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Drivers and Barriers of ChatGPT Adoption in Higher Education: Insights from Multiple Theories

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Abstract

This study aims to discuss the driving forces and obstacles that influence the usage of ChatGPT among higher education postgraduate research scholars. The data analysis was conducted using the partial least squares structural equation modeling (PLS-SEM) with the consideration of 436 valid responses which were collected from post graduate research scholars in Pakistan. The study relies on the behavioral reasoning theory (BRT), the technology acceptance model (TAM-2), and the theory of innovation resistance (IRT) to explain determinants that facilitate and hinder the use of technology. The findings confirmed that perceived ease of use, perceived usefulness, and social influence (reason for) are positively related. Tradition, risk, and usage barriers (reasons against), on the other hand, have a negative relationship with the intention of the users to use ChatGPT. These results indicate that adoption drivers and resistance factors influence simultaneously the usage of ChatGPT in academic context. In addition to integrating three prominent theoretical perspectives on technology adoption and resistance, this study contributes to the literature on AI-based technology adoption and advances understanding of the behavioral mechanisms underlying ChatGPT usage. This study also has practical implications to the institutions of higher learning and policymakers on how to effectively and responsibly integrate the use of generative AI tools in higher learning institutions.

Keywords: Behavioral reasoning theory, technology acceptance model, innovation resistance theory, perceived usefulness, perceived ease of use, social influence, attitude towards ChatGPT, intention to use ChatGPT.

1. Introduction

ChatGPT is the brainchild of open artificial intelligence (AI), a non-profit organization with a deep interest in tying together digital intelligence to the benefit of humanity (Ray, 2023). OpenAI envisions the development of artificial general intelligence (AGI) that can enhance human productivity while ensuring responsible use, development, and deployment of AI models (Singh et al., 2023). ChatGPT is proficient in providing clear and comprehensive responses to user prompts. It is built on the GPT-3.5 model. The system continues to evolve through iterative updates based on user interaction and feedback (Ray, 2023; Singh et al., 2023). In the current world, AI-based conversational tools are evolving how people communicate with technology. These tools are now adopted quickly in customer service, content writing, translation, education, and many other contexts.

Since its release, ChatGPT has played a vital role in academic settings and e-learning (Paul et al., 2023). Wen and Wang (2023) demonstrated that AI platforms like ChatGPT can adequately generate human-like written content. Around one million individuals have adopted this platform worldwide in just one week after its declaration, demonstrating the rapid adoption of generative AI tools (Singh et al., 2023). Moreover, extant literature highlighted the vital role of ChatGPT in higher education, specifically in assisting students with writing tasks while fostering the cultivation of problem-solving abilities (Singh et al., 2023; Wen & Wang, 2023).

Despite the rapid proliferation of ChatGPT, its integration into higher education remains both promising and contested. The generative AI-based tools are also efficient, academic supportive, and highly productive, but they also provoke the issues of overreliance, academic integrity, and replacement of skills. Therefore, this duality generates a compelling motivation to systematically examine the behavioral mechanisms underlying its adoption. The more usage of AI within academia, it is imperative to examine whether research scholars are equipped to engage with this tool effectively within evolving digital academic ecosystems (Sok & Heng, 2024). In addition, ChatGPT is deemed as a significant academic support tool for creating reports, crafting essays, and producing scholarly articles in a systematic way. Likewise, it executes proofreading functions and corrects structural and grammatical errors (Qasem, 2023). Irrespective of such benefits, there is a little knowledge on why people are embracing or opposing such tools especially in emerging economies.

The recent study by Paul et al. (2023) showed that there is little studies that examine the determinants that support and hinder the adoption of generative AI tools, including ChatGPT, in the educational setting. Specifically, the literature lacking the research aimed at investigating the adoption of ChatGPT in the specific environment of South Asia and, more precisely, Pakistan (e.g., Zeb et al, 2024, Dorobăț & Corbea, 2025). Even though emerging research has begun integrating advanced adoption models such as UTAUT3 to explain ChatGPT usage (Parveen et al., 2026), comparative examinations incorporating both enabling and resistance mechanisms remain scarce. Moreover, existing literature is concentrated on technologically developed economies, leaving developing countries underexplored despite their rapidly expanding higher education sectors and increasing digital transformation programs. Pakistan's higher education sector has experienced substantial growth in recent decades, with over 240 recognized universities and degree-awarding institutions under the Higher Education Commission as reported in HEC annual report 2023. Instead of increasing digital infrastructure, empirical research examining AI-based tool adoption within this context remains limited. However, there is a noticeable gap in empirically examining the behavioral intentions of research scholars towards ChatGPT adoption.

Particularly, this study addresses the identified theoretical gap by examining the predictors that support and hinder ChatGPT adoption in educational settings. The primary research question of this research is stated as follows:

- RQ1: What factors (acceptance and resistance determinants) shape research scholars' behavioral intentions regarding ChatGPT utilization in education and research?

To get the answer of this research question, this study proposed a comprehensive conceptual framework based on three dominant underpinning technology adoption theories, including behavioral reasoning theory (BRT), technology acceptance theory (TAM) and innovation resistance theory (IRT) for examining the ChatGPT adoption intention among research scholars. Grounded upon the above discussion, this study aims to examine the research scholars' intentions by carefully examining both the "reasons for" (RF) and the "reasons against" (RA) towards ChatGPT adoption, which add rigor to this research.

After that, this study offers a balanced understanding of both enabling and inhibiting factors influencing ChatGPT adoption by integrating BRT, TAM, and IRT within a single framework. The findings contribute to theory by extending multi-theoretical integration into the generative AI domain and offer practical insights for higher education institutions and policymakers seeking to regulate and optimize AI integration in academic environments.

In the following sections, we explain these three theoretical frameworks which lay the logical foundation of the arguments extended in this study. A presentation of our proposed and testable hypotheses follows this. Subsequently, we explain the research methodology, followed by an analysis of hypotheses, results, and discussion that demonstrated the implications of our findings. The final section comprises a conclusion and implications.

2. Literature Review and Hypotheses Development

2.1. Underpinning Theories

2.1.1 Behavioral Reasoning Theory (BRT)

Exploring antecedents of successful adoption, diffusion, or proliferation of new technologies has gained significant research attention (Ali et al., 2021). Prior research has mostly made appeals to theoretical frameworks including TAM, unified theory of acceptance and use of technology (UTAUT) and theory of planned behavior (TPB) in the context of adoption and diffusion research. However, these underpinning frameworks have been criticized for their exclusive focus on factors that prompt acceptance (e.g., Parveen et al., 2026), neglecting the reasons for rejecting the innovations (Ajina et al., 2023; Dhir et al., 2021).

This limitation becomes particularly salient in the generative AI tools context such as ChatGPT, where adoption is simultaneously driven by perceived benefits and constrained by ethical, cognitive, and habitual concerns. Therefore, a framework that captures both enabling and inhibiting forces is necessary to explain behavioral intentions comprehensively (Westaby, 2005). For precisely the same reason, BRT is being progressively used in such research domains for its equal focus on ‘reasons’ for and the ‘reasons’ against toward new technologies adoption (Ajina et al., 2023; Anayat et al., 2023; Claudy et al., 2013, 2015; Dhir et al., 2021; Sreen et al, 2021; Virmani et al., 2023).

BRT provides a higher-order explanatory structure by linking context-specific reasons to attitudes and intentions, thereby offering a balanced behavioral explanation that is particularly suited for studying emerging and potentially disruptive technologies such as ChatGPT. Accordingly, BRT serves as the overarching theoretical lens in this study, organizing the determinants of ChatGPT adoption into “reasons for” and “reasons against.”

2.1.2. Technology Acceptance Model (TAM)

Davis (1989) introduced the TAM to explain users’ acceptance (or rejection) of innovative products/technologies. TAM maintains that users’ desires or intentions to accept, adopt, or use innovative solutions to their needs are influenced by the perceived usefulness (PU) and perceived ease of use (PEOU). The PEOU is defined as users believe a technology is easy to use. TAM-2, an extension of the original TAM model, adds another variable, namely social norms (or social influence; SI), as another key determinant in shaping users’ intentions to adopt a technology.

While TAM effectively explains positive acceptance mechanisms, it does not sufficiently account for resistance factors that may coexist alongside perceived benefits, particularly in controversial technologies such as generative AI. Within the BRT framework, PU, PEOU, and SI are conceptualized as “reasons for” that positively shape attitudes and intentions toward ChatGPT adoption. This positioning allows TAM constructs to be theoretically anchored within a broader behavioral reasoning structure.

2.1.3 Innovation Resistance Theory (IRT)

Users' resistance can significantly influence the widespread diffusion of innovative products or technologies (Ram & Sheth, 1989). The IRT is considered a relevant theoretical framework to explain the dynamics of the users' resistance towards the innovations adoption (Ram & Sheth, 1989). Behavioral changes in the life of the innovation user might develop an orientation of resistance among the users (Ram & Sheth, 1989). There may exist active and passive forms of resistance to adopting new technologies. Active resistance attributable to the product/technology about value, risk, and usage barriers (Yu & Chantatub, 2016). Likewise, passive resistance could be caused by the discrepancies between users' beliefs about the innovation fostered by image and tradition barriers (Yu & Chantatub, 2016).

Although TAM explains why individuals may accept technology, it does not explain why users resist or delay adoption. IRT complements TAM by focusing explicitly on barriers and resistance mechanisms. Within the BRT structure, usage, tradition, and risk barriers are positioned as "reasons against," thereby capturing the inhibitory forces that may counterbalance positive adoption drivers.

This study integrates BRT, TAM, and IRT to explain ChatGPT adoption in higher education. TAM identifies acceptance drivers including PEoU, PU, and SI, while IRT explains resistance factors—TB, RB, and UB. BRT provides the overarching framework by organizing these determinants into "reasons for" and "reasons against," which shape attitude towards ChatGPT and ultimately influence towards ChatGPT. The integration of these theories is necessary because ChatGPT adoption represents a dual-process phenomenon, involving both facilitating and inhibiting forces. While TAM captures positive cognitive evaluations and IRT captures resistance arising from uncertainty and disruption, BRT unifies these mechanisms within a single reasoning structure. This integrated approach offers a more comprehensive and theoretically grounded elucidation of ChatGPT adoption in higher education than relying on a single theoretical perspective.

2.2. The Conceptual Model

Making appeals to BRT, TAM, and IRT, it has been hypothesized that 'reasons for' ChatGPT adoption like PEoU, PU, and SI and 'reasons against' adoption of ChatGPT like risk, usage, and tradition barriers directly affect intention to use ChatGPT as well indirectly through affecting attitude towards ChatGPT (ATT). Figure 1 showcases our conceptual model.

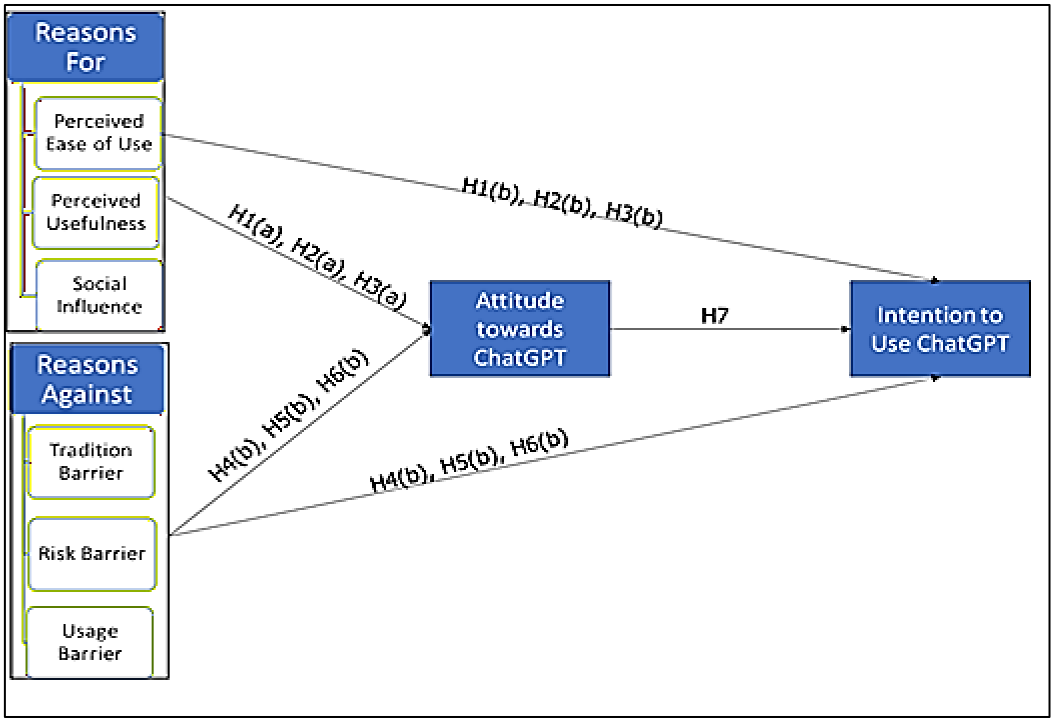

Figure 1: Conceptual Model

2.3 Hypotheses of the Study

Grounded in the integrated BRT, TAM, and IRT, the following hypotheses are developed. TAM provides the foundation for acceptance-related constructs (PEOU, PU, and SI), IRT explains resistance determinants (tradition, risk, and usage barriers), and BRT explains how these "reasons for" and "reasons against" shape attitude and ultimately influence intention to use ChatGPT.

2.3.1. 'Reasons For', Attitude towards ChatGPT and Intention to use ChatGPT

In user behavior, "reasons for" are the driving forces that promote the requisite behavior. Prior studies on innovation have underscored the significance of factors like PEoU, PU, and SI, among others, in fostering positive attitudes, intentions, or actions to adopt innovative technological solutions to their problems. Consequently, this research considers these factors the most significant "reasons for" adopting ChatGPT. Prior research has shown that PEOU, PU, and SI positively influence individuals' intentions to adopt innovative technologies in multiple contexts. Furthermore, previous studies have also corroborated to the unified role of "reasons for" in developing individual attitudes and behavior across different contexts (Ajina et al., 2023; Sreen et al., 2021; Tandon et al., 2020; Tufail et al., 2022).

2.3.1.1. Perceived ease of use, Attitude towards GhatGPT and intention to use ChatGPT

PEoU is one of the critical constructs postulated by TAM as a key determinant of technology adoption. It refers to how easy it is for an individual to use a system to fulfill their e-learning responsibilities. Mahmud et al. (2024) reveals that it corresponds to a users' belief about the prospective technology's user-friendliness. Within the context of ChatGPT, PEOU pertains to users' perception that using and learning ChatGPT involves minimal effort. In addition, PEoU becomes particularly salient because interaction occurs through natural language interfaces, where cognitive simplicity directly influences willingness to experiment with AI-assisted academic tasks. When educational participants, including teachers and students, perceive GI technology (more specifically, ChatGPT), they believe it as easy to use and precious. It is widely recognized that a user's perception of how easy something is to use impacts their inclination to use it, especially digital tools, and instruments. In other words, prospective users are intended to use a digital instrument if they consider that it requires less physical and mental effort.

Extant research conducted in a different context for a various technology (e.g., Ali et al., 2021; Mahmud et al., 2024; Polyportis & Pahos, 2024; Zafar et al., 2023) have attested to the positive influence of PEoU in affecting individuals' attitudes and intentions to adopt new technologies, including GI-driven ChatGPT. Recent studies examining AI adoption in higher education from educators' perspectives further confirm the relevance of TAM constructs in shaping adoption decisions (Al-Mughairi & Bhaskar, 2025). Grounded in TAM and structured within BRT as a "reason for," PEoU is expected to positively shape both attitude and intention toward ChatGPT. Based on prior discussion, we hypothesize.

- H1(a): Perceived ease of use is positively associated with attitude toward ChatGPT.
- H1(b): Perceived ease of use is positively associated with intention to use ChatGPT.

2.3.1.2. Perceived Usefulness, Attitude towards ChatGPT and Intention to use ChatGPT

TAM posits that the user's intentions ultimately dictate how technology is utilized, and the perceived benefits or mutual advantages establish a close link between the intention to adopt and performance-related outcomes. PU corresponds to the strength of a users' belief that technology adoption (such as GI) will improve their job performance.

PU is a significant predictor of user satisfaction. When users perceive technology as valuable, it increases their satisfaction levels, fostering a positive attitude and intention toward a continual use of that technology (Mahmud et al., 2024; Martono et al., 2020; Rafique et al., 2020; Unal & Uzun, 2021). Polyportis & Pahos (2024) and (Dorobăț &

Corbea, 2025) arrived at a similar conclusion about the impact of PU on ChatGPT adoption. Grounded in TAM, PU represents a key determinant of technology acceptance, and within BRT it functions as a “reason for” that shapes favorable attitudes and strengthens intention to use ChatGPT. Based on the preceding discussion, we hypothesize that

- H2(a): Perceived usefulness is positively associated with attitude toward ChatGPT.
- H2(b): Perceived usefulness is positively associated with intention to use ChatGPT.

2.3.1.3. Social Influence, Attitude towards GhatGPT, and Intention to use ChatGPT

Lu, Yu et al. (2003) defined the SI as individuals’ belief that the others’ participation play a significant role in making a decision. SI intentionally and unintentionally influence others’ beliefs, attitudes, and behavior. Besides, it signifies the peers’ influence in strengthening the users’ intentions to use a new-fangled technology. In addition, recommendations from word-of-mouth (WOM), online reviews, ratings, friends, family, and social media marketing are the major sources of creating SI. After that, the development and extension of TAM2 aimed to provide a detailed understanding of users’ intentions with the help of contributing factors PEOU, PU and incorporating the SI. Along with, the SI process involves three interrelated factors that determine users’ acceptation and rejection towards technology adoption, and this is manifested in their actual behavior. Therefore, SI significantly shapes people’s attitudes and behaviors (Paul et al., 2023).

In the context of ChatGPT adoption, users may learn from their social networks or peers about the benefits and drawbacks of GI tools and instruments and adjust their behaviours accordingly. Kim and Koo (2020) and Menon & Shilpa (2023) demonstrated that SI is a strong predictor of users’ intention toward novel technologies adoption. Besides, consumers are intended to adopt the new technology if the members of their social circles have favorable attitudes to adopt it (Polyportis & Pahos, 2024; Mahmud et al., 2024). Grounded in TAM2, social influence (SI) reflects normative pressures affecting technology adoption, and within BRT it operates as a “reason for” that positively shapes attitude and intention toward ChatGPT use. Based on prior discussion, we hypothesize that:

- H3(a): Social influence is positively associated with attitude toward ChatGPT.
- H3(b): Social influence is positively associated with intention to use ChatGPT.

2.3.2. ‘Reasons Against’ Attitude towards ChatGPT and Intention to use ChatGPT

Based on behavioral influence, the inhibitory factors are aptly termed “reasons against,” for they can cultivate unfavorable sentiments when contemplating specific actions as Sreen et al. (2021) and Zafar et al. (2023) explained. In the case of ChatGPT, resistance may stemz from perceived disruption of traditional academic practices, uncertainty regarding reliability, or difficulty in integrating AI into established workflows. These barriers are particularly relevant in higher education contexts where norms, evaluation systems, and academic integrity concerns remain central. In the current research, three distinct barriers, known as the risk, value, and tradition barriers, have been enumerated as the primary factors truncating the adoption of ChatGPT. Individuals contemplating engaging with cutting-edge AI-driven solutions, such as ChatGPT, may experience a sense of unease stemming from the trio of (tradition, usage, and risk) barriers. These factors harm individuals' predispositions and readiness to embrace innovations (Ajina et al., 2023). Extant research has established the negative impacts of "reasons against" on individuals' attitudes and intentions toward usage of innovative technologies (Ajina et al., 2023; Kaur et al., 2020; Sreen et al., 2021; Zafar et al., 2023).

2.3.2.1. Tradition Barriers, Attitude towards ChatGPT and Intention to use ChatGPT

Traditions shape the pervasiveness of items, including goods, services, fashions, etc. Researchers have stated that traditions are deeply established in society and people's lives, and any deviance leads to a significant consumer reaction in different forms, including negative WOM, negative publicity, and boycotting. In addition, tradition barriers (TB) are the barriers that come into play when an innovation causes an alteration in a user's current life routine, influences his/her cultural aspects, or brings behavioral changes. The TB represent the hurdles posed by innovation when it disrupts its users' familiar cultural norms, established routines, and ingrained behaviors (El Badrawy et al., 2012). Several studies have shown that TB are associated with lower adoption intents to purchase online (Lian & Yen, 2014), shopping from mobile applications (Gupta & Arora, 2017), and ChatGPT (Menon and Shilpa, 2023). From a BRT perspective, TB function as "reasons against" by reinforcing habitual and culturally embedded practices that conflict with AI-driven academic tools. When ChatGPT is perceived as disrupting established learning routines or academic norms, it may generate negative evaluations, thereby influencing both attitude and intention. Based on proceeding discussion, we postulate an adverse impact of TB on the attitude towards ChatGPT and intention to use ChatGPT. We hypothesize.

- H4(a): Tradition barrier is negatively associated with attitude toward ChatGPT.
- H4(b): Tradition barrier is negatively associated with intention to use ChatGPT.

2.3.2.2. Risk Barriers, Attitude towards ChatGPT and Intention to use ChatGPT

The risk barriers (RB) are intricately tied to the uncertain and unpredictable nature that often accompanies groundbreaking innovations, as postulated by Kaur et al. (2020a). Furthermore, it pertains to the apprehension and resistance that naturally surface in response to the inherent uncertainties ingrained within any novel invention (Ajina et al., 2023). Ram & Sheth (1989) revealed four risks inherent in innovation adoption: physical, economic, functional, and social. Research has documented a negative association between RB and users' intention to adopt. RB, for example, negatively influence intent to purchase online (Lian & Yen, 2014), shopping from mobile applications (Gupta & Arora, 2017), using games on online platforms (Oktavianus et al., 2017), and making transactions through mobile banking (m-Banking) (Laukkanen, 2016). Previous research on users' behavioral intention to test digitalized innovations adoption suggested a negative relationship with RB as suggested by Mendes et al. (2024). Attributable to the uncertainties they represent, RB might become possible hurdles for a favorable attitude towards and intention to use ChatGPT. Michel-Villarreal et al. (2023), Mendes et al. (2024) found RB negatively influence the new technologies adoption, including the ChatGPT in the higher education sector. Within the integrated BRT–IRT framework, perceived risk represents a salient "reason against" because uncertainty regarding accuracy, ethical implications, or data privacy may weaken favorable evaluations of ChatGPT. BRT explains that such perceived risks enter the cognitive reasoning structure and negatively shape attitudes, which subsequently affect intention. Based on preceding arguments, we hypothesize.

- H5(a): Risk barrier is negatively associated with attitude toward ChatGPT.
- H5(b): Risk barrier is negatively associated with intention to use ChatGPT.

2.3.2.2. Usage Barriers, Attitude towards ChatGPT and Intention to use ChatGPT

Usage barriers (UB) emphasize the limitations imposed by variations, notably in employing innovations compared to old systems (Ram & Sheth, 1989). For instance, UB reflect the skills and abilities to understand the latest systems and technologies to change everyday habits. UB are essential since the complexity of modern technologies' usage might damage their chances of becoming mainstream innovations. The intricacy of GI-driven ChatGPT might be complex for those with limited technical abilities or familiarity with ChatGPT. Many researchers have discovered an untoward positive relationship between usage obstacles and user resistance to digitization connected to innovations, i.e., augmented reality and mobile gaming (Oktavianus et al., 2017), mobile banking (Kaur et al., 2020; Yu & Chantatub, 2016), and Chatbots in higher education (Okonkwo and Ade-Ibijola, 2021). UB reflect operational difficulties that may undermine confidence in interacting with generative AI systems. Within BRT, these barriers are categorized as "reasons against," as perceived complexity or required behavioral adjustments can generate resistance, negatively influencing both attitude and intention toward ChatGPT adoption. We postulate that comparable difficulties may lend drive to the function of usage constraints in degrading scholars' attitudes and intentions to use ChatGPT and hypothesize.

- H6(a): Usage barrier is negatively associated with attitude toward ChatGPT.
- H6(b): Usage barrier is negatively associated with intention to use ChatGPT.

2.3.3. Attitude towards ChatGPT and Intention to use ChatGPT

An attitude, as defined by Eagly and Chaiken (1998), represents a psychological inclination expressed by favoring or disfavoring a specific entity, like innovation. Prior researchers have endeavored to explain antecedents of individuals' intention building in a variety of contexts, making appeals to a variety of underpinning theoretical frameworks, as it's an essential precursor of their actual behavior, indicating that individuals having a favorable attitude are more intended to involve in positive behaviors (Zafar et al., 2023; Tufail et al., 2022). Plenteous prior studies (e.g., Dhir et al., 2021; Sreen et al., 2021; Tandon et al., 2020; Tufail et al., 2022) reported that individuals' attitudes are positively related to individuals' intentions to undertake a particular action. Chen (2023), Ho et al. (2023), and Labrague et al. (2023) found that attitude predicts the intention to use/adopt AI-based solutions tools, and/or instruments. BRT posits that both "reasons for" and "reasons against" shape behavioral intention through their influence on attitude. Consistent with TAM and established attitude–intention paradigms, attitude serves as a central evaluative mechanism that translates cognitive reasoning into behavioral intention. Accordingly, in the context of ChatGPT adoption, attitude is determinants of intention to use. Consonantly, we hypothesize.

- H7: Attitude toward ChatGPT is positively associated with intention to use ChatGPT.

3. Research Methods

3.1. Measurements

We adapted established scales used in previous studies to measure the constructs constituting our conceptual model. The measure of SI (4 items) is borrowed from Lim et al. (2020). PEOU (five items) and PU (six items) were adapted from Baig & Yaqub (2022). The scales to calibrate the TB (five items), the RB (five items), and the UB (four items) were derived from Laukkanen (2016) and Sivathanu (2018). The measurement scale for attitude (four items) and intentions to use ChatGPT (four items) were adapted from Ali et al. (2021). All the responses were recorded using a Likert scale (seven-point) spanning from "strongly disagree (1) to strongly agree (7)". Every measurement scale was based on the former scales that had undergone the assessment of validity with references to the theoretical frameworks (TAM, IRT, and BRT). To ensure robustness in the present study, construct reliability and validity were assessed using series of tests including "Cronbach's alpha, composite reliability, average variance extracted (AVE), and discriminant validity (HTMT)", confirming satisfactory psychometric properties.

To ensure the constructs' face validity and validate the questionnaire, authors got insights from three academician working as assitant professors in the reputable univeristies. After their feedback, we undertook necessary revisions to ensure clarity, precision, and appropriateness for the respondents.

Procedural remedies were established to counter possible common method bias, such as reassurance of respondent anonymity, a stress on that there were no correct or incorrect answers, and the careful design of the questionnaire as a means of alleviating evaluation apprehension. Also, statistical evaluation was done through Harman one-factor test. The findings showed that the former factor explained less than half of the overall variance, which is less than the prescribed level (Harman, 1976) which may not imply that common method bias would be a grave issue. Moreover, the value of the variance inflation factor (VIF) was considered, and all of them were less than the conservative value of 3.3 (Kock & Lynn, 2012).which makes it possible to confirm that there was no great amount of common method bias.

3.2. Sampling and Data Collection

The targeted population of this study comprises of scholars pursuing their (higher) studies at the MS and PhD levels at universities in Southern Punjab, Pakistan. Higher perceived relevance due to their matured higher studies programs and the ease of collecting data have been primary reasons to select this geographical context. We used the a priori method, as suggested by Soper (2021), to determine the sample size. Integrating a medium effect size (0.3) and statistical power of (0.80), eight constructs comprised of 37 items, and a significance level (0.01), the minimum sample size to perceive effect is 220 (Cohen, 1992). Our sample size (n=450) exceeded the suggested minimum. We used cluster random sampling to choose the relevant informants from the various cohorts studying at the Master's and Doctorate levels at the targeted universities. We identified public universities in Southern Punjab, Pakistan as natural clusters for the sampling process. From these clusters, we approached selected institutions and invited eligible MS and PhD scholars to participate through their respective academic departments. Self- administrative questionnaire was employed to collect the data from 450 informants. We distributed and collected the questionnaires physically within university premises to ensure a structured and controlled data collection process. After removing responses with missing and/or inadequate values (Hair et al., 2018), 436 valid responses were considered for further analysis.

3.3. Analytical Strategy

Smart PLS 4.0 has been employed for modeling purposes using recommendations from Hair et al. (2018). The measurement model was evaluated by measuring reliability and (convergent and discriminant) validity. The hypothesized relationships were corroborated by assessing the structural model estimates. PLS-SEM has been deemed appropriate because of its ability to evaluate multiple regression equations concomitantly, and it puts less stringent requirements like normality, sample size, etc.

The choice was made in favor of PLS-SEM instead of covariance-based SEM (CB-SEM) since the main purpose of the given research is prediction-driven and aimed at the maximization of the explained variance of intention to use ChatGPT. The proposed model integrates multiple theoretical frameworks (BRT, TAM, and IRT) and includes several constructs and indicators, making it structurally complex and well-suited for variance-based estimation. Unlike CB-SEM, which emphasizes overall model fit and covariance reproduction for strict theory confirmation, PLS-SEM is more appropriate for assessing predictive relationships and variance explanation in behavioral research contexts. Furthermore, PLS-SEM does not demand rigid multivariate normality assumptions which is beneficial where survey-based data are concerned. Therefore, given the predictive focus and structural complexity of the present study, PLS-SEM was considered more appropriate than CB-SEM.

4. Data Analysis and Results

4.1. Sample Profile

Table 1 contains relevant information about the profile of the informants. The majority were males (62%), studying at Master's levels (87%), aged less than 25 years (84%), and possessed bachelor's degrees in Arts, Humanities, and social science (43%).

Table 1: The Respondents' Demographic Profile

Criterion	**Categories**	**n**	**%**
Gender	Male	270	62
	Female	166	38
Educatioon	Masters	379	87
Level	Doctorate	57	13
Age	Less than 25 Years	366	84
	25-30 Years	48	11
	More than 30 Years	22	5
Academic	Arts, Humanties & Social Sciences	187	43
Background	Sciences	139	32
	Commerce	92	21

4.2. Measurement Model Assessment

We used series of test including "factors loadings, Cronbach's alpha, composite reliability (CR), average variance extraction (AVE), and Heterotrait-Monotrait (HTMT)" values, to assess the quality of the measurement scales by assessing their reliability and validity (convergent and discriminant validity).

4.2.1. Reliability and Convergent Validity

Following the retention of the items of higher factor loading (above 0.6) as proposed by Henseler et al. (2015), the reliability of constructs was established based on the most pronounced test, the Cronbach Alpha, and the CR. The findings showed that Cronbach alpha and CR values of all constructs are more than 0.7 which illustrates the reliability of constructs as posited by Henseler et al. (2015). Moreover, the results indicate that all the constructs' AVE scores are higher than 0.50, demonstrating that constructs have adequate convergent validity as recommended by Fornell and Larcker (1981). Table 2 shows the results of reliability and validity.

Beyond meeting recommended threshold values, the consistently high indicator loadings suggest that the observed items strongly reflect their respective latent constructs. The internal consistency estimates further indicate stability in responses across items measuring the same construct. In addition, the large AVE values indicate that the constructs have significant variance explained by their indicators, which minimizes measurement error. Collectively, these results provide confidence that the measurement model shows acceptable psychometric properties and is suitable for structural model evaluation.

Table 2: Reliability and Convergent Validity

Variables	**Items**	**Loadings**	**Cronbach Alpha** (α)	**CR.**	**AVE**
Attitude towards ChatGPT (ATT)	ATT1	0.914	0.935	0.936	0.838
	ATT2	0.935			
	ATT3	0.944			
	ATT4	0.867			
Intention to Use ChatGPT (ITU)	ITU1	0.907	0.901	0.903	0.773
	ITU2	0.809			
	ITU3	0.927			
	ITU4	0.870			
Perceived Ease of Use (PEoU)	PEOU1	0.897	0.940	0.940	0.805
	PEOU2	0.901			
	PEOU3	0.903			
	PEOU4	0.893			
	PEOU5	0.893			
Perceived Usefulness (PU)	PU1	0.851	0.917	0.921	0.750
	PU3	0.843			
	PU4	0.902			
	PU5	0.91			
	PU6	0.822			
Risk Barrier (RB)	RB1	0.718	0.894	0.931	0.700
	RB2	0.742			
	RB3	0.912			
	RB4	0.888			

	RB5	0.901			
Social Influence (SI)	SI1	0.919	0.908	0.909	0.785
	SI2	0.865			
	SI3	0.855			
	SI4	0.901			
Tradition Barrier (TB)	TBR1	0.849	0.920	0.926	0.759
	TBR2	0.904			
	TBR3	0.893			
	TBR4	0.913			
	TBR5	0.792			
Usage Barrier (UB)	UBR1	0.872	0.910	0.910	0.788
	UBR2	0.889			
	UBR3	0.870			
	UBR4	0.920			

4.2.2. Discriminant Validity

Fornell Larcker's (1981) Criterion and HTMT values were considered to ascertain the discriminant validity of constructs. The Fornell-Larcker criterion demands that the square root of each construct AVE (shown by the diagonal values in Table 3) should be larger than its correlations with other constructs (off-diagonal values). This condition ensures that a construct shares more variance with its own indicators than with other constructs in the model, thereby confirming conceptual distinctiveness. As presented in Table 3, all diagonal values exceed the corresponding inter-construct correlations, indicating that the Fornell–Larcker criterion is satisfied and discriminant validity is established.

Table 3: Fornell-Larcker-Criterion

	ATT	ITU	PEOU	PU	RB	SI	TBR	UBR
ATT	0.915							
ITU	0.920	*0.879*						
PEOU	0.811	0.860	*0.897*					
PU	0.791	0.848	0.861	*0.866*				
RB	-0.653	-0.683	-0.668	-0.684	*0.836*			
SI	0.810	0.874	0.910	0.930	-0.684	*0.886*		
TBR	0.553	0.574	0.650	0.677	-0.648	0.640	*0.871*	
UBR	-0.693	-0.733	-0.706	-0.725	0.841	-0.726	-0.626	*0.888*

ATT=Attitude towards ChatGPT; ITU=Intention to use ChatGPT; RA=Reasons Against; RF=Reasons For; VOC=Openness to Change; PEOU=Perceived Ease of Use; PU=Perceived Use; RB= Risk Barriers; SI=Social Influence; TBR=Tradition Barriers; UBR=Usage Barriers

We also examined the HTMT values to ascertain discriminant validity. The results demonstrated that the HTMT values of all constructs have been below 0.90 as Henseler et al. (2015) suggested, showing constructs have discriminant validity.

4.3. Structural Model Assesment

4.3.1. The Model's Fit, Explanatory, and Predictive Power

4.3.1.1. Goodness of Fit

The goodness of model fit is determined using the standardized root mean square residual (SRMR). According to the result, it has been established that the SRMR value at 0.074 is lower than 0.08 indicating that the model is well fit (Hair et al., 2018).

4.3.1.2. Explanatory Power - Coefficient of Determination (R^2)

R^2 explains how much variation in each dependent variable is due to a change in the independent variables. The values of R^2 "0.75, 0.50, and 0.25" are deemed as "substantial, moderate, and weak", respectively (Chin, 1998; Henseler et al., 2009). As seen in Figure 2, attitude towards ChatGPT is explained in 71% (R2 = 0.71), and ITU is demonstrated in 91% (R2 = 0.91), showing the model's moderate to substantial explanatory power.

Given the high explanatory power for intention to use ChatGPT (R^2 = 0.91), inner collinearity diagnostics were assessed. The variance inflation factor (VIF) values for all predictor constructs were below the recommended threshold, indicating that multicollinearity does not threaten the structural estimates and that the high R^2 reflects strong predictive capability of the integrated model.

4.3.1.3 Predictive Relevance (Q^2)

Stone–Geisser's Q^2 through the blindfolding procedure was used to measure the predictive relevance of the structural model.The Q^2 values for attitude toward ChatGPT ($Q^2 = 0.49$) and intention to use ChatGPT ($Q^2 = 0.65$) were greater than zero, indicating that the structural model demonstrates satisfactory predictive relevance (Hair et al., 2016).

4.3.1.4 Effect Size (f^2)

The contribution of each independent construct to the endogenous variables was determined using the effect size (f^2). The results indicate that PEOU shows a moderate effect on attitude ($f^2 = 0.21$), while PU ($f^2 = 0.09$) and SI ($f^2 = 0.06$) show small effects. TB ($f^2 = 0.03$), risk barrier ($f^2 = 0.03$), and UB ($f^2 = 0.05$) also demonstrate small effects on attitude. For intention to use ChatGPT, attitude toward ChatGPT shows a large effect ($f^2 = 0.58$), whereas PEOU ($f^2 = 0.03$), PU ($f^2 = 0.03$), SI ($f^2 = 0.05$), TB ($f^2 = 0.02$), risk barrier ($f^2 = 0.02$), and UB ($f^2 = 0.02$) demonstrate small effects as Cohen's (1988) guidelines (0.02 = small, 0.15 = medium, 0.35 = large effect size).

4.3.2. Structural Model Path Results

A summary of the analyses of direct effects is presented in Table 4. Hypotheses 1(a), 2(a), and 3(a) were supported, corroborating the associations between ATT and PEoU ($\beta = 0.389$, $p < 0.001$), PU ($\beta = 0.210$, $p < 0.001$), and SI ($\beta = 0.160$, $p < 0.020$). Hypotheses 1(b), 2(b), and 3(b) were also empirically supported, confirming the association between ITU and PEoU ($\beta = 0.129$, $p < 0.005$), PU ($\beta = 0.094$, $p < 0.003$), and SI ($\beta = 0.193$, $p < 0.001$) subsequently. Hypotheses 4(a), 5(a), and 6(a) were also empirically supported, confirming the significance of the association between ATT and TB ($\beta = -0.079$, $p < 0.028$), RB ($\beta = -0.091$, $p < 0.025$), and UB ($\beta = 0.131$, $p < 0.012$) subsequently. Hypotheses 4(b), 5(b), and 6(b) were supported as the findings revealed that the associations between ITU and TB ($\beta = -0.060$, $p < 0.001$), RB ($\beta = -0.011$, and $p < 0.025$), and UB ($\beta = 0.075$, $p < 0.007$) respectively. Finally, hypothesis 7, postulating a significant role of ATT in affecting ITU ($\beta = 0.558$, $p < 0.001$).

Table 4: Hypotheses Testing

Hypotheses	Paths	β- values	p values	Result (supported)
H1(a)	PEoU -> ITU	0.129	0.005	Yes
H1(b)	PEoU -> ATT	0.389	0.000	Yes
H2(a)	PU-> ATT	0.210	0.001	Yes
H2(b)	PU-> ITU	0.094	0.003	Yes
H3(a)	SI -> ATT	0.160	0.021	Yes
H3(b)	SI -> ITU	0.193	0.000	Yes
H4(a)	TB -> ATT	-0.079	0.028	Yes
H4(b)	TB -> ITU	-0.060	0.001	Yes
H5(a)	RB -> ATT	-0.091	0.025	Yes
H5(b)	RB -> ITU	-0.011	0.025	Yes
H6(a)	UB -> ATT	-0.131	0.012	Yes
H6(b)	UB -> ITU	-0.075	0.007	Yes
H7	ATT -> ITU	0.558	0.000	Yes

ATT=Attitude towards ChatGPT; ITU=Intention to use ChatGPT; RA=Reasons Against; RF=Reasons For; PEOU=Perceived Ease of Use; PU=Perceived Use; RB= Risk Barriers; SI=Social Influence; TBR=Tradition Barriers; UBR=Usage Barriers

Beyond statistical significance, the structural model results offer meaningful theoretical and contextual insights into ChatGPT adoption. First, the positive influences of PEOU, PU, and SI on both attitude and intention are consistent with TAM/TAM2, indicating that cognitive simplicity, expected performance gains, and normative endorsement jointly shape adoption decisions in higher education. Notably, PEOU shows a comparatively stronger effect on attitude, suggesting that effortless interaction with ChatGPT plays a foundational role in forming favorable evaluations among research scholars. PU also significantly predicts intention, highlighting that perceived academic productivity and task support remain central motives for continued use. SI further strengthens both attitude and intention, implying that peer and academic-community endorsement may legitimize AI tool usage and reduce hesitation in academic environments.

On the resistance side, tradition, risk, and usage barriers significantly weaken both attitude and intention, supporting IRT. The negative effect of TB suggests that perceived misalignment with established academic routines and norms can reduce openness to generative AI. Similarly, RB indicate that concerns related to reliability, ethics, and academic integrity can suppress adoption tendencies. UB also reduce attitude and intention, implying that perceived operational difficulty or required behavioral adjustment can trigger resistance. These findings align with the "reasons for" and "reasons against" logic of BRT, where enabling and inhibiting evaluations jointly shape technology-related judgments.

Finally, attitude toward ChatGPT is deemed as the strongest predictor of intention to use, showing that evaluative judgment is pivotal for translating adoption drivers and barriers into behavioral intention. Comparatively, acceptance-related determinants demonstrate stronger effects than resistance barriers, indicating that perceived academic benefits outweigh perceived concerns in shaping ChatGPT adoption decisions within this context. Overall, the results confirm that ChatGPT adoption is best explained through an integrated framework that captures both acceptance mechanisms (TAM/TAM2) and resistance mechanisms (IRT), unified through BRT's reasoning-based pathway.

5. Discussion

Hypotheses 1(a&b), 2(a&b), and 3(a&b), which postulated a significant role of PEoU, PU, and SI (altogether RF) in affecting ATT and IU, respectively, have also been empirically supported, confirming a positive role of RF in effecting attitudes and intentions to use Chat GPT. These findings concurred with prior research findings (Ajina et al., 2023; Ali et al., 2021; Dhir et al., 2021; Mahmud et al., 2024; Menon and Shilpa, 2023; Polyportis & Pahos, 2024; Mahmud et al., 2024; Zafar et al., 2023; Zahid et al., 2022). PEOU, PU, and SI, being the individual determinants of RF, reflect that user-friendliness, perceived higher efficacy, and ubiquity of ChatGPT among academics play an important positive role in the proliferation of ChatGPT among students. In particular, students have become adept at working smart and are driven to complete their tasks in distinctive, time-efficient ways. Along with ChatGPT plays a pivotal role by offering students valuable suggestions and serving as a motivating force, inspiring them to incorporate it as an effective coping mechanism for expeditiously accomplishing their work.

The proposed Hypotheses 4(a&b), 5(a&b), and 6(a&b) depict a significant role of TB, RB, and UB, respectively (altogether RA) in affecting ATT and ITU, have also been empirically supported, confirming a negative role of RF in truncating ATT and the intention to use ChatGPT. The results of these hypotheses align with the previous studies (e.g., Ajina et al., 2023; Dhir et al., 2021; Hopalı et al., 2022; Kaur et al., 2021; Mahmud et al., 2024; Menon and Shilpa, 2023; Okonkwo and Ade-Ibijola, 2021; Tufail et al., 2022; Zafar et al., 2023). Importantly, the three barriers impede the widespread adoption of novel innovations, such as ChatGPT, though this adverse impact has not been as strong as the positive impact of RF. Such impediments could be attributed to the cultural and habitual rigidity of the users, who tend to adhere steadfastly to the established norms and routines. Additionally, risks stemming from uncertainty, safety, and adverse stereotyping also foster reluctance among potential users. Also, many users may be hesitant to fully recognize the potential of ChatGPT to deliver desired outcomes.

The proposed positive association between ATT and ITU (H7) has been supported, confirming ATT's positive role in effectuating ITU ChatGPT. These results align with prior research on adopting innovative technologies such as Chen (2023), Ho et al. (2023), Labrague et al. (2023), Pillai and Sivathanu (2020), Zahid et al., 2022), and Zafar et al. (2023). It means that a positive attitude towards ChatGPT strongly induces a positive intention to use ChatGPT among the research scholars.

6. Research Implications and Conclusion

6.1 Theoretical Contributions

This study presents several contributions to technology adoption in general and ChatGPT adoption in particular by integrating the three leading theoretical frameworks encompassing technology adoption (i.e., BRT, IRT, and TAM). First, this study focuses on the intricate relationship between the adoption of ChatGPT and its context-specific reasons, both positive and negative, particularly within academic settings. At the same time, the empirical results of this research contribute a robust and nuanced comprehension of the impacts exerted by reasons (for and against), often referred to as facilitators and inhibitors, on individuals' attitudes and intentions regarding the utilization of ChatGPT. Second, the study is a significant addition to the theoretical basis in the use of ChatGPT. Although the literature on these theories has been consolidated, the current study is among the previous studies that have concurrently utilized BRT, TAM, and IRT to explore technology adoption, particularly in GI-based technologies such as ChatGPT context. It was necessary to integrate BRT, TAM, and IRT since the adoption of ChatGPT faces both acceptance mechanisms (described by TAM) and resistance mechanisms (described by IRT). TAM explains the role of PEOU, PU, and SI in facilitating adoption, and IRT describes the role of tradition, risk, and UB in preventing adoption. BRT presents the framework based on reasoning that combines these reasons for and reasons against in order to justify how people shape intention. Therefore, the integrated framework provides a more detailed explanation compared to any theory in isolation. Besides that, empirically, the results support TAM based on the positive implication of PEOU, PU, and SI, IRT based on the negative implication of resistance barriers, and BRT based on the argument that facilitating and inhibiting reasons have a joint effect on the formation of the intention.

Third, the study is based on its context on the fact that the majority of technology adoption research has been performed in technologically advanced nations. Specifically, it is focused on adoption of new technology such as ChatGPT in the South Asian setting that makes Western developed theories broader by exploring them in new geographical and cultural settings. In addition, another contribution made in this study is its extension to higher education.

6.2 Practical Implications

Following the discussion of the theoretical contributions, this research has important implications to higher education administrators and policymakers with the analysis of the facilitating and inhibiting factors that affect the adoption of ChatGPT. First, PEOU and PU are effective in improving attitude and intention, universities are recommended to invest in structured training workshops to show how ChatGPT can be ethically applied to academic writing, research design, and data interpretation. The positive evaluations can be reinforced with the help of practical orientation sessions and faculty-led demonstrations, and uncertainty can be minimized.

Second, SI have a significant influence on adoption intention, universities can foster responsible peer endorsement by organizing best-practice sharing sessions, guided AI usage policies and university-supported communities of practice. The formal policy statements can allow institutional approval of AI use in the academic settings and facilitate the minimization of reluctance among scholars. Third, since tradition, risk, and usage barriers do not contribute positively to adoption, institutions ought to establish explicit ethical usage models that serve to deal with concerns on academic integrity, data reliability, and citation transparency. Ensuring that AI disclosure policies are standardized will help decrease the perceived risk and bring the use of ChatGPT closer to the current academic standards instead of portraying it as a disruptive technology.

After that, at the regulatory level, recommendations on national use of AI can be formulated by the higher education commission (HEC) of Pakistan to guide the use of AI in universities and this includes standard policies on disclosure, integration of plagiarism detection and responsible use of AI-assisted research practices. The creation of a regulatory framework would decrease the level of ambiguity and perception of risk and promote ethical and controlled adoption. Additionally, HEC and higher education administration can implement AI literacy courses in the postgraduate curricula to increase digital literacy and decrease UB. Investment by the institution in AI training infrastructure would make adoption productive without compromising research ethics and originality in research.

However, the results imply that successful adoption of ChatGPT should be implemented by dual approach: enhancing the drivers of acceptance by means of training and institutional support and reducing the drivers of resistance by ethical control, transparency, and institutional regulation.

6.3 Limitations and Future Research Directions

Along with theoretical contributions and practical implications, this study has few limitations that point to proposed areas for future research. First, the data was collected from a specific group of postgraduate research scholars enrolled in public universities in Southern Punjab, Pakistan due to which the results have limited generalizability. The institutional and national contexts might have different results since the rates of digital literacy, AI governance models, and institutional AI policies are quite different. As an illustration, universities that are situated in a more established AI regulatory framework as well as in higher levels of digital competence might have a reduced impact of resistance and increased influence of acceptance. In future, studies should thus replicate this model under situations that are marked with more AI control, increased technological preparedness or more rigorous academic integrity policies to look at any structural variations. Second, the study uses the cross-sectional type of research design which limits determination of the temporal precedence and causal direction among the reasons for, reasons against, attitude and intention to use ChatGPT. Even though the structural paths are in theory-based, the single time-point data do not allow tracking the change in attitudes and factors of resistance with time as users become more familiar with generative AI tools. The longitudinal design would enable the researcher to investigate in future whether resistance could reduce over time, whether PU would be enhanced with repeated exposure as well as whether intention would translate into long-term behavioral adoption.

Third, this research mainly concerned the Pakistan situation. The changing character of AI regulation, uneven digital infrastructure, and dissimilar institutional support systems could affect adoption dissimilarly to developed economies where AI policies are established. Cross-country comparisons between developing nations and developed nations can thus give further insight into regulatory maturity-based and digital ecosystem-based adoption trends.

Moreover, the current research evaluated the intentions of users towards ChatGPT. To obtain a more detailed insight, future studies should be conducted on real-life behavior regarding the adoption of ChatGPT. Further, despite the fact that the role of attitude is very important in predicting intention in the present study, the psychological processes mediating the effects of cognitive evaluation on behavioral intention remain limited. Future studies can eamine the possible mediating variables (e.g., trust in AI, perceived ethical acceptability, academic self-efficacy), the moderating variables (e.g., digital literacy, prior AI experience, institutional support), to have a more accurate understanding of the boundary conditions and the indirect relations through which adoption of ChatGPT will occur. Lastly, post graduate research scholars have been addressed in the present study. Future studies can go further by studying the intention of the undergraduate students to adopt ChatGPT.

6.4. Conclusion

Our research delved into examining users' perspectives, encompassing both the positive and negative aspects of ChatGPT in their educational journey. Along with enhancing ease of usage, perceived value, and proliferating social discourse on the efficacy and instrumentality of ChatGPT in realizing desired academic outcomes could strengthen students' attitudes and intentions to use ChatGPT. Moreover, the false perceptions, stereotypes, and stigmas that enkindle the tradition, value, and risk barriers to impede the adoption of ChatGPT need to be adequately addressed. After that, the study offers significant theoretical contributions and practical implications. ChatGPT, like other AI tools, has a range of potential applications, particularly in academic research within higher education. In particaulr, it's important to note that ChatGPT, while beneficial, also has certain drawbacks. Hence, policymakers must be mindful of the quality and integrity of academic outcomes in the face of the challenges stemming from the widespread adoption of ChatGPT.

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Availability of Data

The dataset is available from the corresponding author upon reasonable request.

Declaration of AI Use

The manuscript was primarily written and revised by the authors. AI-based tools were used only in a limited manner for language polishing and minor grammatical refinement to improve clarity and readability of the manuscript. No AI tools were used for generating data, analysis, or the core intellectual content of the study. The theoretical arguments, methodology, results, and interpretations were entirely developed by the authors.

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