectively in educational setting remain unexplored. Current study seeks to explore these factors, focusing on mediating role of attitude in shaping students' intent to utilize ChatGPT. This study employs descriptive and causal research designs. Quantitative method enabled gathering of responses from 215 individuals of Kathmandu valley that were enrolled in both undergraduate and graduate programs across both private and government institutions through use of cross-sectional questionnaire. Questionnaire uses a 5- point Likert scale. Data are evaluated via Hayes Process Macro. The regression analysis indicated that system quality is most influential predictor of students' behavioral intent to use ChatGPT, alongside hedonic motivation and social influence. Correlation analysis exhibits substantial positive correlations among independent indicators and students' behavioral intention, suggesting that increases in these factors correlate with higher usage intentions. The mediation analysis shows that attitude fully mediates the implications of perceived usefulness, social influence, with strong indirect effects and no significant direct effects. Hedonic motivation, privacy, and system quality are partially mediated, with system quality having the strongest indirect effect. Overall, attitude plays a critical role in amplifying each of these elements on students' behavioral intent to utilize ChatGPT. Educators and institutions leverage such insights to integrate ChatGPT effectively into educational practices, supporting personalized learning experiences. For developers and AI providers, research will provide a deeper understanding of factors that drive adoption, enabling them to enhance the design and functionality of AI tools. For researchers, the current study enhances broader insights of AI's function within academic contexts, laying the foundation for future investigations into factors influencing AI adoption in learning environments. This study contributes on understanding how students in the Kathmandu Valley interact with ChatGPT, a widely used AI tool, and explores the key factors influencing their behavioral intentions, with a focus on attitudes as a mediator.

Keywords: Attitude, Behavioral intention, Hedonic motivation, System Quality

1. Introduction

Artificial intelligence (AI) has evolved into an innovative instrument for driving advancement and change across many sectors in the digital age. Being able to evaluate extensive data sets, derive insights from trends, and engage with users has resulted in notable technological improvements (Karki et al., 2023; Rudolph et al., 2023). When researchers first started investigating the fundamentals of machine intelligence and automated systems in the 1950s, the roots of AI-driven innovations, such as chatbots, existed (King & ChatGPT, 2023; Oravec, 2019).

The ability of a system to correctly understand outside input, learn from it, and apply the information gained to carry out particular activities and objectives through adaptive mechanisms is known as artificial

intelligence (AI) (Haenlein et al., 2019). Since AI technology is becoming more widely used, it plays a bigger part in education by facilitating interactive involvement in blended learning environments, individualized learning experiences, and adaptive assessments (Zhang & Aslan, 2021). Generative AI tools like ChatGPT have become crucial parts of students' academic journeys as the demand for flexible and self-directed learning keeps growing (Rudolph et al., 2023).

Constructivist Learning Theory forms the basis for exploring how ChatGPT contributes to students' educational growth. Constructivism emphasizes active construction of knowledge, where learners interact with tools, materials, and their environment to develop understanding (Taber, 2012). In this regard, ChatGPT supports constructivist learning by fostering autonomous and interactive learning experiences, enabling students to explore concepts, pose inquiries, and obtain instant feedback to deepen their understanding (Makewa, 2019).

Furthermore, a technology-supported constructivist environment empowers students to analyze, interpret, and organize information to close knowledge gaps (Ghimire et al., 2022; Kılıç et al., 2003). This method corresponds to the Technology Acceptance Model (TAM), emphasizing the importance of perceived utility, user-friendliness as primary factors shaping individuals' intentions to adopt technology (Karki and Dahal, 2024; Shao, 2020; Woodeson, 2021). ChatGPT's capability to offer rapid, accurate, and applicable support enhances its perceived usefulness, while its user-friendly design ensures ease of use. These factors, combined with constructivist principles, create an optimal learning environment where students actively engage, develop problem-solving skills, and manage their knowledge acquisition processes.

ChatGPT, a product of OpenAI, is particularly effective in accelerating the educational journey of students (Liu & Ma, 2023), offering quick, accurate answers to queries (Ullah et al., 2024), fostering cognitive growth and success (Rai & Dahal, 2024; Yu, 2023). It is widely used for academic purposes, such as clarifying concepts, assisting with assignments, and providing explanations of complex topics (van Dis et al., 2023). Beyond academic application, ChatGPT serves as a general reference resource, enabling students to instantly access information on diverse subjects (Cao et al., 2023). The platform's 24/7 availability enhances its appeal as a source of rapid aid (Baidoo-Anu & Owusu Ansah, 2023).

By January 2023, ChatGPT had surpassed a hundred million daily subscribers, positioning itself among the most rapidly expanding consumer applications (Duong et al., 2023). It has evolved through four versions with increasing capabilities: ChatGPT-One with one hundred seventeen million parameters, ChatGPT-two with one billion five hundred million, ChatGPT-three with one hundred seventy-five billion, and ChatGPT-four boasting an impressive hundred trillion parameters. This growth regarding features significantly enhanced its performance, allowing it to create text that accurately resembles natural language (OpenAI, 2023).

ChatGPT is versatile, handling activities like transcription, crafting promotional content, analyzing reports, and writing code (Elbanna & Armstrong, 2023; Lee, 2023). Additionally, it can be used for client support, publishing, and dialect interpretation, offering replies in several languages (Keiper et al., 2023). OpenAI's programming interface enables creators to integrate ChatGPT into diverse applications and systems (OpenAI, 2022).

Despite its rapid adoption, many aspects of ChatGPT's use remain underexplored. Understanding students' motivations for using ChatGPT is critical, especially considering its increasing integration into academic and non-academic contexts (Foroughi et al., 2023). Considering ChatGPT's growing presence in enrollees' academic plus personal lives, understanding the factors driving its adoption is essential. The study explores how perceived usefulness, hedonic motivation, privacy, social influence, and system quality influence students' behavioral intentions toward ChatGPT, with attitude as a mediating variable. By examining these elements, the research aims to offer key takeaways concerning underlying motivations and barriers influencing ChatGPT's usage. This understanding shall improve AI's use in education,

ensuring it aligns with students' needs and expectations while maximizing their educational potential.

2. Literature Review and Hypothesis Development

Constructivist Theory

Constructivist learning underscores the requirement for students to actively explore and grasp new information (Piaget, 1980; Schunk, 2012), a process that ChatGPT can facilitate. ChatGPT acts as a bridge, incorporating past knowledge and experiences to make it easier for students to develop new understanding by promoting interactive discussions and student participation. Furthermore, by giving tailored suggestions for additional education, assisting students in recognizing their mistakes, and pointing them toward progress, its capacity to deliver personalized feedback further strengthens this process (Dahal & Joshi, 2024; Ippolito et al., 2022; Vygotsky, 1962). This feature makes ChatGPT a useful "More Knowledgeable Other" in educational practice (Geng & Razali, 2020).

Additionally, authentic evaluation, which measures students' capacity to utilize their skills and understanding in practical situations, is highly regarded by constructivist theory (Wiggins, 1990). By drawing on students' past experiences and providing tailored feedback that points them toward improvement and greater comprehension, incorporating ChatGPT into assessment techniques can promote active knowledge creation. As an MKO, ChatGPT facilitates the identification of mistakes and the creation of new information. A fundamental tenet of constructivism, adaptive learning postulates that prior information continuously shapes learning (Schunk, 2012). This idea is supported by ChatGPT's logical algorithms, which produce fresh discoveries by drawing on preexisting knowledge (Hein, 1991). As a result, ChatGPT is an effective tool for promoting constructivist education.

Technology Acceptance Model (TAM)

TAM has been widely examined; applied across various settings, including higher education, online instruction, and senior high schools (Shroff et al., 2011; Wojciechowski & Cellary, 2013). It outlines four main elements: perceived utility (PU), perceived ease of interaction (PEI), attitude toward adoption (ATA), and behavioral intention to adopt (BIA). Over time, a framework has been extended to involve elements like trust, improving its explanatory effectiveness. Consequently, researchers have highlighted various challenges and limitations of TAM, suggesting further refinement to address emerging contexts and future research requirements. Earlier studies have suggested integrating trustworthiness, social presence, enjoyment-based motivation, and learner perspectives into TAM. This study incorporated these factors into the framework to assess their significance and impact (Davis, 1989).

The growing interest in Chatbots within academic literature reflects advancements in AI systems. Initially, Chatbots utilized computational linguistics to interpret user inputs and retrieve the most relevant responses from a predefined database. However, to address real-time NLP challenges and provide instant responses, Chatbots have increasingly adopted advanced linguistic approaches (Dwivedi et al., 2023; Cotton et al., 2023; Kushwaha & Kar, 2021). In the service delivery sector, researchers widely agree that the successful implementation of AI technology depends significantly on customer acceptance (Belanche et al., 2020; Lu et al., 2019). Studies such as those by Balakrishnan et al. (2021) and Lim & Zhang (2022) have utilized TAM (Davis et al., 1989) to investigate user engagement of AI-driven technologies. Based on the Technology Acceptance Model (TAM), a person's decision to adopt technology depends on two main elements: perceived usefulness, meaning the individual assumes technology will enhance efficiency, and perceived ease of use, indicating that operating technology needs little effort.

Due to its simplicity and adaptability, TAM has found broad application and has been extended within several sectors of research (Giovanis et al., 2012; Khadka et al., 2024; Min et al., 2021; Song et al., 2021). Its utility became particularly prominent amidst the swift technological developments of the 2000s. For example, TAM was used to explore variables driving adoption of digital banking services in Saudi Arabia, leveraging data from the Global Financial Index Database (2017) to evaluate how perceived ease of use and perceived value affect user acceptance.

2.1 Relationship between Variables

Perceived Usefulness

Perceived usefulness reflects how much individuals think adopting a new technology will improve their capability to complete tasks efficiently. Its perceived utility is an essential determinant of an information technology's acceptance and broad adoption. For example, consumers' behavioral intent to interact with social networks for news consumption is greatly influenced by usability (Han et al., 2023). People will more likely adopt a technology when they see its benefits (Ghimire et al., 2024). However, according to Ryan and Worthington (2021), users' behavioral intentions are not equally influenced by perceived usefulness and ease of use in TAM. Even if students may not find online interventions particularly user-friendly, their conviction in the potential benefits of such technologies may motivate them to utilize them. Likewise, students could consider emerging technology simple to navigate, yet ultimately ineffective. Numerous researches have highlighted perceived utility as key determinant in boosting technology acceptance (Wu & Wang, 2005). Virtual assistants, for example, are widely accepted when users perceive their usefulness. Hence, investigating the impact of perceived value in molding perceptions about the application of ChatGPT for learning would be an intriguing field of study.

H1: There is a significant relationship between perceived usefulness and behavioral intention to use ChatGPT.

Hedonic Motivation

Hedonic motivation is an applicant's desire to employ certain technology because of its intrinsic satisfaction, satisfaction, or curiosity (van der, 2004; Venkatesh & Xu, 2012). According to the study, hedonic motivation is vital in adopting technology in many educational settings. Dajani and Abu Hegleh (2019) discovered that hedonic motivation is essential to university students' engagement with animation. Similarly, works of Azizi et al. (2020), Twum et al. (2022), and Zwain (2019) investigated impacts concerning the execution of learning via mobile devices, virtual learning environment, and digital learning platforms, respectively. In the context of ChatGPT, hedonic motivation relates to students' enjoyment and engagement with the tool and their willingness to learn about emerging AI-driven technologies.

H2: There is a significant relationship between hedonic motivation and behavioral intention to use ChatGPT.

Privacy

Privacy pertains to a person's belief and perceived authority regarding the gathering, utilizing, and distributing their private data (Basak et al., 2016). This concept significantly affects user habits, notably adoption and usage of technological tools. Privacy is inseparably linked to the Technology Acceptance Model (TAM), as users' perceptions of privacy and their ability to control personal information can significantly affect their perception of a technology's value and ease of use (Al-Sharafi et al., 2016; Basak et al., 2016; Wu et al., 2023). If users believe their data is being gathered or utilized without explicit

agreement, technology may appear less advantageous or user-friendly, even if it provides actual benefits (Hajian et al., 2016). To maintain user engagement, service suppliers should address confidentiality issues while considering societal impact (Zhou & Li, 2014). When consumers see their interactions with the system as confidential and safe, their trust in the technology grows, increasing its perceived utility (Basak et al., 2016). Furthermore, systems prioritizing privacy and data protection tend to provide greater user comfort and ease, improving perceived ease of use. This feeling of confidence and comfort motivates individuals to investigate system capabilities and engage with its features (Featherman et al., 2010). Transparent communication and explicit privacy policies are critical for effective data protection measures and establishing user confidence (Dragan and Manulis, 2018). Handling data protection and applying risk-reduction approaches can help to build user trust and influence technology adoption (Joinson et al., 2010). Finally, maintaining data privacy and management increases user trust and certainty in adopting technology (Sicari et al., 2015).

H3: There is a significant relationship between privacy and behavioral intention to use ChatGPT.

Social Influence

Al-Adwan and Al-Debei (2023) emphasize the importance of social formations, including peers, teachers, and family members, in children's decisions to adopt and continue utilizing technology. This shows that people adopt attitudes and behaviors of their reference groups to conform to social standards. Students, in particular, are motivated by a need for social approval and integration, which makes them prone to use tools like ChatGPT if they believe their peers support their worth. For example, Foroughi et al. (2023), Menon and Shilpa (2023), and Strzelecki (2023) all found that students are inclined to access ChatGPT if they assume it is supported by people they respect. Thus, social influence has a profound effect in directing students' choices to use ChatGPT, since it satisfies the psychological need for social recognition and validation.

H4: There is a significant relationship between social influence and behavioral intention to use ChatGPT.

System Quality

System quality is an analysis of an information system based on essential properties such as perceived usability, functionality, accessibility, and adaptability (Al-Fraihat et al., 2020). In current research, system quality is related to how "user-friendly" ChatGPT is and how simple it is to use. Al-Fraihat et al. (2020) discovered effectiveness of an educational system has a favorable impact on user satisfaction and indirectly influences system adoption. E-learning platform features like interactive learning tools help to increase user satisfaction and system utilization. Similarly, Alzahrani et al. (2019) discovered that system quality strongly predicts student satisfaction with digital library systems. As a result, ChatGPT's system quality is projected to affect student happiness and overall user experience profoundly.

H5: There is a significant relationship between system quality and behavioral intention to use ChatGPT.

Students Attitude

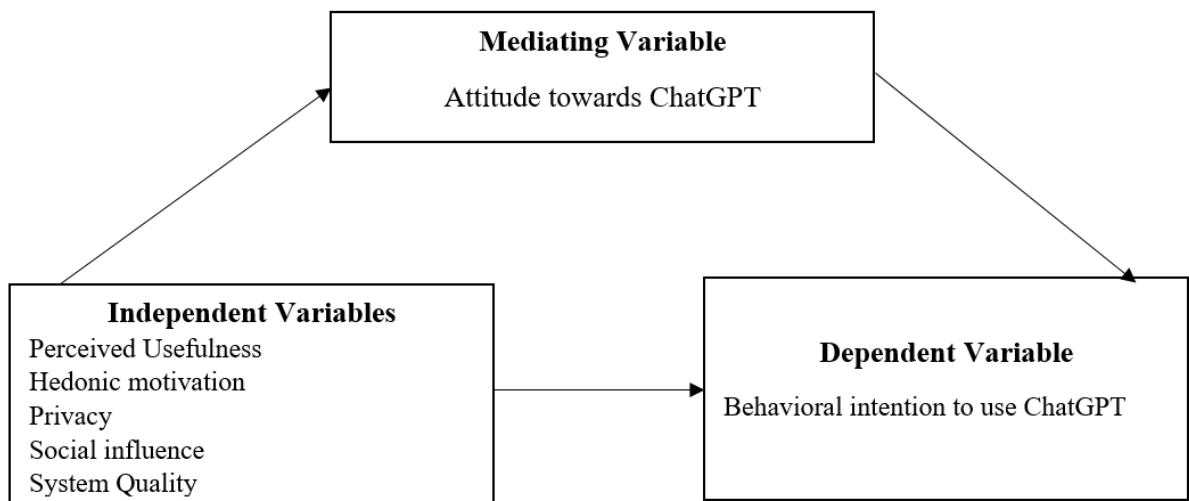
Attitude is an individual's tendency to react positively or negatively towards things, individuals, organizations, events, or any other definable feature of their surroundings (Ajzen, 1989). It involves

components concerning actions, thought processes, and emotional states (De Luna et al., 2019). Technology Acceptance Model (Davis, 1989) and Theory of Planned Behavior (Ajzen, 1991) acknowledge attitude as an essential element influencing users' behavior and intention to incorporate specific technology. Furthermore, attitudes are often highlighted as crucial in the widespread use of digital payment systems (De Luna et al., 2019). Gupta and Arora (2017) assert that positive sentiments help to enhance mobile banking adoption. Scholars have generally maintained that attitude has emotional and intellectual aspects (Kabra et al., 2023; Montano & Kasprzyk, 2015). Davis (1985) proposed that perceived utility and ease of usage positively affect perception toward information technology. When users develop a positive stance on technology's utility and usability, their propensity to adopt it grows. TAM has been widely employed to predict and clarify many information technologies, with most hypotheses having empirical support (Larue & Watling, 2021). For example, Adu-Gyamfi et al. (2022) applied TAM to investigate motorists' attitudes toward in-vehicle tracking systems. Similarly, research has shown that perception of usefulness influences users' goals to persist in continuing e-government platforms (Hamid et al., 2016), attitudes toward e-commerce (Sahoo et al., 2022), and willingness to adopt driver assistance technologies (Rahman et al., 2018). Based on these findings, attitude is anticipated to have profound consequences on acceptance, integration of immersive technologies like ChatGPT.

- H6(a): Attitude mediates the relationship between perceived usefulness and behavioral intention.*
- H6(b): Attitude mediates the relationship between hedonic motivation and behavioral intention.*
- H6(c): Attitude mediates the relationship between privacy and behavioral intention.*
- H6(d): Attitude mediates the relationship between social influence and behavioral intention.*
- H6(e): Attitude mediates the relationship between system quality and behavioral intention.*

Behavioral Intention

Behavioral intention is a powerful indicator of real-world technology utilization because it reflects users' ability and desire to interact with ChatGPT in everyday scenarios (Chai et al., 2021). Foroughi et al. (2023) investigated educators' behavioral intents to implement ChatGPT in their instructional methods. The outcomes revealed that perceived utility, convenience of use, and social norms influenced educators' intentions to utilize ChatGPT, emphasizing the necessity of addressing these issues to increase technology adoption.



(Source: Tiwari et al., 2021; Albayati, 2024; Foroughi et al., 2024)

Figure 1: Conceptual Framework

3. Research Methods

Research Design

To examine determinants affecting students' acceptance and utilization of ChatGPT, the study employs both descriptive and causal research designs. It identifies and explores these factors by comparing different student groups based on their perceptions and usage patterns. A cross-sectional study design is applied, and the unit of analysis is individual students.

Population and Sampling

Participants in this study are students from various academic disciplines within the Kathmandu Valley who use or have the potential to use ChatGPT. These students are enrolled in undergraduate and graduate programs across private and government institutions, ensuring a diverse representation of student experiences and attitudes towards ChatGPT. Focusing on the Kathmandu Valley allows for a targeted examination of student behaviors and perceptions in this specific geographic and educational context. The non-probability convenience sampling method is used with actual sample size of 215. The unit of analysis is individual analysis as the questionnaire is distributed to each individual. A total of 215 questionnaires were completed from 300 distributed questionnaires, yielding a response rate of 71.67%.

Data Collection Method

Statistics for this research are gathered through a questionnaire survey approach. The questionnaire is designed to capture primary data from students in the Kathmandu Valley regarding their perceptions, attitudes, and behavioral intentions towards using ChatGPT. The survey includes sections that assess variables such as perceived usefulness, hedonic motivation, privacy concerns, social influence, system quality, and overall attitudes towards ChatGPT. By utilizing this method, the study aims to obtain a direct and reliable insight into the factors influencing students' adoption and use of ChatGPT, ensuring that the findings reflect their real experiences and intentions. The variables in our study have been measured using a five-point Likert scale that ranged from Strongly Agree to Strongly Disagree, where 1 represents Strongly Agree, 2 represents Agree, 3 represents Neutral, 4 represents Disagree, and 5 represents Strongly Disagree.

Method of Data Analysis

Data are analyzed using correlation, regression, and mediation analysis.

4. Data Analysis and Results

4.1 Respondents' profile

Table 1: Demographic profile of respondents

Characteristics	Categories	Frequency	Percentage (%)
Gender	Male	50	23.3
	Female	165	76.7
Age	16-18	21	9.8
	19-21	68	31.6
	22-24	107	49.8
	24 and above	19	8.8

Education Level	High School	46	21.4
	Bachelors	153	71.2
	Masters	16	7.4
Type of Institution	Private	169	78.6
	Government	46	21.4

Source: Questionnaire Survey

The demographic profile of respondents highlights key characteristics such as gender, age, education level, and type of institution. The majority of participants are female, with the largest age group being 22-24, and most respondents are enrolled in Bachelor’s programs attending private institutions.

4.2 Assessment of Measurement Model

Cronbach's alpha coefficient, as suggested by Cronbach (1994), was used to assess the instrument's reliability. According to Nunnally & Bernstein (1978), a Cronbach’s alpha value of 0.5 is considered acceptable, while a value of 0.7 or higher is deemed more satisfactory. Study’s findings show that reliability analysis yielded Cronbach’s alpha values exceeding 0.7 for all variables, confirming a high level of reliability across measured constructs.

Table 2: Reliability Analysis

Variables	No of Items	Cronbach's Alpha
Perceived Usefulness	6	0.701
Hedonic Motivation	5	0.822
Privacy	5	0.793
Social Influence	5	0.722
System Quality	5	0.746
Attitude	5	0.807
Behavioral Intension	5	0.874

(Source: SPSS Output)

4.3 Assessment of Structural Model

Pearson's correlation measures the relationship between independent and dependent variables, with coefficients near 1 indicating a strong positive correlation, -1 indicating a strong negative correlation, and 0 indicating a minimal linear relationship (Nickolas, 2023).

Table 3 shows that system quality has the strongest correlation with Behavioral Intention, highlighting its key role in influencing users’ intention to adopt ChatGPT.

Table 3: Correlation Analysis

	Behavioral Intension	Perceived Usefulness	Hedonic Motivation	Privacy	Social Influence	System Quality
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Behavioral Intension 1

Perceived Usefulness	.455**	1				
Hedonic Motivation	.462**	.526**	1			
Privacy	.317**	.365**	.405**	1		
Social Influence	.444**	.404**	.511**	.393**	1	
System Quality	.601**	.435**	.346**	.444**	.376**	1
N	215	215	215	215	215	215

** correlation is significant at the 0.01 level (2-tailed).

Source: SPSS Output

Table 4: Regression Analysis

Model	Unstandardized		Standardized		Collinearity			R square	F value
	Coefficients		Coefficients		Statistics				
	B	Std. Error	Beta	t	Sig.	Tolerance	VIF		
(Constant)	-0.112	0.204		-0.546	0.586				
Perceived Usefulness	0.152	0.093	0.103	1.625	0.106	0.638	1.567		
Hedonic Motivation	0.208	0.070	0.196	2.980	0.003	0.597	1.674		
Privacy	-0.061	0.058	-0.064	-1.065	0.288	0.707	1.414		
Social Influence	0.193	0.077	0.156	2.505	0.013	0.668	1.497		
System Quality	0.602	0.080	0.458	7.531	0.000	0.698	1.432	0.460	35.667

Dependent Variable: Behavioral Intention

(Source: SPSS Output, 2024)

Table 4 presents the regression analysis highlighting the significant relationships of the independent variables, i.e., system quality, hedonic motivation, and social influence, with the dependent variable, i.e., behavioral intention. However, perceived usefulness and privacy don't show a substantial correlation with behavioral intents. The collinearity statistics confirm that there are no multicollinearity issues among the variables, as all VIF values remain below 2.5. The R Square value of 0.460 means that 46% of the variation in Behavioral Intention is described by independent determinants in the study. F-value of 35.667 with significance level of $p < 0.001$ confirms that the model is statistically significant.

Table 5: Mediation Analysis

Relationship	Total Effect	Direct Effect	Indirect Effect	Confidence Interval		t-statistics	Conclusion
				Lower Bound	Upper Bound		
A → Y < > M	0.6538	0.0933	0.5604	0.4161	0.7112	7.2565	Full

							Mediation
	0.000	0.2155					
							Partial
B → Y < > M	0.4913	0.1487	0.3425	0.2372	0.4628	7.6066	Mediation
	0.000	0.0043					
							Partial
C → Y < > M	0.3024	0.0946	0.2078	0.122	0.3053	4.8794	Mediation
	0.000	0.0302					
							Full
D → Y < > M	0.5509	0.0999	0.4511	0.3323	0.581	7.2389	Mediation
	0.000	0.1114					
							Partial
E → Y < > M	0.7892	0.1749	0.6144	0.465	0.7869	10.9644	Mediation
	0.000	0.0277					

Source: SPSS Output

(A= Perceived Usefulness, B= Hedonic Motivation, C= Privacy, D= Social Influence, E=System Quality, Y= Behavioral Intention and M= Attitude)

Table 5 shows that attitude fully mediates the effects of perceived usefulness and social influence, with strong indirect effects and no significant direct effects. Hedonic motivation, privacy, and system quality are partially mediated, with system quality having the strongest indirect effect. Overall, attitude plays a critical part in enhancing the impact of these variables on students' behavioral intents to utilize ChatGPT.

5. Discussions

Findings of this study provide key understandings towards the elements influencing students' behavioral intentions to use ChatGPT. System quality emerged as the most significant factor, indicating that students prioritize a medium that is easy to use, efficient, and reliable. This aligns with findings from Komba (2024), Foroughi et al. (2024), and Alzahrani et al. (2019), who stressed the necessity of usability and accessibility in promoting technology adoption. These studies collectively highlight that a well-designed system enhances user satisfaction and encourages continued use. However, in contrast to Abdalla et al. (2024), who discovered that privacy concerns have a substantial effect on adoption, such study suggests that students in Kathmandu don't prioritize privacy concerns.

Hedonic motivation, which relates to the satisfaction students receive when using ChatGPT, also plays a significant part in influencing behavioral intention. This is consistent with Tiwari et al. (2021), Dajani and Abu Hegleh (2019), and Azizi et al. (2020), who found that enjoyment is a critical factor in adopting educational technologies. However, Cavazos et al. (2024) cautioned that while enjoyment can drive adoption, excessive focus on entertainment risks overshadowing academic utility. This study supports the positive role of enjoyment but suggests that balancing engagement with academic effectiveness remains important.

The study also highlights the social influence's role, which reflects peer influence and societal recommendations on students' decisions to adopt ChatGPT. This study's results correspond with findings by Tan et al. (2024) identified peer support and discussions as key motivators for technology adoption. However, unlike Abdalla et al. (2024) and Leelavathi and Surendhranatha (2024), who noted that privacy

and ethical concerns often dampen trust in AI tools, this study found social influence to outweigh such concerns in the context of Kathmandu students.

Interestingly, perceived usefulness, which is typically a crucial factor of technology acceptance, had a weaker direct impact in this study. This finding contrasts with Alotaibi et al. (2020), who reported that the belief in a tool's practical benefits strongly influences its adoption. Based on this study, students appeared to value ease of usage and enjoyment of ChatGPT more than its direct utility for improving performance, suggesting that the tool's adoption is influenced by factors beyond its functional benefits.

Finally, attitude emerged as a critical mediating factor, shaping how variables like system quality, enjoyment, and social influence impact behavioral intention. This finding is consistent with Albayati (2024) and Foroughi et al. (2024), who also found that favourable opinion toward a technology considerably improves adoption intent. The study's mediation effect indicates how crucial it is to cultivate positive perceptions to promote the adoption of AI tools like ChatGPT.

Findings align with the TAM presented by Fred Davis and the Constructivist Learning Theory introduced by Jean Piaget. TAM explains how system quality and the mediating role of attitude influence behavioral intention, while a weaker direct impact of perceived usefulness highlights the importance of attitudes. Constructivist Learning Theory supports the significance of hedonic motivation and social influence, pointing out the relevance of engaging, interactive environments and social dynamics in molding learning behaviors. These frameworks underscore the need for tools like ChatGPT to integrate technical usability with psychological and social engagement.

It's worth noting that the significance of these elements may differ among various groups of students, and pinpointing the most influential ones can be challenging. Additionally, the results of this study may be specific to the sample of students surveyed. Therefore, future researchers should consider exploring additional factors that could impact students' adoption and usage processes. By incorporating a broader range of factors into future studies, scholars can gain deeper insights into the complex dynamics underlying the adoption and usage of ChatGPT.

6. Conclusion

Present research highlights the variables affecting students' adoption and usage of ChatGPT, emphasizing its transformative potential in education. Using a comprehensive conceptual framework, the research analyzed key factors, including perceived usefulness, hedonic motivation, privacy concerns, social influence, and system quality, through a structured survey of 215 students in the Kathmandu Valley. Statistical methods like descriptive analysis, correlation, and regression evaluation were employed to investigate relationships between these variables and behavioral intention. A detailed mediating analysis revealed the critical role of attitude as an intermediary, enhancing comprehension of adoption dynamics and sustained usage.

Findings highlight system quality, hedonic motivation, and social influence being the most important indicators of behavioral intention, with system quality emerging as the most critical. This underscores the importance of usability, reliability, and design in fostering positive user experiences. The mediating role of attitude was crucial, fully or partially bridging the relationship between these factors and behavioral intention, demonstrating that cultivating positive perceptions is essential for sustained adoption. While perceived usefulness and privacy concerns showed limited direct impacts, their indirect effects through attitude remain vital for building trust and acceptance. These findings successfully address the study's research questions, offering a clear understanding of the dynamics determining adoption and sustained usage.

This serves as a critical foundation for ongoing research by determining key aspects that require deeper

inquiry and development to refine AI implementation strategies in educational settings. It highlights the necessity of understanding the nuanced interplay between technological capabilities, user perceptions, and educational objectives. This entails exploring how ChatGPT might be customized to meet diverse learning needs, improve accessibility, and foster inclusivity across varied student demographics. Moreover, there is a clear need to continuously evaluate the evolving expectations of users to ensure that these tools remain up-to-date, engaging, and impactful. By addressing these dimensions, future efforts can pave the way for more targeted and impactful AI-driven learning solutions, ultimately maximizing their potential to boost educational results. Such an approach contributes significantly to the advancement of modern education, ensuring that AI technologies align seamlessly with learners' needs while driving innovation and academic success.

7. Implications and Limitations

The study's findings highlight several actionable steps to improve ChatGPT's integration in learning environments. First, since system quality is a key factor influencing students' intentions, developers should focus on creating a tool that is easy to use, reliable, and efficient. Enhancing features like performance, intuitive design, and responsiveness will ensure positive user experiences and encourage long-term use.

Fostering positive attitudes toward ChatGPT is also essential, as it plays a significant role in influencing behavioral intentions. Educators and developers can achieve this by promoting the benefits of ChatGPT in learning, showcasing its practical applications, and addressing any misunderstandings or doubts about its effectiveness. Highlighting its role in improving learning outcomes can strengthen students' perceptions and increase acceptance.

Although privacy concerns have a limited direct impact, they are still important for building trust. Developers should ensure transparent data policies and strong security measures to protect users' information, which will help establish confidence in the tool. Additionally, leveraging social influence, such as peer recommendations and institutional support, can encourage students to adopt ChatGPT. Positive endorsements from teachers, classmates, and influencers can make the tool more appealing and credible.

To ensure inclusivity, ChatGPT should be tailored to meet diverse learning needs and made more accessible to underrepresented groups. Developers should focus on features that accommodate different educational backgrounds and preferences, ensuring that all students can benefit equally. Institutions can also integrate ChatGPT into their learning systems by organizing training sessions for both learners and instructors to demonstrate its practical applications and benefits effectively.

Lastly, developers should continually improve ChatGPT by collecting feedback from users and conducting regular evaluations. This will help keep the tool relevant and aligned with students' evolving needs. Ongoing research is also necessary to identify new opportunities and challenges, ensuring that ChatGPT continues to enhance learning outcomes and support innovation in education.

This research has its own set of limitations. The sample size of 215 participants may not sufficiently capture the full diversity of the student population, potentially limiting the applicability of the results. The study was carried out at a few chosen Kathmandu Valley institutions, restricting the universality of results to different locations or academic settings. Response bias, including social desirability bias, may have influenced participants' answers, thereby impacting the reliability and accuracy of the data. Adopting a non-probability sampling method limits the validity of the study, as it does not ensure proportional representation of all subgroups within the intended demographic.

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