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INTENTION TO ADOPT CHATGPT BY ACADEMICIANS UTILIZING DIFFUSION INNOVATION MODEL

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ABSTRACT

In this era of fourth industrial evaluation, users' acceptance and adoption of Artificial Intelligence (AI) by its users complements a large literature and practical dimension shift, especially after the 2020 pandemic in the research area. The purpose of this study is to explore and investigate the central constructs and factors influencing academicians' intention to adopt ChatGPT in Bangladesh by academicians in their traditional workflows. This paper adopts Diffusion Innovation Theory (DIT). This paper analyzed a total of 148 academicians from both public and private universities, to find the intensity and willingness of their intention of using AI in their work purpose. The convenience sampling method was used in this study's quantitative approach to gather data. The study's findings revealed that complexity and compatibility are the most contributing factors in the adoption of ChatGPT by the academicians in Bangladesh, while conversely the variables relative advantage and observability don't affect the adoption intention on a large scale. An external variable social influence is integrated as a moderator in this study. This study's practical consequences are relevant for universities in Bangladesh. The study also suggests universities may develop training programs to adopt new technologies and give facilities to make their education system more effective and smoother. The findings and implications of this study not only affect the workflow of the *academicians on a large scale but also offer meaningful insights for educational leaders to build a technology-advanced & AI-based academic environment to standardize the learning sessions and environment.*

Keywords: *ChatGPT, Diffusion Innovation model, Compatibility, Relative Advantage, Complexity, Trialability, Observability, Social Influence, Adoption of ChatGPT.*

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1. INTRODUCTION

The Fourth Industrial Revolution has initiated the period of blistering and robust development of the ability to apply artificial intelligence (AI) into different spheres of professional and academic activity (Wamba-Taguimdje et al., 2020a; Yang et al., 2024a). The pace of AI-based tools adoption has increased after the COVID-19 pandemic, as the digital technologies gained essentiality in the continuity of academic activities (Al-Rahmi et al., 2019a). A recent example of AI-driven tools, ChatGPT, a generative AI application created by OpenAI, which has been popular due to the ability to accomplish academic writing, problem solving, and administration and it is a shift in the paradigm of processing information, conducting research, and sharing knowledge (Budhathoki et al., 2024a). This disruptive wave demands extensive research on the adoption and acceptance of these new technologies by people, especially those in the academic world. The spread of these innovations is a very significant subject of research since it directly affects the success and the overall adoption of these tools in learning and research environments. Besides, it requires an in-depth enquiry into the way people, especially scholars, embrace and embrace these new technologies (Liu & Zhang, 2024a). The implementation of ChatGPT is especially relevant to academicians in higher education because it provides sources with the possibility of increased teaching productivity, better sharing of knowledge, and more meaningful interactions with students (Raman et al., 2024a). In Bangladesh, where universities are attempting to adopt technological advancements, the importance of AI-based solutions, like ChatGPT, become increasingly vital to enhance educational activities and research output (Menon & Shilpa, 2023a; Raman et al., 2023a).

The existing body of literature on technology adoption has made extensive use of such frameworks as the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) (University of Arkansas et al., 2016; Venkatesh et al., 2003, 2012a). These models have given meaningful insights into perceptions of some factors including usefulness and ease of use. Nevertheless, there is a significant amount of literature that recognizes the value of a bigger theoretical framework, including the Diffusion of Innovation Theory (DIT) by Rogers (1995). DIT is an extended model to learn how the distribution of new ideas and technologies among a social system takes place over a period with emphasis on the features of the innovation itself and the process of decision making of an individual (Yuen et al., 2021a). Besides, the DIT further enhanced by Rogers (2003) has been extensively used to describe how attributes of innovation relative advantage, compatibility, complexity, trialability and observability affect the adoption behavior. The existing literature affirms that more innovations that satisfy the needs of the users, simplify them, and deliver tangible benefits are more likely to be adopted (Dixit et al., 2023a; Yuen et al., 2021b). Moreover, social influence and perceived risk have been incorporated into the adoption models through recent empirical studies that show that they have a considerable effect on the behavioral intentions of users (Chatterjee et al., 2020a; Jangir et al., 2022a). Research in the higher education sector reveals that compatibility, simplicity, and trialability are becoming the determinants that academicians use to implement AI technologies (Liu & Ma, 2024a; Ma et al., 2025a).

Although the research on the topic of technology adoption is abundant, there is still a significant gap in the literature on the specific context of the adoption of the AI tools by the academicians in developing countries. The given issue is that the existing research has mostly targeted students or general users in the Western context (Liu & Zhang, 2024b; Wang et al., 2025; Yuen et al., 2021b), and the behavioral patterns and factors that influence them among faculty members in such countries as Bangladesh had not been explored. Besides, the body of literature concerning ChatGPT adoption has been predominantly student-centered, but little has been said regarding academicians, who are the main actors in the dissemination of technology in educational institutions (Budhathoki et al., 2024a; Raman et al., 2024a). The mode of decision-making of an academician, who must reconcile the conventional work processes with the opportunities presented by a new resource is unique and needs special research to be completely understood (Wang et al., 2021). The decision-making of an academician who must weigh between

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conventional working processes and potential advantages of a new tool is unique and must be thoroughly investigated. Additionally, the adoption of developing countries like Bangladesh could be affected by infrastructural concerns and cultural factors (Almaiah et al., 2022a; Badghish & Soomro, 2024a). One more aspect that has not been examined thoroughly involves the importance of perceived privacy risk that does not necessarily dictate adoption, yet it may moderate the dynamics between the attributes of innovation and behavioral intentions (Pavlou, 2014; Kim et al., 2008). The importance of filling these gaps is to learn how academicians who are knowledge gatekeepers adopt and use generative AI technologies such as ChatGPT.

Consequently, the main purpose of the research is to examine and research the key constructs and determinants of the intention of academicians to use ChatGPT in Bangladesh, using the Diffusion of Innovation Theory. Through its underserved demographic and extremely pertinent technology, this paper aims to equip a detailed insight into the forces of adoption. The objectives of the study are to determine the determinants of adoption that are deemed as central according to the DIT model and to measure the level of intention and interest of the academicians to use ChatGPT in their professional life. This paper will attempt to offer a granular insight into the drivers of adoption by focusing on a narrow research gap and a well-timed technology. It studies the impact of relative advantages, compatibility, complexity, trialability, and observability on the adoption process, and incorporates the perceived privacy risk as a moderator. Through comparing the answers to the academicians of both state and private universities, the study provides empirical data on the dynamics of adopting the generative AI tools into higher education.

The current study is innovative in its use of the Diffusion of Innovation Theory to the use of a modern AI tool, ChatGPT, by a certain population of academicians in Bangladesh. This way, it addresses a major shortcoming in theory and empirical evidence that only provides a specific and situational analysis. The results will offer some fresh evidence on how the relative advantage, compatibility, complexity, trialability, and observability principles affect the choice of an academician to implement revolutionary technology and, as such, enlarge the usage of DIT framework in a non-Western setting, nowadays. This way, it closes a big theoretical and empirical gap, providing a narrow and situational analysis. Besides, the research has several new contributions. In theory, it lends DIT the perceived privacy risk as a moderator, thereby increasing the explanatory power of the model regarding AI adoption. In a practical sense, the study can guide universities and policymakers in Bangladesh to develop effective training interventions, improve the compatibility of AI with academic processes, and solve the privacy issue to ensure easier adoption. This study also helps to achieve SDG's goal number 9, which is to ensure the efficiency and quality of the industry, innovation and infrastructure. The current study not only contributes to the literature on the diffusion of innovation, as it centers on scholars in a developing nation, but also offers valuable information in a timely manner to promote the development of AI use in higher learning institutions.

2. REVIEW OF LITERATURE

2.1 Theoretical Underpinning

This study is based on Everett M. Rogers' Diffusion of Innovation Theory (DIT), which provides a thorough framework for comprehending the adoption of new ideas and technologies within a social system over time. The theory suggests that the uptake of an innovation is shaped by a blend of personal decision-making processes, communication pathways, temporal factors, and the social framework within which the innovation disseminates (Grübler, 1991)

In DIT theory, there are outlines five critical attributes of innovations that significantly influence their rate of adoption, which this study expands to include a sixth attribute relevant to modern digital technologies: Relative Advantage, Compatibility, Complexity, Trialability, Observability (Rogers, 2003). Relative advantage refers to the extent to which individuals acknowledge an innovation as possessing distinct advantages over prior alternatives—such as enhanced efficiency, prestige, economic gains, or convenience—correlates positively with the speed of its adoption. Compatibility means innovations that resonate with the individual's developed values, practices, and experiences tend to achieve swift acceptance. Complexity is the greater the complexity of an innovation, the more gradual adoption tends to be. Trialability refers to innovation that may be evaluated in segments or without complete commitment to mitigate the hazards for the adopter and promote the likelihood of adoption. Observability is the visibility of the positive aspects associated with an innovation frequently contributes to an elevated rate of adoption, driven peer dynamics and the concept of social validation as well as the concept of social influence pertains to the effects exerted by significant individuals in a user's life – such as peers, supervisors, friends or family – on the user's choice regarding the adoption and utilization of technology (Rogers, 2003). If these notable individuals perceive technology favorably and advocate for its implementation, the likelihood of user adoption will increase.

Within this framework, ChatGPT—a generative AI model developed by OpenAI—serves as the focal innovation. The application of diffusion of innovation theory (DIT) enables the analysis of adoption patterns and the identification of key factors that influence users' willingness to integrate ChatGPT into their personal, academic, or professional practices (S. David et al., 1994). The defined dimensions elucidate the distinct levels and stages of adoption among various consumer segments, particularly innovators, early adopters, early majority, late majority as well as laggards. The theory considers the impact of interpersonal communication, social influence, and media in shaping perceptions and either facilitating or hindering the diffusion process. This study utilizes the Diffusion of Innovation Theory to analyze the dynamics surrounding the adoption of ChatGPT, uncover patterns among different user groups, and enhance the overall comprehension of how generative AI technologies spread within modern digital environments.

2.1.1 Relative Advantage

Relative advantage is one of the main factors in DIT. Relative Advantage is defined as a degree to which an innovation is perceived as providing more benefits than its predecessor

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(David et al., 1994). The degree to which ChatGPT is perceived as more effective or beneficial compared to existing tools such as search engines, writing aids, or tutoring platforms. Innovation may be advantageous when it provides economic benefits, social status, and gratification (Yuen et al., 2021c). For instance, it was studied how ChatGPT could create easily understandable clinical letters using Generative AI, enhancing efficiency, consistency, accuracy, patient satisfaction, and cost-effectiveness in healthcare systems (Al-Rahmi et al., 2019b; Saifuzzaman et al., 2023). A compelling perception of relative advantage may position ChatGPT as a preferred choice over alternatives, leading students to exhibit a greater intention of utilizing it (Raman et al., 2023b).

Relative advantage denotes the perceived superiority of an innovation compared to existing alternatives (Rogers, 2003). The relative advantage serves as a crucial determinant in the decision—making process of users regarding technology adoption, especially when new innovations demonstrate quantifiable enhancements compared to current tools. In the realm of artificial intelligence, individuals frequently reference enhancements in productivity, educational results, and decision-making assistant as evident benefits (Wamba-Taguimdje et al., 2020b). ChatGPT offers enhanced productivity, efficiency, and accessibility in generating content, solving problems, and facilitating learning, thereby replacing traditional search engines or human-mediated support. Prior studies confirm that technologies offering functional or performance advantages are more likely to be adopted (Dixit et al., 2023b; Dwivedi et al., 2024; Jeyaraj, 2023). In educational contexts, learners have embraced artificial intelligence writing tools such as Grammarly and ChatGPT due to their perceived enhancements in writing quality as well as efficiency in time management (Krouska et al., 2024).

H1: Relative Advantage increases the intention to adopt and use the ChatGPT.

2.1.2 Compatibility

Compatibility refers to the degree to which a service is perceived as consistent with users' existing values, beliefs, habits, and present and previous experiences (David & Greenstein, 1990; Rogers, 2003). The extent to which ChatGPT aligns with the users' existing values, technological habits, and needs. The COVID-19 pandemic has significantly increased the adoption of virtual and e-learning processes, making them an essential aspect of students' lives (Raman et al., 2023b). This variable has been consistently linked to users' behavioral intentions to adopt and utilize new technologies (Ma et al., 2025b). For instance, a study demonstrated a positive impact of compatibility of use on employees' behavioral intention to adopt an AI customer service system within organizations (Chatterjee et al., 2020b). Furthermore, studies have shown a significant increase in user interaction time and a notable surge in adoption rates post-integration of ChatGPT (Liu & Ma, 2024b; Menon & Shilpa, 2023b; Shang et al., 2024).

Compatibility refers to the extent to which an innovation corresponds with the values, experiences and requirements of prospective adopters (Rogers, 2003). For ChatGPT, compatibility may refer to its seamless integration with digital routines, platforms, and user expectations. Technologies that are compatible with current practices demonstrate a greater likelihood during adoption (Chatterjee et al., 2020b). Technologies that seamlessly align with users' established practices and digital environments tend to experience higher rates of adoption. For example, platforms utilizing artificial intelligence that are compatible with learning management systems or organizational tools experience a more rapid adoption.

H2: Compatibility of ChatGPT affects the intention to adopt the ChatGPT.

2.1.3 Complexity

Complexity is defined as the extent to which an innovation can be considered relatively difficult to understand and use (David & Greenstein, 1990). The level of complexity involved comprehending and utilizing ChatGPT effectively. Consumers generally adopt innovations that require new skills and knowledge at a slower pace than those that are simpler (Yuen et al., 2021c). Complexity may lead users to misunderstand the function of the technology (Holak & Lehmann, 1990). Complexity is included to capture one of the five innovation characteristics adopting a new technology (Min et al., 2019). Based on this definition, the current study uses these terms to refer to the extent of difficulty viewed by the academician that affects his/her intensity and willingness of their intention.

Complexity refers to the perceived difficulty in understanding and using an innovation (Rogers, 2003). Despite ChatGPT's natural language interface, some users may still perceive it as complex due to unfamiliarity with AI technologies or concerns over accuracy and reliability. Prior research has shown that higher complexity correlates negatively with adoption intention (Venkatesh, 2022; Yang et al., 2024b). Complex systems may hinder user adoption of technology, especially when they demonstrate a lack of transparency or are regarded as "black-box" models (Shin, 2021). In decision support systems that utilize artificial intelligence, the aspects of usability and simplicity have been identified as significant contributors to their adoption.

H3: High complexity in ChatGPT decreases the intention to adopt ChatGPT.

2.1.4 Trialability

Trialability is the extent to which an innovation can be experimented with on a limited basis before full adoption (Rogers, 2003). The degree to which prospective users may evaluate ChatGPT on a restricted basis prior to engaging in its consistent utilization. Trialability innovation tends to have less uncertainty perceived by individuals who consider adopting it and those individuals tend to learn through this experience (Al-Rahmi et al., 2019c; Saifuzzaman et al., 2023). As for the current study, this concept refers to how an academician views his/her use of ChatGPT having a significant impact on intensity and willingness of their intention.

Trialability refers to the extent to which users can test an innovation prior to its complete execution (Rogers, 2003). ChatGPT's freemium model and ease of access allow users to explore its functionalities without financial or technical constraints. Literature suggests that technologies that allow users to test and evaluate them informally are adopted more readily (Liu & Ma, 2024b; Prakash et al., 2024). The capacity to engage in experimentation with technology significantly increases users' propensity to embrace it. Studies indicate that allowing users to experiment with AI-based systems without the burden of long-term commitment or expense mitigates uncertainty (Zhao et al., 2023). Trial experiences additionally offer cognitive reassurance that the technology is in accordance with individual or organizational standards (Chen et al., 2022).

H4: Trialability of ChatGPT increases its intention to adopt.

2.1.5 Observability

Observability is the extent to which innovation is visible to the members of a social system and the benefits can be easily observed and communicated (Rogers, 2003). The visibility of innovation results and benefits others in the social environment. Consumers are more likely to adopt new innovations when their effects or benefits are visible to them (Min et al., 2019). It is assumed that friends and colleagues of an adopter frequently ask him/her for feedback. Visibility is seen as a factor that stimulates peer discussion of new ideas (Al-Rahmi et al., 2019b). Based on these points, the acceptability viewed by academicians of the use of ChatGPT that has an impact on their performance defines the term trialability.

Observability signifies clarity regarding the effects and benefits associated with the actualization of an innovation (Rogers, 2003). The wide circulation of ChatGPT-generated content on social media, educational platforms, and professional networks makes its benefits highly visible, enhancing its attractiveness. Recent studies emphasize that observable technologies experience faster diffusion due to social modeling and mimicry (Jeyaraj, 2023). Technologies that demonstrate clear advantages are often embraced more swiftly. Within the context of generative artificial intelligence (AI), platforms such as Reddit, YouTube, and TikTok serve as facilitators of enhanced observability, as they publicly display various use cases and outcomes. The adoption of AI tools is increasingly influenced by the public demonstration of successful applications by peers or organizations (Zhang et al., 2020).

H5: Observability affects the intention to adopt ChatGPT.

2.2 Perceived Privacy Risk

Perceived privacy risk (PPR) refers to concerns about the misuse of sensitive or personal information when using technology. Privacy risks are particularly relevant for ChatGPT, given its reliance on user input for generating output. Research by Pavlou (2003) indicates that higher privacy concerns negatively impact adoption intentions. Kim et al. (2008) argue that perceived privacy risks are a psychological barrier, moderating the relationship between behavioral intention and actual use. According to Lim et al. (2025), artificial intelligence is a novel and sophisticated technology that may cause users to perceive hazards, which might ultimately impact their trust and behavioral intention toward the instrument. Furthermore, because they are worried about their data, who can access it, and how secure it is, consumers perceive danger when there is inadequate security to safeguard their personal information. This has an impact on consumers' trust and adoption of a variety of technical domains, including Internet banking, mobile payment services, and online shopping. In this context, PPR moderates the relationship between behavioral intention and actual usage, with academics more likely to abstain from adoption if privacy concerns are unaddressed. So, the following hypotheses have been developed.

The stated hypotheses of moderating variable as well as direct relation PPR:

H6a: Perceived Privacy Risk moderates the relationship between Relative Advantage and Intention to adopt ChatGPT

H6b: Perceived Privacy Risk moderates the relationship between Compatibility and Intention to adopt ChatGPT

H6c: Perceived Privacy Risk moderates the relationship between Complexity and Intention to adopt ChatGPT

H6d: Perceived Privacy Risk moderates the relationship between Trialability and Intention to adopt ChatGPT

H6e: Perceived Privacy Risk moderates the relationship between Observability and Intention to adopt ChatGPT

H7: Perceived Privacy Risk affects the intention to adopt ChatGPT

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2.3 Conceptual Framework

The conceptual framework is represented in the figure below.

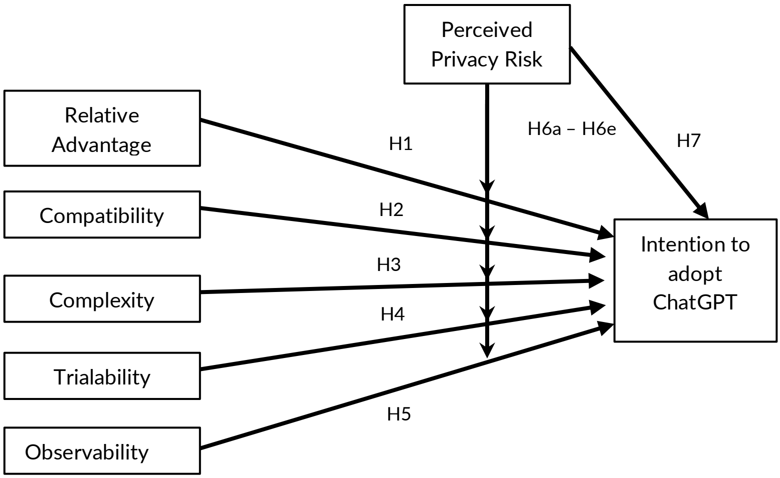

Figure 1. Conceptual framework for intention to adopt ChatGPT

3. RESEARCH METHODOLOGY

The result of this study is evaluated objectively without reference to subjective perspective. This study is based on positivist research philosophy (Saunders et al., 2007). The deductive research technique is used to find the compatibility between literature and hypotheses of this study (Saunders et al., 2007). The impact of independent variables- relative advantage, complexity, compatibility, trialability and observability on dependent variable intention to adopt ChatGPT is evaluated through quantitative methods with a descriptive research design (Aleksandras Melnikovas, 2018).

3.1 Sampling Procedure

The target population of the study is the academicians (both male and female) of the universities in Bangladesh. The sampling frame consists of people who are not old citizens, as ChatGPT can be more appreciated by young professionals. This study employs the convenience sample approach due to its cost-effectiveness. According to Malhotra et al. (2010), convenience sampling techniques may also be used to estimate population parameters based on sample statistics, even though probability sampling techniques are the optimal sampling approach for this type of investigation. However, we consider the study's drawback, which is the inability to use probability sampling approaches because of various resource restrictions (i.e., time and money). The ten (10) times rule states that 80 (8*10 = 80) is the minimal sample size needed to determine the sample size. However, Sarstedt (2019) proposed that to do data analysis in structural equation modeling, a sample size of at least 100 is necessary (Hair et al., 2020). Nevertheless, data collection took place between July and August of 2024, and a measurement tool (questionnaire) comprising 25 items with a 5-point Likert scale was used to collect the data. This resulted in 200 responses in total; following data cleaning, 154 responses were used for analysis, which is more than we needed. Additionally, the measuring scale was pre-tested using a pilot study consisting of 20 respondents before the questionnaire was administered, and it was adjusted accordingly.

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3.2 Measurement Items

The items selected to create the constructs utilized in this study's structural model were taken from earlier research, where each construct's convergent validity was guaranteed. For example, items of each construct are grouped based on the study done by Al-Rahmi et al. (2019a), Moore & Benbasat, (1991), Mohammadi (2015), and Venkatesh et al. (2012), Budhathoki et al. (2024). A 5-point Likert scale is used to measure each of these items. However, the questionnaire also asks for standard demographic data. This is represented in Table 1 below.

Table 1. Constructs and measurement items

Relative Advantage	1. Using ChatGPT enables me to accomplish tasks more quickly and makes my job easier 2. Using ChatGPT improves my quality and effectiveness of work. 3. Using ChatGPT gives me greater control over my job.	Al-Rahmi et al., (2019a), Moore & Benbasat (1991), Mohammadi (2015)
Compatibility	1. Using ChatGPT is compatible with all aspects of my work. 2. I think using ChatGPT fits well with the way I like to work. 3. Using ChatGPT fits into my work style.	Moore & Benbasat (1991), Mohammadi (2015)
Complexity	1. My interaction with ChatGPT is clear and understandable. 2. It is easy to get ChatGPT to do what I want it to do. 3. I believe the usage of ChatGPT is easy for me. 4. Learning to operate through ChatGPT is easy for me.	Mohammadi (2015), Moore & Benbasat (1991)
Trialability	1. Before deciding whether to use ChatGPT, I was able to properly try them out. 2. I was admitted to using ChatGPT on a trial basis long enough to see what it could do.	Mohammadi (2015) Moore & Benbasat (1991)
Observability	1. Most of my colleagues use ChatGPT. 2. I would have no difficulty telling others about the results and benefits of using ChatGPT.	Mohammadi (2015) Moore & Benbasat (1991)

	3. I could communicate to others the consequences of using ChatGPT.	
Perceived Privacy Risk	1. I think my personal privacy information will be used for other purposes if I use ChatGPT. 2. Because of security issues, I face the risk of personal information leakage if I use ChatGPT. 3. I think that when I use ChatGPT, my personal information will be abused by cybercriminals.	Y.-S. Chen & Huang (2017)
Intention to adopt ChatGPT	**1.** I intend to use the ChatGPT applications. **2.** I predict I will use ChatGPT applications in the next 3 months. **3.** I plan to use ChatGPT applications in the next 3 months	Budhathoki et al. (2024) (Venkatesh et al., 2012b)

Source: The authors' own work.

3.3 Demographic Profile of the Respondents

As demonstrated in Table 2 below, the demographic profile analysis of the respondents depicted that the ratio between males and females is almost equal (55.84:42.86).

Table 2. Demographic Profile of the Respondents

Variable	Categories	N	Percentage
Gender	Female	86	55.84
	Male	66	42.86
	Others	02	1.3
Age	25-35 years	120	77.92
	36-45 years	24	15.58
	46-55 years	10	6.5
Designation	Professor	14	9.09
	Associate Professor	12	7.79
	Senior Lecturer/Assistant	52	33.77
	Professor	76	49.35
	Lecturer		

Source: The authors' own work.

The highest responses come from the age group 25–35 years (77.92%), this can be reasoned that people in this age group use

ChatGPT more compared to other age groups. Concerning the education level, respondents at the lecturer level are the most (49.35%), followed by Senior Lecturer/Assistant Professor (33.77%). This information also corresponds with the age group information. Additionally, respondents from Port City International University, Chittagong, Bangladesh, participated most (59.74%), followed by Presidency University (10.38%).

4. RESULTS

4.1 Descriptive Analysis

Table 3 shows that the descriptive analysis conducted in this study involved the calculation of several statistical measures, namely mean, standard deviation, skewness, and kurtosis associated with the latent variables.

Table 3. Descriptive Statistics

Latent Variables	Mean	Median	Standard deviation	Excess kurtosis	Skewness
Relative Advantage	3.7876	0.184	0.8978	0.248	-0.973
Compatibility	4.0563	-0.068	0.8629	3.274	-1.501
Complexity	4.1495	0.120	0.9321	1.664	-1.226
Trialability	3.2643	0.061	1.000	-0.459	-0.553
Observability	4.013	-0.018	0.9625	0.529	-0.866
Perceived Risks	3.000	0.075	0.9732	0.136	-0.386
Adoption	3.6316	0.410	1.000	0.466	-0.714

Source: The authors' own work.

The outcomes demonstrated that complexity generated the highest mean value with a score of 4.1495, accompanied by a standard deviation of 0.9321. The table includes several variables, likely representing different items or constructs in a survey or questionnaire. Skewness indicates a distribution with a longer tail to the left.

4.2 Structural Equation Modelling

4.2.1 Direct Paths

Table 4 Illustrates the results of the structural model (direct paths) including beta, t-statistics, confidence interval, and p-values. The results showed that some of the relationships were statistically significant.

Table 4. Results of direct and moderating paths (SEM Model)

Hypothesis	Latent Variables	Beta	t statistics	p values	Results
H1	Relative Advantage -> Adoption	-0.134	1.624	0.104	Rejected
H2	Compatibility -> Adoption	0.526	5.854	0.000	Supported
H3	Complexity -> Adoption	0.278	2.655	0.008	Supported
H4	Trialability -> Adoption	0.259	3.280	0.001	Supported
H5	Observability -> Adoption	-0.121	1.544	0.123	Rejected
H6a	PR*Relative Advantage -> Adoption	1	1	n/a	Supported
H6b	PR*Compatibility -> Adoption	1	1	n/a	Supported
H6c	PR*Complexity -> Adoption	1	1	n/a	Supported
H6d	PR*Trialability -> Adoption	1	1	n/a	Supported
H6e	PR*Observability -> Adoption	1	1	n/a	Supported
H7	PR -> Adoption	0.215	1.408	0.159	Rejected

Source: The authors' own work.

The influence of compatibility on intention of adoption was MOST significant and positive at ($p < 0.000$, 0.05). The effects of complexity and trialability on adoption were significant and positive at ($p < 0.05$, 0.000). Therefore, all the hypotheses of

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H2, H3 and H4 were supported in this study. The results also showed that compatibility had the highest influence on adoption (beta = 0.526, $p < 0.000$) indicating that one unit change in compatibility will ensure a 0.526 unit change in adoption, considering other effects as constant. Perceived risks moderate the relationship between relative advantage, compatibility, complexity, trialability, observability, and adoption ($p<0.000$). Consequently, H2, H3, and H4 hypotheses were accepted and got significance. In structural equation modelling (SEM), total effect measures the overall impact of an independent variable on a dependent variable, taking into account both direct and indirect effects through other variables. T statistics and P values are related to hypothesis testing. The t-value is used to assess the statistical significance of the total effect. The p-value indicates the probability of observing a t-statistic as extreme as the one calculated, assuming the null hypothesis (that the total effect is zero) is true. For example, Complexity -> Adoption: The total effect of complexity on adoption is 0.526. The t-statistic is 2.655, and the p-value is 0.008. This means that there is a positive relationship between complexity and adoption, and the effect is statistically significant at the 0.05 level.

4.2.2 R Square

Table 5 Demonstrates the R square value, which indicates a statistical measure that represents the proportion of the variance in a dependent variable that is explained by the independent variable(s). The higher the R square value, the better the model fits the data.

Table 5. R Square

Indicators	R-square	R-square adjusted
Adoption	0.643	0.624

Source: The authors' own work.

This table depicts an R-value of 0.643 which is considered to be a moderate positive variance in the adoption of ChatGPT that is explained by the independent variables. Similarly, the R square table above illustrates the adjusted R square value. The adjusted R square value is a modified version of the R square that provides an adjustment for the number of independent variables in this model. It is generally regarded as a more reliable measure of model fit, especially when comparing models with different numbers of predictors. Here, the value of the adjusted R Square is 0.624, which indicates a difference of less than 0.05 between the R square and the adjusted R square. Consequently, it provides a reliable measure of model fit.

4.2.3 Measurement Model Analysis

Table 6 Interprets the reliability and validity including convergent validity and discriminant validity are assessed in the measurement model analysis phase. This study contained both first- and second-order constructs (e.g. adoption of ChatGPT in academics).

Table 6. Construct and Discriminant Validity (SEM Model)

Latent Variables	Items	Factor Loadings	Scale Type	Cronbach's alpha	(AVE)	VIF
Relative Advantage	1	0.890	Reflective	0.803	0.716	1.976
	2	0.883				2.281
	3	0.759				1.492

Compatibility	1	0.885				2.237
	2	0.927		0.884	0.812	3.385
	3	0.890				2.598
Complexity	1	0.890				2.989
	2	0.903		0.903	0.774	2.713
	3	0.865				2.693
	4	0.862				2.402
Trialability	1	0.918		0.880	0.808	3.770
	2	0.940				4.420
Observability	1	0.905				3.329
	2	0.926		0.923	0.867	3.686
	3	0.962				6.063
Perceived Risks	1	0.901				2.335
	2	0.389		0.912	0.369	4.416
	3	0.379				4.323
PR*Relative Advantage-> Adoption	-	-		1	0	n/a
PR*Compatibility -> Adoption	-	-		1	0	n/a
PR*Complexity -> Adoption	-	-	Formative	1	0	n/a
PR*Trialability -> Adoption	-	-		1	0	n/a
PR*Observability -> Adoption	-	-		1	0	n/a
Adoption	1	0.909				2.826
	2	0.943	Reflective	0.903	0.838	3.958
	3	0.894				2.701

Source: The authors' own work.

Construct reliability and validity of first-order constructs were presented followed by those of second-order constructs. Cronbach's alpha is 0.903 which indicates construct reliability.

Cronbach's alpha shows the measure of internal consistency reliability for a set of items. It assesses how effectively the items in a scale indicate the same underlying construct. Higher Cronbach's alpha values indicate better internal consistency. So, the value represented in the table for Cronbach's Alpha is 0.903 indicating a great internal consistency among the latent variables. SEM is a statistical method used to evaluate the complex relationships between the latent variables and observed variables. The AVE table portrays the AVE values for each latent variable in a structural equation model (SEM). AVE measures the proportion of variance in a latent variable that is explained by its measured indicators. Higher AVE values indicate better convergent validity, meaning that the indicators are good measures of the underlying latent variable. Moreover, factor loading and AVE of 0.838 or over and 0.50 or over, respectively, indicate convergent validity of the constructs (Hair et al., 2020). As the results indicated in the Table, sufficient validity and reliability were observed among the latent variables of this study.

Table 7 presents the Standardized Root Mean Square Residual (SRMR) values for a saturated model and an estimated model. SRMR is a fit index used in structural equation modeling (SEM) to assess how well the model fits the observed data.

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Table 7. Validity (SEM Model)

SRMR				
Indicators	Original sample (O)	Sample mean (M)	95%	99%
Saturated model	0.096	0.049	0.065	0.074
Estimated model	0.097	0.05	0.065	0.074

Source: The authors' own work.

A saturated model is a model that perfectly fits the data, with as many parameters as data points. It is used as a reference point for comparison. The SRMR value for the saturated model is 0.096. Estimated model means the model that the researcher has specified and estimated. The SRMR value for the estimated model is 0.097. Lower SRMR values indicate better model fit. In this case, both the saturated model and the estimated model have very low SRMR values, suggesting a good fit to the data. Nevertheless, the estimated model has a slightly higher SRMR value than the saturated model. This is expected, as the saturated model is designed to fit the data perfectly. Generally, SRMR values below 0.08 are considered to indicate a good model fit. Both models in this table meet this criterion. It's important to consider other fit indices along with SRMR to get a comprehensive assessment of model fit.

4.2.4 Discriminant Validity

Table 8 A two-stage disjoint approach suggested by (Sarstedt et al., 2019) was adopted in this study to form an adoption of ChatGPT second-order construct- consisting of the latent variable scores of independent variables of this study.

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Table 8. Discriminant Validity (SEM Model)

Discriminant Validity	A	Complexity	Compatibility	Triala-bility	Observa-bility	Relative Advantage	PR	PR as moderator
Adoption	1	-	-	-	-	-	-	-
Complexity	0.676	1	-	-	-	-	-	-
Compatibility	0.809	0.849	1	-	-	-	-	-
Trialability	0.654	0.464	0.614	1	-	-	-	-
Observability	0.542	0.717	0.771	0.502	1	-	-	-
Relative Advantage	0.613	0.834	0.802	0.671	0.519	1	-	-
Perceived Privacy Risks	0.152	0.286	0.186	0.165	0.124	0.160	1	-
PR as moderator	0.116	0.132	0.186	0.045	0.090	0.077	0.240	1

Source: The authors' own work.

As the elements of adoption to ChatGPT represented different aspects of behavior, the intention to use the ChatGPT variable was considered a reflective-formative construct. Therefore, the reliability and validity of the new model were required to be assessed. A formative second-order construct was assessed with the values of variation inflation factor (VIF) below 5 for identifying collinearity among the indicators and the size of outer weights of the indicators (Sarstedt et al., 2019). The outer weights indicated the relative effects of first-order constructs on the higher-order constructs where all the outer weights were positive and significant. The results confirmed the reliability and convergent validity of both first- and second-order constructs. The table shows the construct reliability and validity after generating second-order constructs. The measure of discriminant validity is the heterotrait-monotrait ratio (HTMT) which estimates the actual correlations among constructs (Hair et al., 2020). Values of HTMT below 0.90 indicate the presence of discriminant validity.

5. DISCUSSION AND IMPLICATIONS

This research is about finding the five variables impact on intention to adopt ChatGPT by academicians, as well as finding a moderating effect of perceived risk in these decisions of adoption. The result shows that complexity, compatibility and trialability have significant positive effects on intention of adoption and on the other hand, relative advantage and observability attributes don't have any significance in the adoption decision. The accepted result of mediating effects was shown where perceived risk mediates decisions of all attributes in intention to adopt ChatGPT. But the direct effect of perceived risk on intention to adopt ChatGPT is not seen. It means risk often works as a moderator instead of directly in decision of ChatGPT adoption.

In DOI theory, it was predicted that perceived risk has direct effects on adoption decisions (Rogers, 2003). There are also studies that support the result of our analysis. But the result is found opposite in this study. It can be justified by stating that users of AI neglect relative advantages if the benefits of alternatives are not direct (Almaiah et al., 2022b). Besides, users show a reluctance to switch to new AI as they are already used to the ongoing one. Besides if a new or existing AI software fails to ensure ethical concern of users, then relative advantages can't translate in the adoption decision. Recent studies found that ChatGPT adoption isn't related or shaped by the relative advantage if there's high privacy concern in users' minds (Raman et al., 2024b). Another variable observability is also found non-significant in adoption decisions. Sometimes the visibility may be internal like backed automation or proper algorithms in AI, which makes observability less influential. If the benefits are not visible, it reduces the significance of observability (Almaiah et al., 2022c). Besides, if trialability affects adoption decision, it overshadows the significance of observability as users personally evaluate the result or process of the AI or technology (Jilani et al., 2022a). The last hypothesis of this study is surprisingly also rejected; it means perceived privacy risk doesn't affect the intention to adopt ChatGPT. It can be justified by stating that users may tolerate risk to some extent if the other attributes' presence is high. In most studies, perceived risk is addressed as a moderator (Jangir et al., 2022b).

Compatibility is the strongest attribute that affects the intention of the adoption decision of ChatGPT. This finding supports few previous studies where compatibility or matching values of users to AI drives the adoption of that AI as it helps to reduce the disruption (Badghish & Soomro, 2024b). Prioritizing "fit with workflow" over other benefits is a common scenario while adopting any technology or AI software as it lessens the adoption length shorter. In case of technological adoption, researchers found that completability drives uptake (Badghish & Soomro, 2024b). In contexts where professional or organizational routines are entrenched, compatibility becomes more influential than perceived relative advantage (Maghaydah et al., 2024). The complexity is in adverse relation with adoption decisions; the lower the complexity, the greater the chances of adoption. The finding is a reflection of previous research. Sometimes, low complexity is the main crucial attribute of adoption decision (Almaiah et al., 2022d). User friendly technology or AI is more likely to be adopted by users. So, ease of use is a major determinant of intention of adopting ChatGPT.

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The hypothesis related to trialability and intention to adopt ChatGPT is accepted. The attribute of trialability is stated as less probability of occurring perceived risk or failure to fulfill the expected result. Previous studies stated that trialability is a strong predictor of adoption intention because it reduces the preparatory time and ensures that the users get the benefits (Jilani et al., 2022b).

All moderating hypotheses are accepted, meaning perceived privacy risk may not have a direct effect on adoption decisions, but it moderates the decisions related to other attributes. The finding indicates that if perceived risk is high, non-significant attributes become more decisive. Recent empirical work on FinTech and AI adoption shows perceived risk often moderates the effect of performance/compatibility and facilitating conditions (Jangir et al., 2022b). Perceived privacy risk often affects indirect trust towards other adoption drivers.

5.1 Social Implications

The findings of the study demonstrate that factors such as compatibility, simplicity, and trialability perform a crucial role in the adoption of ChatGPT. Socially, this signifies that as AI tools become more user-friendly and integrated into daily practices, they have the potential to promote greater digital inclusion. The effective adoption of ChatGPT by scholars establishes a benchmark for broader societal engagement, facilitating the normalization of AI literacy. Furthermore, indirectly addressing privacy concerns enhances trust in AI technologies, which is essential for mitigating social resistance to digital transformation (Kim et al., 2008; Jangir et al., 2022). Through the responsible integration of AI, society stands to gain enhanced equitable access to knowledge, improved communication of ideas, and the fostering of innovation.

5.2 Academic Implications

The integration of ChatGPT among scholars has significant implications for their professional processes. The research indicated that compatibility serves as the most significant factor, suggesting that when ChatGPT is in alignment with scholarly values and pedagogical methods, its adoption is more probable. This indicates that educators may leverage ChatGPT to develop creative instructional strategies, boost research efficiency, and streamline administrative responsibilities (Badghish & Soomro, 2024; Liu & Ma, 2024). The simplicity of the system facilitates the integration of AI by faculty members, minimizing the need for advanced technical expertise, thereby decreasing resistance and conserving valuable time. The concept of trialability offers scholars the opportunity to explore the functionalities of ChatGPT in areas such as lesson planning, grading, and research assistance prior to its complete implementation. In summary, the integration of ChatGPT has the potential to transform the educational landscape by incorporating artificial intelligence into teaching methodologies, scholarly inquiry, and student participation.

5.3 Managerial Implications

At the managerial level, universities and educational institutions are instrumental in promoting adoption. It is essential for managers to concentrate on formulating strategies for AI adoption that emphasize the alignment with current workflows, facilitate a framework for experimentation, and implement policies that address privacy and ethical considerations. Through the reduction of complexity via faculty training and technical support, managers can facilitate a more seamless adoption process (Chatterjee et al., 2020; Shin, 2021). Furthermore, managerial initiatives that promote the utilization of AI, highlight successful case studies, and incorporate ChatGPT into institutional frameworks will facilitate its normalization. Effective managerial implications encompass more than just technical support; they also involve cultivating an environment conducive to AI integration that empowers scholars and promotes sustainable adoption.

5.4 Theoretical Implications

This study theoretically improves the Diffusion of Innovation (DOI) model by applying it in the context of ChatGPT adoption among academicians. The findings show that standard DOI characteristics, like compatibility, complexity, and trialability, sustain their predictive effectiveness, although others—such as relative advantage and observability—may fluctuate according to technological environment and ethical factors. This confirms recent claims that the Diffusion of Innovations (DOI) framework needs modification when used in the context of emerging AI technologies, where potential risks and trust issues act as limiting factors (Raman et al., 2024; Almaiah et al., 2022). The moderating effect of perceived privacy risk enhances the model by showing that psychological and moral issues affect adoption indirectly rather than directly. This improves the theoretical development of innovation adoption models by focusing the changing interactions among technological design, user behavior, and institutional context. Further study may

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incorporate the Diffusion of Innovations (DOI) with frameworks as the Technology Acceptance Model (TAM) or the Unified Theory of Acceptance and Use of Technology (UTAUT) to further explain AI-related behavioral patterns (Venkatesh, 2022; Lim et al., 2025).

6. CONCLUSION, LIMITATIONS AND FUTURE DIRECTION OF THE STUDY

The emergence of AI-based applications such as ChatGPT has completely transformed the academic and research world. This research was aimed at investigating and exploring the forces that affect the acceptance of ChatGPT by academicians in Bangladesh through the Diffusion of Innovation Theory. The study that involved the examination of data involving 148 academicians was capable of determining the determinants that critically influenced their intention to adopt this new technology. The results show that the notions of the Diffusion of Innovation Theory are quite applicable in this perspective, and certain constructs have a strong effect on the readiness and willingness of an academician to implement ChatGPT into their working process. The findings of the study provide an insightful demonstration of the strength of adoption and behavioral patterns controlling adoption. The study has achieved its goals by examining the key constructs such as relative advantage, compatibility, complexity, trialability, and observability that affect the adoption intention and giving empirical research based on a particular and unexplored demographic. Notably, perceived privacy risk did not show a direct relationship, but a moderating effect on adoption, and affected the relationships between all the five innovative attributes and adoption intentions. These findings indicate that academicians give more weight to easy to use, compatible and testable technologies whereas issues around privacy define the intensity of the other factors influencing adoption. The reconceptualization of DIT theory in this paper dispels the conventional belief that attributes associated with innovation drive adoption as well as the contingent role of risk perception. In practice, the research highlights the necessity of universities paying more attention to compatibility and usability during the implementation of AI tools, and at the same time, paying attention to the issue of privacy and ethical issues. This would have serious consequences to policy makers and educational leaders in Bangladesh since there is a need to not only prepare higher educational systems with technology, but also mechanisms of building trust in implementing AI in higher education.

Nevertheless, one major weakness of this study like others is that the sample size is relatively small, and this could restrict the implementation of this study to a wider population. These findings can guide future studies to conduct a more comprehensive and detailed study using a bigger and varied sample of academicians in different nations. The use of convenience sampling limits external validity of results and the cross-sectional study design is unable to inform long-term adoption behavior. The research in future should use probability-based sampling methods, longitudinal designs, and mixed methods to generalize these results.

In addition, additional research is necessary to determine why relative advantage, and observability did not have a significant effect on adoption in this situation and to run tests to establish whether the same trends are present in other developing nations or among other stakeholders including students and policy makers. Overall, this paper adds a significant amount of knowledge related to adopting generative AI into higher education, including the possibilities and challenges related to the integration of ChatGPT. With the focus on compatibility, usability, trialability, and risk management, the findings provide practical advice about the successful introduction of AI to the academic setting and commence further discussion on the spread of innovations in developing economies.

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