Predicting Adoption Intention of ChatGPT- A Study on Business Professionals of Bangladesh

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Research Article

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Abstract

This study examines the adoption intention of ChatGPT, an AI-based tool, among business professionals. A sample of 350 participants was surveyed to gather data on demographic characteristics, attitudes towards AI, performance expectations, trust, effort expectancy, facilitating conditions, behavioral intention to use, and actual use of ChatGPT. The findings indicate that the respondents had a positive perception of ChatGPT, considering it as an efficient and convenient tool for academic and professional work. They reported that ChatGPT enabled them to accomplish tasks more quickly and increased their efficiency. The study also found that the majority of participants had a strong behavioral intention to use ChatGPT, and this intention strongly predicted their actual usage. Factors such as attitudes towards AI, performance expectations, trust, effort expectancy, and facilitating conditions significantly influenced adoption intention. Specifically, individuals with positive attitudes towards AI and higher expectations of performance were more likely to have a stronger intention to use ChatGPT. Moreover, trust in the tool, lower perceived effort required, and the presence of favorable conditions were associated with higher adoption intention. These findings highlight the importance of individuals' beliefs, perceptions, and contextual factors in shaping their adoption intention of AI technologies. The study concludes that promoting the perceived benefits and usefulness of ChatGPT, building trust in its capabilities, minimizing perceived effort required, and creating facilitating conditions are crucial for encouraging the adoption of AI technologies among business professionals. The insights from this study can inform developers and organizations in enhancing the adoption and effective usage of ChatGPT and similar AI tools.

1. INTRODUCTION

1.1 Introduction

ChatGPT is merely one instance of an artificial intelligence and natural language processing (NLP) technology that has the ability to transform professional communication and increase output. ChatGPT’s potential for success, however, hinges on the readiness of professionals to embrace and properly use the technology. To fully take advantage of ChatGPT in the workplace, it is essential to have a firm grasp on the elements that impact the adoption decisions of professionals. The Unified Theory of Acceptance and Use of Technology (UTAUT) is among the widely recognized and used frameworks to explain technology adoption behavior (Tamilmani, Rana, Wamba, et al., 2021). Despite the growing interest in ChatGPT and its potential benefits, there is limited research on the adoption intention of ChatGPT among professionals in Bangladesh. This study aims to explore the adoption intention of ChatGPT among Business Professionals in Bangladesh. Bangladesh is a rapidly developing country that has witnessed significant growth in its information technology and digital sectors. The government’s ‘Digital Bangladesh’ initiative and the proactive adoption of innovative technologies by the private sector have played a significant role in driving the country’s digital transformation. However, the adoption of advanced AI technologies like ChatGPT is still in the embryonic stages in Bangladesh. The lack of awareness and understanding of the capabilities of ChatGPT, its potential applications, and the benefits it can bring to work, is a significant barrier to its intention to adopt. Moreover, professionals perceive ChatGPT as complex and challenging to
use, have potential concerns about privacy and security, and resource constraints. This study's focus is the adoption of AI and NLP technologies like ChatGPT in professional and Educational settings and its relevance in the Bangladeshi context. This study's findings will contribute to enhancing the adoption and effective use of ChatGPT in the professional context in Bangladesh. The ongoing advancements in AI and NLP technologies, coupled with the country's digital transformation, create a conducive environment for the adoption of ChatGPT. Therefore, understanding the factors influencing the intention to adopt ChatGPT among professionals is crucial in harnessing its full potential. This chapter has presented an overview of the background and current situation of the study, highlighting the significance of the study in the Bangladeshi context.

1.2 Background of the Study

ChatGPT, powered by natural language processing and artificial intelligence, has emerged as a cutting-edge technology with the potential to revolutionize communication and enhance productivity in professional settings. It has the ability to generate human-like text responses, engage in conversations, and provide valuable insights. The adoption of ChatGPT in the workplace can streamline communication, automate tasks, and enable professionals to access information and support more efficiently. ChatGPT can only be successful if professionals are ready to actively embrace and make use of it. To fully take advantage of ChatGPT in the workplace, it is essential to have a firm grasp on the elements that impact the adoption decisions of professionals. The Unified Theory of Acceptance and Use of Technology (UTAUT) is one of the most well-known and widely-used theoretical frameworks for explaining people's propensity to accept new technologies (Esmaeilzadeh et al., 2019). UTAUT suggests that users' intentions to adopt and use a technology are affected by four main factors: performance expectancy (the extent to which a technology is perceived to be useful), effort expectancy (the extent to which a technology is perceived to be easy to use), social influence (the extent to which others influence one's use of a technology), and facilitating conditions (the extent to which resources and support are available) (Chao, 2019). Despite the growing interest in ChatGPT and its potential benefits, there is limited research on the adoption intention of ChatGPT among professionals in Bangladesh. Bangladesh is a developing country with a growing economy and a diverse range of industries, including IT, finance, healthcare, marketing, and consulting (Dey et al., 2019). The adoption of cutting-edge technologies like ChatGPT can significantly impact the productivity and efficiency of professionals in these industries (Dey et al., 2019; Zarifhonarvar, 2023). Therefore, the purpose of this research is to use UTAUT as a theoretical framework to examine the variables that affect the adoption intention of ChatGPT among professionals in Bangladesh. The study will be conducted in Bangladesh, focusing on professionals from various industries who are either currently using or have the potential to use ChatGPT for work-related tasks. The findings of this study will provide valuable insights into the factors that shape professionals' intention to adopt ChatGPT in the Bangladeshi context, which can inform organizations seeking to implement ChatGPT in their workplaces. ChatGPT's perceived benefit, simplicity of use, social impact, supportive conditions, and alignment with job requirements in the professional environment of Bangladesh may be better understood with the help of UTAUT as a theoretical framework. The rapid advancements in natural language processing and artificial intelligence have made ChatGPT a promising technology for
professionals in various industries. To fully take advantage of ChatGPT in the workplace, nevertheless, it is essential to understand the elements that impact the intention of professionals to embrace it. This research seeks to use the UTAUT frameworks, which provide excellent insights into technology adoption behavior, to examine the variables that affect the adoption intention of ChatGPT among professionals in Bangladesh. The results of this research may add to the wealth of knowledge and have real-world ramifications for businesses in Bangladesh who are considering introducing ChatGPT to their workforce.

1.3 Current Situation of Study

Artificial intelligence (AI) and natural language processing (NLP) technologies, such as ChatGPT, have been making significant strides in revolutionizing the way professionals interact and work globally (Adiguzel et al., 2023). As an AI-powered conversational agent, ChatGPT has the potential to enhance productivity, streamline communication, and provide valuable insights in a professional setting (George & George, 2023). The degree of its acceptance, nevertheless, varies considerably across nations and industries. This study focuses on the adoption of ChatGPT among professionals in Bangladesh, a rapidly developing South Asian nation witnessing significant growth in its information technology (IT) and digital sectors. Bangladesh has seen a remarkable surge in digital transformation, driven by the government’s 'Digital Bangladesh' initiative and the private sector’s proactive adoption of innovative technologies (Ahmed et al., 2019). This transformation has spurred the growth of the IT sector, making it one of the fastest-growing industries in the country. The increasing number of businesses and professionals are becoming more tech-savvy, and there’s an escalating interest in leveraging advanced technologies to improve operational efficiency and productivity. In this thriving digital environment, AI and NLP technologies like ChatGPT offer promising prospects. Yet, despite the potential benefits, their adoption in the professional context is still in the nascent stages. A few pioneering organizations have started exploring the possibilities of ChatGPT, using it for various tasks ranging from customer service to providing internal technical support. Nevertheless, the overall adoption rate of ChatGPT remains relatively low compared to its potential. Several factors contribute to this state of affairs. Firstly, the awareness and understanding of AI technologies among professionals are still limited. Many professionals are not fully aware of the capabilities of ChatGPT, its potential applications, and the benefits it can bring to their work. This lack of awareness and understanding is a significant barrier to the intention to adopt ChatGPT. Secondly, there are concerns about the complexity of the technology. ChatGPT, like many AI technologies, is often perceived as complex and challenging to use. Professionals may be hesitant to adopt ChatGPT because they are uncertain about how to use it effectively and are concerned about the potential learning curve. Thirdly, there are potential concerns about privacy and security. As a conversational AI, ChatGPT may need to process sensitive information. Professionals may be reluctant to adopt ChatGPT due to concerns about how this information is handled and the potential risks associated with it (Dwivedi et al., 2023). Finally, there are resource constraints. Implementing AI technologies like ChatGPT requires a significant investment in infrastructure and training. Many organizations, particularly small and medium enterprises (SMEs), may not have the necessary resources to make this investment. Despite these challenges, there’s growing interest and potential for adopting ChatGPT among Bangladeshi professionals. The ongoing advancements in AI and NLP technologies, coupled with the country’s digital
transformation, create a conducive environment for the adoption of ChatGPT. In order to take full advantage of ChatGPT, it is essential to have an understanding of the elements impacting the adoption intention of professionals. This study was conducted to help fill this knowledge gap and make ChatGPT more widely used in Bangladesh’s business world.

1.3.1 Current Situation of AI Adoption among Business Professionals in Bangladesh

The focus of this study, the adoption of AI and NLP technologies like ChatGPT in professional settings, holds significant relevance in the Bangladeshi context. Over the past decade, Bangladesh has been experiencing a technological revolution, with both the government and private sector investing heavily in digitalization initiatives (Anshari & Almunawar, 2022; Kakon, 2022). As part of these efforts, there’s been a significant push towards the adoption of cutting-edge technologies across various sectors, aimed at improving operational efficiency, productivity, and the overall quality of service delivery. Despite this, the adoption of advanced AI technologies, such as ChatGPT, is still in the embryonic stages in Bangladesh. The awareness and understanding of AI and NLP technologies and their potential benefits among professionals are gradually increasing, but many are still hesitant to embrace these technologies (Paschen et al., 2020). This hesitation stems from various factors. First, there's the perceived complexity of AI technologies. For many professionals, the notion of AI and NLP conjures images of intricate, hard-to-understand technologies. They might perceive the adoption of ChatGPT as a complicated process that requires extensive technical knowledge, which acts as a deterrent. Secondly, professionals often worry about the steep learning curve associated with new technologies. They may have concerns about the time and effort required to learn how to use ChatGPT effectively, and the impact it could have on their current workload and responsibilities. Thirdly, there are concerns around privacy and security. As an AI-powered conversational agent, ChatGPT might need to handle sensitive information, and professionals may worry about how this data is processed and stored. This concern is heightened by the increasing reports of cyber threats and data breaches globally (Lund & Wang, 2023). Lastly, there's a lack of specific research focusing on the adoption of ChatGPT in the Bangladeshi context. While there are numerous studies on technology adoption globally, few have focused on AI and NLP technologies, and even fewer on the adoption of ChatGPT among Bangladeshi professionals. This lack of contextual research creates a gap in understanding the specific factors that influence the intention to adopt ChatGPT in Bangladesh. In light of these challenges, it becomes evident that understanding the factors influencing the intention to adopt ChatGPT among professionals in Bangladesh is crucial. By addressing this research gap, the present study aims to contribute to the broader efforts of promoting the effective adoption and use of AI technologies in Bangladesh’s professional sector. This would, in turn, support the country’s ongoing digital transformation efforts, helping it keep pace with global technological advancements. The IT sector in Bangladesh is witnessing a period of rapid growth and transformation. Fueled by the government’s ‘Digital Bangladesh’ initiative, there has been a surge in digitalization efforts across various industries. The initiative aims to leverage technology for sustainable economic growth, employment generation, and strengthening governance (Hassan, 2017). As a result, many businesses and professionals in
Bangladesh are becoming more tech-savvy and are beginning to recognize the potential benefits of incorporating technology into their operations. Despite this wave of digital transformation, the adoption of advanced AI technologies, such as ChatGPT, remains relatively low in Bangladesh, especially when compared to more technologically advanced countries. Several factors contribute to this situation. Firstly, there is a noticeable skills gap in the country. Although the number of IT graduates is increasing, there is a lack of professionals with specialized skills in AI and machine learning. This skills gap hinders the effective implementation and use of advanced AI technologies like ChatGPT (Jony et al., 2022). Secondly, limited resources pose another challenge. While larger organizations might have the financial capability to invest in advanced technologies, many small and medium enterprises (SMEs) struggle to allocate sufficient resources for technological upgrades (Polas et al., 2022). Thirdly, there are concerns about the cost-effectiveness of AI technologies. Many organizations, especially SMEs, are hesitant to invest in advanced technologies like ChatGPT without a clear understanding of the return on investment (M. R. Hoque et al., 2016). They often perceive these technologies as expensive and beyond their reach. Despite these challenges, there is a growing recognition of the benefits that AI technologies can bring to businesses. From improving productivity to enhancing customer service, AI tools like ChatGPT can provide a significant competitive advantage (Chui et al., 2022). Therefore, it is expected that as awareness increases and technology becomes more accessible, the adoption of AI technologies, including ChatGPT, will rise in Bangladesh. Moreover, initiatives are underway to address the challenges hindering technology adoption. From government programs aimed at improving IT education and promoting digital literacy to private sector initiatives focused on providing affordable technology solutions, these efforts are expected to facilitate the adoption of advanced technologies like ChatGPT in the future. As such, the current situation presents a unique opportunity to explore and understand the factors influencing the intention to adopt ChatGPT among professionals in the evolving IT sector of Bangladesh.

1.4 Rationale of the Study

The rationale for conducting this research study as an MBA internship thesis on predicting the adoption intention of ChatGPT among professionals is grounded in the field of Management Information Systems (MIS) and its relevance to the Faculty of Business Administration at American International University Bangladesh. Management Information Systems (MIS) is a multidisciplinary field that encompasses the study of technology, business, and management, with a focus on how organizations can leverage information systems and technology to achieve their strategic objectives. ChatGPT, as a cutting-edge technology powered by natural language processing and artificial intelligence, has the potential to transform communication and productivity in professional settings, making it a relevant topic for research in the field of MIS. As an MBA intern specializing in MIS, conducting research on the adoption intention of ChatGPT among professionals can contribute to the knowledge and understanding of technology adoption in organizational settings. Conducting this research study as an MBA internship thesis can provide practical implications for organizations in Bangladesh and beyond. It can offer insights into the specific factors that shape professionals’ adoption intention of ChatGPT, which can help organizations in formulating effective strategies to promote its adoption and integration into their
workflows. For instance, understanding the perceived usefulness of ChatGPT can inform organizations on how to align the technology with the needs and expectations of professionals, while considering the ease of use can guide organizations in designing user-friendly interfaces and providing adequate training and support. Additionally, this research study can contribute to the academic knowledge in the field of MIS by adding to the existing literature on technology adoption and organizational behavior. It can provide empirical evidence and insights that can be further built upon by future researchers and scholars in the field of MIS. As an MBA intern, conducting this research study can demonstrate the intern's research capabilities, analytical skills, and ability to apply theoretical concepts in real-world business contexts, which are essential competencies for a career in MIS or related fields.

1.5 Problem Statement

The adoption of Artificial Intelligence (AI) technology, particularly in the form of ChatGPT, among Business Professionals has the potential to bring about significant improvements in communication and productivity. However, despite the promising benefits, there is limited understanding of the factors that influence professionals' intention to adopt such technologies, particularly in a developing country context like Bangladesh. While existing studies have explored the capabilities and limitations of ChatGPT, there is a lack of research focusing on the user adoption aspect. Therefore, there is a need to investigate the relationship between Attitude towards AI (ATAI), Performance Expectancy (PE), Effort expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Hedonic Motivation (HM), Trust (T), Behavioral Intention to Use (BIU), and Actual Use of ChatGPT among Business Professionals. Hence, the problem this study seeks to address is to understand the factors that influence Bangladeshi professionals' intention to adopt ChatGPT.

1.6 Objectives of the Study

1.6.1 Broad/General Objective:

The broad objective of this study is to predict the adoption intention of ChatGPT among Bangladeshi Business Professionals.

1.6.2 Specific Objectives:

- To examine the relationship between attitude towards AI and behavioral intention to use ChatGpt among professionals and graduate students.
- To investigate the impact of performance expectancy (PE) on behavioral intention to use ChatGpt among professionals and graduate students.
- To analyze the influence of effort expectancy (EE) on behavioral intention to use ChatGpt among professionals and graduate students.
- To explore the effect of social influence (SI) on behavioral intention to use ChatGpt among professionals and graduate students.
• To assess the impact of facilitating conditions (FC) on behavioral intention to use ChatGpt among professionals and graduate students.
• To examine the relationship between hedonic motivation (HM) and behavioral intention to use ChatGpt among professionals and graduate students.
• To investigate the influence of trust (T) on behavioral intention to use ChatGpt among professionals and graduate students.
• To analyze the relationship between behavioral intention to use (BIU) and actual use of ChatGpt among professionals and graduate students.

1.7 Research Question

The research questions are as follows:

RQ1

*How does attitude towards AI affect the behavioral intention to use ChatGpt among professionals and graduate students?*

RQ2

*What is the impact of performance expectancy (PE) on the behavioral intention to use ChatGpt among professionals and graduate students?*

RQ3

*How does effort expectancy (EE) influence the behavioral intention to use ChatGpt among professionals and graduate students?*

RQ4

*What is the effect of social influence (SI) on the behavioral intention to use ChatGpt among professionals and graduate students?*

RQ5

*How do facilitating conditions (FC) impact the behavioral intention to use ChatGpt among professionals and graduate students?*

RQ6

*What is the relationship between hedonic motivation (HM) and the behavioral intention to use ChatGpt among professionals and graduate students?*

RQ7
How does trust (T) influence the behavioral intention to use ChatGpt among professionals and graduate students?

RQ8

What is the relationship between behavioral intention to use (BIU) and actual use of ChatGpt among professionals and graduate students?

1.8 Significance of Study

This research carries substantial significance from both scholarly and pragmatic standpoints. This study expands the current knowledge base on the adoption of technology and makes a valuable contribution to the under-examined domain of ChatGPT adoption among professionals. This study examines the applicability and evaluates the resilience of the Unified Theory of Acceptance and Use of Technology (UTAUT) framework in the context of nascent artificial intelligence (AI) technologies within a developing nation, such as Bangladesh. The present study may serve as a basis for subsequent researchers to investigate and comprehend the implementation of analogous AI technologies in comparable circumstances. This study offers significant practical implications for companies intending to integrate ChatGPT or comparable artificial intelligence technologies into their operational processes. Organisations can devise efficacious strategies to promote the acceptance and utilisation of technologies among professionals by comprehending the factors that impact their adoption intention. As a result, it may result in enhanced productivity, efficacy, and a general competitive edge for enterprises.

1.9 Scope of Research

The scope of this research is confined to Bangladeshi professionals in various industries such as IT, finance, healthcare, marketing, and consulting. The focus will be on professionals who are either currently using or have the potential to use ChatGPT for their work-related tasks. The research will examine the adoption intention of ChatGPT from the perspective of two theoretical frameworks, UTAUT. The study does not include other AI technologies or other professional contexts outside of Bangladesh.

1.10 Organization of Study

The study is organized into six chapters to systematically address the research objectives. Chapter 1 serves as an introduction, providing an overview of the study's background, problem statement, and research questions. It also outlines the objectives, significance, and scope of the study, setting the foundation for the subsequent chapters. Chapter 2 focuses on the literature review, examining relevant works on ChatGPT, UTAUT frameworks, and technology adoption. It presents a conceptual framework and develops hypotheses for the study based on the reviewed literature. Chapter 3 delves into the research methodology, describing the research design, sample selection, data collection methods, and data analysis techniques employed in the study. Chapter 4 is dedicated to the analysis and interpretation of the collected data, including demographic characteristics, descriptive statistics, correlation analysis, regression analysis, and structural equation modeling. Chapter 5 presents the findings derived from the
data analysis, organized according to demographic information and statistical analyses. It concludes with a summary of the findings. Finally, Chap. 6 offers recommendations and conclusions based on the study’s findings and discusses them in detail, providing insights and implications for future research and practical applications.

2. LITERATURE REVIEW

2.1 Introduction

This chapter provides a comprehensive theoretical framework and literature review related to the adoption and utilization of artificial intelligence (AI) technologies, with a focus on business professionals. The chapter begins with a historical literature review of prominent frameworks and theories in the field of technology acceptance and adoption, including the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), Technology-Organization-Environment (TOE) Framework, Task Technology Fit (TTF), and Innovation Diffusion Theory (IDT). These frameworks have significantly contributed to our understanding of users’ behavior towards technology and have been widely applied in various research contexts. The subsequent sections of this chapter delve into the utilization of AI for business professionals, recent issues, and developments in AI adoption, both from a general perspective and an individual perspective. The adoption of AI in business processes has gained significant attention in recent years, as it holds the potential to revolutionize operations, enhance decision-making, and drive growth. The chapter explores the factors that influence AI adoption, such as performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and trust, highlighting their importance in promoting the adoption of AI technologies among business professionals. The chapter also addresses recent issues and developments in AI adoption, particularly focusing on the questions of trust, privacy, and ethical considerations. As AI technologies become more advanced, concerns about the transparency, explainability, and accountability of AI systems arise. The chapter discusses the importance of ensuring transparency, disclosing the use of AI agents, and improving the explainability of AI algorithms to build trust and address ethical concerns. Additionally, it highlights the significance of privacy protection and the need for data security regulations and user control over data in AI adoption. Furthermore, the chapter examines empirical research conducted in the field of AI adoption, particularly studies that have utilized the Unified Theory of Acceptance and Use of Technology (UTAUT) model. It provides an overview of empirical findings regarding the factors that influence individuals’ intention to adopt AI-based systems and technologies, such as attitude towards AI, performance expectancy, effort expectancy, social influence, facilitating conditions, trust, and hedonic motivation. The chapter also identifies empirical literature gaps, emphasizing the need for research that explores adoption intention across different domains and specifically investigates the adoption of AI language models like ChatGPT.

2.2 Historical Literature Review

In the field of technology acceptance and adoption, several frameworks and theories have been developed to understand and explain users’ behavior towards technology. Here’s a historical literature
review of five prominent frameworks: Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), Technology-Organization-Environment (TOE) Framework, Task Technology Fit (TTF), and Innovation Diffusion Theory (IDT).

**Technology Acceptance Model (TAM)**

The Technology Acceptance Model (TAM) was initially introduced by Fred Davis in 1986 and subsequently expanded by Fred Davis and Richard Bagozzi in 1989. The Technology Acceptance Model (TAM) is centred on the examination of an individual's willingness to accept and integrate technology into their daily routine. The proposition is that the perceived usefulness and perceived ease of use are the primary factors that impact an individual's attitude and intention towards technology adoption. The Technology Acceptance Model (TAM) has been extensively employed and verified in diverse settings and sectors, serving as a fundamental basis for subsequent scholarly investigations (Ashraf et al., 2014; Wibowo, 2019).

**Unified Theory of Acceptance and Use of Technology (UTAUT)**

In 2003, Venkatesh et al. synthesised eight pre-existing technology acceptance models to create the Unified Theory of Acceptance and Use of Technology (UTAUT). The UTAUT model posits that the acceptance and usage of technology is significantly influenced by four primary factors, namely performance expectancy, effort expectancy, social influence, and facilitating conditions. The analysis takes into account moderating variables, including but not limited to gender, age, and level of expertise. The Unified Theory of Acceptance and Use of Technology (UTAUT) has garnered considerable interest and has been implemented across diverse fields to comprehend the behaviour of technology adoption (Cai et al., 2021; Emon, 2023; Ly, 2019; Rejali et al., 2023).

**Technology-Organization-Environment (TOE) Framework**

Tornatzky and Fleischer introduced the Technology-Organization-Environment (TOE) Framework in 1990. The TOE framework places emphasis on the interdependence of technological, organisational, and environmental factors in influencing the decisions made regarding the adoption of technology. The study takes into account various contextual factors that impact the adoption and implementation of technology within an organisation. These factors include technological complexity and compatibility, organisational structure and culture, as well as environmental factors such as competition and regulatory environment. The Technology-Organization-Environment (TOE) framework offers a comprehensive perspective on the implementation of technology within organisational contexts (Baker, 2012; Kulkarni & Patil, 2020; Leung et al., 2015).

**Task Technology Fit (TTF):**

The theory of Task Technology Fit (TTF) was introduced by Goodhue and Thompson in the year 1995. The concept of Task-Technology Fit (TTF) centres on the congruence between the attributes of a given task and the functionalities of a particular technology. TTF theory posits that the degree of congruence
between the demands of a given task and the capabilities of a particular technology significantly impacts the level of user acceptance and proficiency in utilising said technology. The significance of incorporating task-related variables, such as intricacy, interconnectivity, and novelty, in conjunction with technology-related variables, is underscored by TTF in the examination of technology adoption (Bozaykut et al., 2016; Bravo & Bayona, 2020; G. Chen et al., 2015).

Innovation Diffusion Theory (IDT)

The Innovation Diffusion Theory (IDT) was initially formulated by Everett Rogers in 1962. The field of IDT elucidates the process by which novel ideas are assimilated and disseminated throughout a given societal framework. The text delineates the pivotal determinants that impact the process of adoption, encompassing the attributes of the innovation in question (such as relative advantage and compatibility), communication modalities, temporal factors, social structure, and adopter classifications (namely innovators, early adopters, early majority, late majority, and laggards). The IDT framework offers a theoretical construct for comprehending the process of technology diffusion and adoption within a given societal context (F. B. A. Rahman et al., 2021; Wani & Ali, 2015).

These frameworks and theories have significantly contributed to our understanding of technology acceptance and adoption. Researchers have built upon these foundations and extended them to different contexts, industries, and technologies, enabling a comprehensive understanding of user behavior towards technology.

2.2.1 Utilization of AI for Business Professionals

In recent years, the utilization of AI in business processes has gained significant attention and has become a topic of extensive study. Various industries and business professionals have recognized the potential of AI to revolutionize their operations, enhance decision-making, and drive growth. Researchers and practitioners have explored the benefits and challenges associated with AI adoption in order to understand how to effectively integrate this technology into business settings. The Technology Acceptance Model (TAM) is a frequently employed framework for examining the uptake of technology, encompassing AI. The Technology Acceptance Model (TAM) centres on the various determinants that impact an individual's inclination to adopt a specific technology (Kumar Bhardwaj et al., 2021).

Performance expectancy is a critical factor in the adoption of artificial intelligence. AI systems are assessed by business professionals with respect to their perceived potential to enhance productivity, augment efficiency, and provide precise and insightful analyses. When individuals hold the belief that artificial intelligence (AI) can offer advantages, they are more inclined to adopt and employ the technology in their routine activities (Enholm et al., 2022; Mohr & Kühl, 2021; M. Rahman et al., 2021). The adoption of AI by business professionals is influenced significantly by the factor of effort expectancy. The concept pertains to the subjective perception of the level of intricacy and user-friendliness that are attributed to artificial intelligence systems. If professionals perceive AI technologies as difficult to understand or use, they may resist their adoption. However, if AI systems are user-friendly, intuitive, and
require minimal effort to operate, professionals are more likely to embrace them and integrate them into their work processes (Enholm et al., 2022).

The adoption of AI by business professionals is significantly influenced by social factors. The aforementioned factor pertains to the impact exerted by peers, supervisors, and other significant personnel within a given institution. The likelihood of professionals adopting AI technologies is positively correlated with the promotion of AI usage and its benefits by influential individuals. Moreover, in the event that an organisation fosters a culture that values innovation and is receptive to novel technologies, the integration of AI is apt to be more readily accepted by corporate personnel (Flavián et al., 2022). The utilisation of AI in business processes is also influenced by facilitating conditions, which encompass the availability of essential resources, infrastructure, and technical support. The provision of necessary resources and support by organisations can enhance professionals' confidence in the adoption and utilisation of AI technologies (Grover et al., 2022). The Unified Theory of Acceptance and Use of Technology (UTAUT) has been employed as an additional framework for examining technology adoption. The UTAUT model is an extension of the Technology Acceptance Model (TAM) and integrates supplementary variables such as perceived usefulness, perceived ease of use, and individual traits. These factors additionally contribute to comprehending the adoption and utilisation of artificial intelligence by professionals in the business realm (Blut et al., 2021). The concept of perceived usefulness pertains to the degree to which artificial intelligence (AI) technologies are perceived as advantageous in facilitating the completion of tasks and attainment of objectives. The likelihood of business professionals incorporating AI into their daily work is positively correlated with their belief in the technology's ability to enhance decision-making, address intricate challenges, and optimise overall performance. The construct of perceived ease of use in the Unified Theory of Acceptance and Use of Technology (UTAUT) bears resemblance to the concept of effort expectancy in the Technology Acceptance Model (TAM) (Nordhoff et al., 2021; Sarfaraz, 2017). The significance of user-friendliness, simplicity, and comprehensibility of AI systems is underscored. The likelihood of business professionals incorporating AI technologies into their work routines is positively correlated with their perceived ease of use and operability of said technologies (Natale, 2021). The utilisation of AI by business professionals is also influenced by individual characteristics, such as prior experience and technical expertise. Individuals possessing greater expertise and familiarity in the realm of artificial intelligence may exhibit a greater propensity to embrace and implement AI-based technologies within their organisational workflows (Flavián et al., 2022). The adoption of artificial intelligence (AI) among business practitioners is subject to diverse determinants that are scrutinised in models such as Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT). The intention to adopt and the actual use of AI technologies are influenced by various factors such as performance expectancy, effort expectancy, social influence, facilitating conditions, perceived usefulness, perceived ease of use, and individual characteristics (AL-Nuaimi et al., 2022; Gado et al., 2022; Nascimento & Meirelles, 2021). Through comprehension of these variables, enterprises can devise tactics to encourage the adoption of artificial intelligence and guarantee its triumphant assimilation into corporate operations. The proficient utilisation of artificial intelligence
has the potential to enable professionals in the business industry, foster innovation, and reveal novel prospects for expansion and competitiveness.

### 2.2.2 Recent Issues and Development of AI Adoption

One of the recent issues surrounding AI adoption is the question of trust. As conversational agents like ChatGPT and Quilbot become more advanced, they are often able to generate responses that mimic human language and behavior. This can make it difficult for users to distinguish between a human and an AI agent, raising concerns about deception and manipulation. Users may question whether the information provided by these agents is reliable and unbiased, leading to a lack of trust in the technology. To address this issue, it is crucial to ensure transparency in AI systems (Emon, Hassan, et al., 2023; Jacovi et al., 2021; Liao et al., 2020; Shin, 2021). Developers should clearly disclose when users are interacting with AI agents and provide information about the limitations of the technology. Additionally, efforts should be made to improve the explainability of AI algorithms so that users can understand how decisions are being made. This can help build trust by making the technology more understandable and accountable (Liao et al., 2020; Liao & Varshney, 2021; Shin, 2021). Another important concern is privacy. Conversational agents often require access to large amounts of data to generate meaningful responses. This raises questions about data security and user privacy. Users may worry about their conversations being stored, analyzed, or used for targeted advertising purposes without their consent. To address these concerns, data protection regulations and policies must be implemented. Developers should ensure that user data is handled securely and only used for the intended purposes. Users should have control over their data and be able to easily understand and manage the permissions granted to AI systems (Emon et al., 2023; Liao et al., 2020; Shin, 2021). Ethical considerations are also at the forefront of AI adoption. Conversational agents have the potential to perpetuate biases and discriminatory behaviors present in the data they are trained on. This can result in unfair or harmful outcomes, such as biased recommendations or discriminatory language. To mitigate these issues, developers should actively address bias in training data and algorithms. They should employ diverse and inclusive datasets to train AI models and implement bias detection and mitigation techniques (Liao et al., 2020; Shin, 2021). Additionally, the development of ethical guidelines and standards for AI adoption can help ensure that these technologies are used in a responsible and fair manner. Furthermore, the impact of AI on employment is another aspect to consider. As AI technologies continue to advance, there is a concern that they may replace certain jobs or reduce the demand for human labor. This can have significant societal and economic implications, including potential job displacement and income inequality (W. Wu et al., 2020; Zhou et al., 2020). To address these concerns, policymakers and organizations should focus on reskilling and upskilling initiatives to prepare the workforce for the changing job landscape. Collaboration between AI systems and human workers can also be explored to augment human capabilities and create new opportunities. Recent advancements in conversational AI technologies like ChatGPT and Quilbot have brought about exciting possibilities, but they also come with challenges that need to be addressed. Building trust, ensuring privacy, addressing ethical considerations, and managing the impact on employment are crucial aspects of AI adoption. By addressing these issues, we can foster the responsible and beneficial use of AI technologies in our society.
2.2.3 Recent Issues and Development of AI Adoption from Individual Perspective

Recent issues and developments in AI adoption from an individual perspective have highlighted the significance of various factors that influence the acceptance and use of AI technologies such as ChatGPT. Attitudes towards AI, performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and trust are key factors that shape individuals’ intentions to adopt and utilize AI technologies. Analyzing these factors can provide valuable insights into promoting the adoption of ChatGPT among Business Professionals. Attitudes towards AI play a crucial role in its adoption. Positive attitudes towards AI are associated with a higher likelihood of adoption. Individuals who view AI as a useful tool for enhancing productivity and efficiency are more likely to adopt and utilize AI technologies like ChatGPT. Educating users about the potential benefits of AI and addressing any concerns or misconceptions can help foster positive attitudes towards AI adoption. Performance expectancy, which refers to the perceived benefits and usefulness of AI technologies, influences individuals’ intention to adopt AI. If users perceive ChatGPT as a valuable tool that can improve their productivity, provide accurate information, or assist in complex tasks, they are more likely to adopt it. Highlighting the specific features and capabilities of ChatGPT that align with users' needs can enhance their performance expectancy.

Effort expectancy is another important factor. Individuals are more likely to adopt AI technologies that are perceived as easy to use and require minimal effort to interact with. ChatGPT should be designed with a user-friendly interface and intuitive functionalities to minimize the perceived effort required for its utilization. Providing clear instructions and tutorials can also contribute to reducing effort expectancy. Social influence plays a significant role in AI adoption. Individuals are influenced by the opinions and behaviors of others, including friends, colleagues, and experts. Leveraging social networks and communities to create awareness and generate positive word-of-mouth can greatly enhance the adoption of ChatGPT. Encouraging influential individuals to share their positive experiences with the technology can further amplify its adoption. Facilitating conditions refer to the availability of necessary resources and support for AI adoption. Providing individuals with the required infrastructure, such as compatible devices and reliable internet connectivity, can facilitate the adoption of ChatGPT. Additionally, offering technical support, training programs, and documentation can help users overcome any potential barriers and increase their confidence in using AI technologies. Hedonic motivation, which relates to the enjoyment and pleasure derived from using AI technologies, can influence adoption decisions. Designing ChatGPT to provide an engaging and enjoyable user experience can enhance hedonic motivation. Incorporating interactive features, personalization options, and gamification elements can make the interaction with ChatGPT more enjoyable and increase user satisfaction. Trust is a critical factor in AI adoption. Individuals need to trust that ChatGPT will provide accurate and reliable information, protect their privacy, and perform as expected. Establishing transparency about the technology’s limitations, ensuring data security and privacy, and regularly updating and improving the system can foster trust among users.
Understanding the factors that influence AI adoption from an individual perspective is essential for promoting the use of technologies like ChatGPT among Business Professionals. By addressing user attitudes, highlighting performance expectancy, reducing effort expectancy, leveraging social influence, providing facilitating conditions, enhancing hedonic motivation, and building trust, organizations can encourage individuals to adopt and utilize AI technologies effectively.

2.2.4 Empirical and Theoretical Literature Gaps of AI Adoption

One of the empirical literature gaps in AI adoption is the limited understanding of adoption intention across different domains. Many studies have investigated AI adoption in specific contexts, such as healthcare, finance, or customer service. While these studies provide valuable insights into the factors influencing adoption within those domains, they do not necessarily generalize to other industries or sectors. Different domains may have unique characteristics, challenges, and requirements that can impact AI adoption differently. Therefore, there is a need for research that explores adoption intention across diverse domains to provide a more comprehensive understanding of the factors influencing AI adoption. Furthermore, while there has been a significant focus on the adoption of AI technologies in general, there is a lack of empirical research specifically examining the adoption of AI language models like ChatGPT. ChatGPT and similar models have gained substantial attention and are being implemented in various applications, ranging from customer support to content generation. However, there is limited empirical research that specifically investigates the factors that drive or hinder the adoption of these AI language models. Understanding the factors influencing ChatGPT adoption is crucial for several reasons. Firstly, the adoption of AI language models raises ethical concerns related to bias, privacy, and accountability. Empirical research can shed light on how organizations are addressing these concerns and inform best practices for responsible adoption. Secondly, the adoption of AI language models also depends on user acceptance and trust. Factors such as transparency, explainability, and perceived usefulness are likely to influence users' willingness to adopt and interact with AI language models. More empirical studies are needed to explore these factors and their impact on adoption intention. Additionally, the theoretical literature on AI adoption could benefit from further development. While existing studies have identified various factors influencing adoption, there is a need for more comprehensive theoretical frameworks that integrate these factors and provide a holistic understanding of AI adoption. Such frameworks could help researchers and practitioners identify the most relevant factors and their interrelationships, guiding the development of effective adoption strategies. Moreover, as AI technology continues to evolve rapidly, there is a need for up-to-date research that captures the current state of AI adoption. Many studies in the literature may be based on data and insights from several years ago, which may not reflect the current landscape. The adoption of AI is a dynamic process influenced by technological advancements, market dynamics, and regulatory changes. Therefore, there is a need for ongoing empirical research that keeps pace with the evolving nature of AI adoption. While there is a growing body of literature on AI adoption, there are several empirical and theoretical gaps that need to be addressed. Future research should focus on exploring adoption intention across different domains, investigating the specific factors influencing the adoption of AI language models like ChatGPT,
developing comprehensive theoretical frameworks, and keeping pace with the dynamic nature of AI adoption. By addressing these gaps, researchers and practitioners can gain deeper insights into the adoption process and develop strategies to promote the responsible and effective use of AI technologies.

2.3 Theoretical Review

2.3.1 History, Nature, Contents and Explanations of UTAUT

The criticality of user acceptance in new information system (IS) implementations has been a pivotal argument by (Tursunbayeva et al., 2020). Over recent years, the burgeoning interest in understanding and interpreting user responses towards IS has contributed to the development of numerous theoretical models, drawing insights from diverse fields such as IS, psychology, and sociology (Chao, 2019). A popular choice among these models is the Technology Acceptance Model (TAM), which has received significant scholarly attention and support (Marangunić & Granić, 2015; Mugo et al., 2017; Zhong et al., 2021). TAM is primarily focused on analysing perceived utility and ease of use, thereby providing insights into users' responses towards new systems. However, it has also faced criticism from some quarters for its superficial exploration of human responses (Ali & Anwar, 2021). Critics have argued that TAM fails to investigate the intricate relationship between attitudes and usage, as well as intentions and usage, thereby leaving a considerable knowledge gap. (Venkatesh et al., 2003) aimed to bridge this gap by introducing the Unified Theory of Acceptance and Use of Technology (UTAUT). The UTAUT model offers a more comprehensive framework by integrating key elements from eight existing theories and models, thereby improving the prediction and explanation of the adoption of new technologies. The successful application of UTAUT in diverse areas like home-health services, mobile health, and field communication technology has made significant contributions to the adoption of new technology (Cimperman et al., 2016; R. Hoque & Sorwar, 2017). This study aims to leverage the UTAUT model to evaluate the factors involved in adopting an AI-driven customer relationship management (CRM) system. Despite the model's success, its ability to reliably predict user responses to new technologies has been questioned by some scholars (Chao, 2019). Furthermore, Li (2020) has expressed concerns over the practicality of the four moderators used in the UTAUT model, suggesting that a simpler model, through an acceptable initial scoring approach, might achieve similar predictive power. This led to the evolution of the original UTAUT model into UTAUT 2, proposed by (Venkatesh et al., 2012). The authors added three new factors - hedonic motivation, price value, and habit - into the model, thereby enhancing its ability to capture consumer acceptance. This updated model (UTAUT 2) offers a more robust predictive capability (Tamilmani, Rana, & Dwivedi, 2021). It has been successfully utilised in various areas such as AI in healthcare and m-commerce, further establishing its effectiveness and practical relevance (Agarwal & Sahu, 2022; Albahri et al., 2022; Khan et al., 2022; Vinerean et al., 2022). However, it is crucial to note that the applicability of certain factors, such as hedonic evaluations may vary depending on the context. For example, the hedonic factor may not be relevant in situations where the technology usage is not intended to be enjoyable. Similarly, the price-value factor may not hold significance in situations where the cost of the technology is not directly perceived by the users, such as when purchases of ChatGPT Plus. The context of technology usage, thus, plays a significant role in determining the relevance of different factors in the
UTAUT model. In the light of these considerations, it is clear that while the UTAUT and UTAUT 2 models offer compelling frameworks for understanding user acceptance and adoption of new technologies, they are not one-size-fits-all solutions. Both the nature of the technology and the context in which it is used can significantly influence the relevance and impact of the different elements in these models. The AI Technologies like ChatGPT that this study focuses on represents a complex and evolving technology. As such, factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions from the original UTAUT model will likely play a significant role in its adoption. For example, users may be more likely to accept and use the system if they believe it will enhance their productivity (performance expectancy), if they find it easy to use (effort expectancy), if they observe their peers using it (social influence), and if they have the necessary resources and support to use it (facilitating conditions). In addition to these factors, the two elements added in UTAUT 2 – hedonic motivation and Trust – could also influence the adoption of the ChatGPT. For instance, users might find the system more appealing if they derive enjoyment from using it (hedonic motivation). However, as mentioned before, the relevance of these factors can vary depending on the context. For example, the hedonic factor might not be as important in a professional context where the primary goal is to improve productivity, not to provide enjoyment. Moreover, the unique features and capabilities of the AI technologies like ChatGPT might necessitate the consideration of other factors not included in the UTAUT or UTAUT 2 models. For instance, trust in the system’s AI capabilities might be a critical factor influencing user acceptance. Similarly, concerns about data privacy and security, which are particularly relevant in the context of AI technologies, could also impact the adoption of the system. While the UTAUT and UTAUT 2 models provide valuable frameworks for understanding user acceptance and adoption of new technologies, they should be used flexibly, and supplemented with other factors as needed, to accurately reflect the complexities and nuances of different technologies and usage contexts. Future research could explore the development of an enhanced model that incorporates these additional factors, thus providing a more nuanced and comprehensive understanding of user acceptance and adoption of complex and evolving AI technologies like ChatGPT.

2.3.2 Theoretical Development, Gaps, and Expectations

Theoretical development in technology adoption models has been a dynamic and evolving area of research. Models such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) have served as the foundation for understanding individuals' intentions to adopt and use various technologies (de Sena Abrahão et al., 2016). With the advent of artificial intelligence (AI) and its applications, there is a need to extend and modify these models to capture the unique characteristics of AI technologies. In the case of ChatGPT, a language model developed by Open AI, there are still gaps in our understanding of how specific factors influence individuals' adoption intentions.

One important factor that requires further exploration is trust. Trust is a critical component in technology adoption as it affects individuals' willingness to rely on and use a particular technology (Beldad & Hegner, 2018). In the context of ChatGPT, users need to trust that the system will provide accurate and reliable
information, respect their privacy and data security, and act in their best interests. Building trust in AI systems can be challenging due to their complex nature and potential for bias or unintended consequences (Kelly et al., 2019). Future research should delve into the factors that contribute to trust in ChatGPT, such as system transparency, explainability, and accountability. Understanding how trust develops and its impact on adoption intentions can inform the design and implementation of AI systems that inspire confidence and enhance user acceptance. Another factor that warrants further investigation is hedonic motivation. While many technology adoption models have primarily focused on utilitarian factors such as usefulness and ease of use, the hedonic aspects of technology use, such as enjoyment and entertainment value, are increasingly relevant in the context of AI technologies. ChatGPT, with its conversational capabilities and ability to generate creative responses, offers users a unique and engaging experience. Exploring the role of hedonic motivation in the adoption of ChatGPT can help us understand why individuals choose to use the system beyond its functional benefits. Additionally, examining how the hedonic aspects interact with utilitarian factors can provide a more comprehensive understanding of adoption intentions and user behavior.

The theoretical development of technology adoption models should also consider the social and cultural factors that shape individuals’ adoption intentions. AI technologies, including ChatGPT, are not developed and adopted in a vacuum but within specific sociocultural contexts. Factors such as social norms, perceived societal impact, and cultural values can influence individuals’ attitudes and intentions towards AI adoption. For instance, individuals from collectivist cultures may prioritize the opinions of their social networks when considering the adoption of AI technologies. Future research should explore the interplay between these sociocultural factors and individual adoption intentions to provide a more nuanced understanding of AI technology adoption.

To bridge these gaps and develop a more comprehensive theoretical framework for understanding the adoption of ChatGPT, researchers should employ a multi-method approach that combines qualitative and quantitative methods. Qualitative studies can help uncover in-depth insights into users' perceptions, attitudes, and experiences with ChatGPT. These studies can be conducted through interviews, focus groups, or observations to capture the richness and complexity of users' adoption processes. On the other hand, quantitative studies can provide broader insights by examining the relationships between various factors and adoption intentions on a larger scale. Surveys and experiments can be used to collect quantitative data, allowing for statistical analysis and the identification of significant predictors of adoption intentions. While technology adoption models have provided valuable insights into the factors that influence individuals' intentions to adopt and use technology, there are still gaps in our understanding of how specific factors, such as trust and hedonic motivation, impact the adoption of AI technologies like ChatGPT. Future research should address these gaps by investigating the role of trust and hedonic motivation, considering the influence of social and cultural factors, and employing a multi-method approach.

2.3.3 Theoretical Justifications and Relationships (Between and Among) Each Variable and Dimensions:
In the context of technology acceptance and usage, there are various theoretical models that explore the relationships among the variables you mentioned. One prominent model is the UTAUT, which can provide insights into the theoretical justifications and relationships between and among these variables and dimensions.

1. **Attitude towards Artificial Intelligence (ATAI):** The term ATAI applies to the comprehensive assessment or positive inclination of an individual towards artificial intelligence. The phenomenon under consideration is subject to the influence of multiple factors, among which are perceived utility, simplicity of operation, social impact, and hedonic drive. A favourable disposition towards artificial intelligence is expected to lead to an increased inclination to utilise systems that are based on AI (Montag et al., 2023; Sindermann et al., 2022).

2. **Performance Expectancy (PE):** The concept of PE pertains to an individual's perception of the potential benefits that can be derived from the utilisation of AI technology in terms of enhancing their performance and productivity. There exists a positive correlation between one's attitude towards artificial intelligence and their behavioural intention to utilise it. This relationship bears significant implications. Individuals are more inclined to develop a favourable attitude towards AI when they perceive it as advantageous and anticipate that it will have a positive influence on their performance (Alfalah, 2023; Upadhyay et al., 2022; Venkatesh et al., 2003).

3. **Effort Expectancy (EE):** Effort Expectancy (EE) pertains to the subjective perception of the level of ease involved in the adoption and utilisation of AI technology. The focus of this study pertains to the perceived ease of learning and operating artificial intelligence (AI) systems by individuals. A positive correlation exists between elevated levels of EE and a favourable disposition towards AI, as well as an increased propensity to engage in AI utilisation (Sohn & Kwon, 2020; Upadhyay et al., 2022; Venkatesh et al., 2003).

4. **Social Influence (SI):** Social Influence (SI) applies to the impact that other individuals have on an individual's behaviour and attitude. This pertains to the subjective norms and the influence of social interactions in relation to the adoption and utilisation of artificial intelligence. Favourable attitudes towards AI and increased behavioural intention to use it can be influenced by positive social factors, such as recommendations from credible sources or observing positive experiences of others with AI (Sohn & Kwon, 2020; Upadhyay et al., 2022; Venkatesh et al., 2003).

5. **Facilitating Conditions (FC):** Facilitating Conditions (FC) pertain to the provision of essential resources and support that enable the utilisation of AI. The aforementioned comprises of elements such as technological framework, institutional backing, and the accessibility of educational resources and guidance. Individuals' positive attitude towards AI and their behavioural intention to use it are more likely to be influenced by the perception of adequate facilitating conditions (Chatterjee & Bhattacharjee, 2020; Venkatesh et al., 2003).

6. **Hedonic Motivation (HM):** HM relates to the enjoyment and pleasure individuals derive from using AI technology. It encompasses factors such as entertainment, curiosity, and the enjoyment of novel experiences. Higher hedonic motivation leads to a more positive attitude towards AI and an
increased likelihood of behavioral intention to use it (Aldossari & Sidorova, 2020; Venkatesh et al., 2012).

7. **Trust**: Trust is relevant to the level of confidence and dependence that an individual places on artificial intelligence technology. The aforementioned factors, namely system reliability, security, privacy, and transparency, exert a significant influence on it. The significance of trust in influencing an individual's perspective towards AI and their inclination to utilise it cannot be overstated. A positive correlation exists between elevated levels of trust and a greater propensity to adopt AI, as well as a more favourable attitude towards it (Chatterjee & Bhattacharjee, 2020; Venkatesh et al., 2012).

8. **Behavioral Intention to Use (BIU)**: Behavioural Intention to Use (BIU) applies to an individual's personal inclination or intention to utilise artificial intelligence (AI) technology. The factors that impact it include attitudes towards artificial intelligence, perceived usefulness, perceived ease of use, social influence, facilitating conditions, hedonic motivation, and trust. The likelihood of an individual's intention to use AI is positively influenced by several factors, including a favourable attitude towards AI, perceived usefulness and ease of use, higher social influence, facilitating conditions, hedonic motivation, and trust (Sharma et al., 2022; Shi et al., 2021; Venkatesh et al., 2003).

9. **Actual Use (AU)**: Actual Use refers to the extent to which individuals actively engage in the utilization of artificial intelligence (AI) technology in real-world settings. It represents the observable behavior of individuals employing AI systems or applications to perform tasks, achieve goals, or fulfill specific needs. Actual Use serves as an outcome measure and can be influenced by various factors, including BIU, PE, EE, SI, FC etc (Malodia et al., 2021).

These variables and dimensions are interconnected, and their relationships can be explained through the UTAUT framework, highlighting the importance of attitude, perceived usefulness, perceived ease of use, social influence, facilitating conditions, hedonic motivation, trust, and behavioral intention to use AI.

### 2.4 Theoretical Literature Matrix and Meta-analysis
<table>
<thead>
<tr>
<th>Author(s)</th>
<th>Year</th>
<th>Title</th>
<th>Aim</th>
<th>Methodology</th>
<th>Findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pfeil et al.</td>
<td>2011</td>
<td>Understanding the use of learning management systems by undergraduate university students using the UTAUT model: Credible evidence from Saudi Arabia &quot;</td>
<td>To investigate factors that influence Facebook usage among college students and the general user population, using UTAUT as a theoretical framework</td>
<td>Survey</td>
<td>The authors found that performance expectancy, social influence, and effort expectancy were the most significant predictors</td>
</tr>
<tr>
<td>Venkatesh et al.</td>
<td>2016</td>
<td>&quot;Unified Theory of Acceptance and Use of Technology: A Synthesis and the Road Ahead&quot;</td>
<td>To present a synthesis of the existing literature on technology acceptance and use and provide directions for future research</td>
<td>Literature review and conceptual analysis</td>
<td>The authors propose a unified theory (UTAUT) that integrates eight key constructs from previous models and identify several directions for future research</td>
</tr>
<tr>
<td>Deng et al.</td>
<td>2014</td>
<td>&quot;Exploring the Role of Readiness for Change in ERP Implementation: A Study of Chinese Firms&quot;</td>
<td>To examine the role of readiness for change in the acceptance and use of enterprise resource planning (ERP) systems, using UTAUT as a theoretical framework</td>
<td>Survey</td>
<td>The authors found that readiness for change was a significant predictor of ERP acceptance and use, and that UTAUT provided a useful framework for understanding the complex factors that influence technology adoption in organizations</td>
</tr>
<tr>
<td>Author(s)</td>
<td>Year</td>
<td>Title</td>
<td>Aim</td>
<td>Methodology</td>
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<tr>
<td>Nistor et al.</td>
<td>2018</td>
<td>&quot;Evaluating UTAUT in a context of emerging technologies&quot;</td>
<td>To evaluate the applicability of UTAUT in the context of emerging technologies such as blockchain, using a systematic review of the literature</td>
<td>Systematic review</td>
<td>The authors found that UTAUT was still a useful framework for understanding technology acceptance and use in the context of emerging technologies, but that additional constructs and factors may need to be added to the model</td>
</tr>
<tr>
<td>Ali et al.</td>
<td>2020</td>
<td>&quot;Exploring Mobile Banking Adoption in Pakistan: A Partial Least Squares Structural Equation Modeling Approach&quot;</td>
<td>To examine the factors that influence mobile banking adoption in Pakistan, using UTAUT as a theoretical framework</td>
<td>Survey</td>
<td>The authors found that performance expectancy, effort expectancy, and social influence were significant predictors of mobile banking adoption, but that the relationship between facilitating conditions and adoption was weaker than expected</td>
</tr>
<tr>
<td>Alalwan et al.</td>
<td>2021</td>
<td>&quot;The Role of Trust and Social Influence in Shaping Mobile Banking Adoption Intentions: An Extended UTAUT Model&quot;</td>
<td>To extend the UTAUT model by adding trust and social influence as additional factors that influence mobile banking adoption intentions</td>
<td>Survey</td>
<td>The authors found that trust and social influence were significant predictors of mobile banking adoption intentions, and that the extended UTAUT model provided a better fit to the data than the original UTAUT model</td>
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</table>

### 2.5 Empirical Review

Empirical investigations have been carried out to explore the determinants that impact the adoption and utilisation of systems and technologies based on artificial intelligence by individuals. Numerous scholarly inquiries have employed the Unified Theory of Acceptance and Use of Technology (UTAUT) framework to investigate the determinants that impact the assimilation of artificial intelligence (AI)-based systems and
technologies. (Huang et al., 2018) conducted a study that investigated the implementation of a smart chatbot system within the healthcare industry. The research revealed that the factors of performance expectancy, effort expectancy, social influence, and facilitating conditions had a significant impact on the users' inclination to utilise the system. Furthermore, the research revealed that users' inclination to utilise the system was also impacted by their trust in the system and hedonic motivation. (Brill et al., 2019) conducted a study to examine the utilisation of personal assistants that are based on artificial intelligence. The research revealed that the variables of performance expectancy, effort expectancy, social influence, and facilitating conditions exerted a noteworthy impact on the users' inclination to utilise the personal assistant. The research additionally discovered that users' inclination to utilise the personal assistant was positively influenced by their trust in the system and hedonic motivation. (Mogaji et al., 2021) conducted a study to investigate the determinants of AI-based chatbot adoption within the banking sector. The research revealed that the variables of performance expectancy, effort expectancy, social influence, and facilitating conditions exerted a significant impact on the users' inclination to utilise the chatbot. The research additionally revealed that the level of trust placed in the chatbot had a noteworthy impact on the users' inclination to utilise the chatbot.

In general, empirical studies indicate that various factors, such as performance expectancy, effort expectancy, social influence, facilitating conditions, trust, and hedonic motivation, have an impact on the adoption and utilisation of AI-based systems and technologies by individuals. The results align with the Unified Theory of Acceptance and Use of Technology (UTAUT) model, and offer significant implications for designers and developers of artificial intelligence (AI) systems and technologies, in terms of encouraging their adoption and utilisation.

2.5.1 Critical Literature Review and Justification to Create the Relationships (Between and Among) Each Variables and Dimensions

Numerous scholarly inquiries have examined the interconnections and dimensions of the UTAUT model concerning artificial intelligence-based systems and technologies. Presented herein is a comprehensive literature review and rationale for the interrelationships and interdependencies among each variable and dimension:

**ATAI and BIU:**

Research has indicated that there exists a favourable correlation between ATAI and BIU. This implies that individuals who exhibit a more optimistic outlook towards AI are inclined towards utilising AI-based systems and technologies (Venkatesh et al., 2012). The correlation between an individual's attitude towards a technology and their perception of its usefulness and ease of use is a justifiable basis for their intention to use said technology.

**PE and BIU:**
The relationship between Performance Expectancy (PE) and Behavioural Intention to Use (BIU) has been established through research. The findings suggest that individuals who hold the perception that the utilisation of AI-based systems and technologies will improve their performance and productivity are more inclined to intend to use these technologies. This relationship has been documented in studies conducted by (Rho et al., 2015; Venkatesh et al., 2003). The correlation between the adoption of a technology and an individual's perception of its potential to enhance their performance and productivity can be rationalised.

**EE and BIU:**

The relationship between EE and BIU has been established in previous research, indicating that individuals who perceive the ease and simplicity of using AI-based systems and technologies are more inclined to adopt these technologies (Venkatesh et al., 2003). The correlation between ease of use and user adoption of technology can be substantiated by the observation that individuals are more inclined to utilise a technological system if they perceive it as user-friendly and requiring minimal exertion.

**SI and BIU:**

Research has shown that there exists a noteworthy affirmative correlation between social influence (SI) and behavioural intention to use (BIU). This suggests that individuals who hold the perception that significant others in their lives endorse the use of artificial intelligence (AI)-based systems and technologies are more inclined to have the intention to utilise such technologies (Bu et al., 2021; Venkatesh et al., 2003). The correlation between social influence and an individual's beliefs and attitudes towards a technology can be rationalised, as it can have a substantial impact on their inclination to utilise said technology.

**FC and BIU:**

Research has indicated that there exists a noteworthy affirmative correlation between FC and BIU. This implies that individuals who possess the essential resources and assistance to operate AI-based systems and technologies are inclined towards utilising these technologies (Venkatesh et al., 2003). The rationale for this association can be substantiated by the premise that the availability of resources and assistance can enhance an individual's capacity to utilise a technological tool, thereby influencing their inclination to employ said technology.

**HM and BIU:**

Research has demonstrated a noteworthy affirmative correlation between HM and BIU. This suggests that individuals who experience satisfaction and delight from utilising AI-based systems and technologies are more inclined to have the intention to use these technologies (L. Chen et al., 2021; Venkatesh et al., 2012). The rationale for this association can be substantiated by the premise that hedonic motivation has the potential to exert an impact on an individual's conduct and perceptions vis-à-vis a technological innovation, thereby influencing their inclination to adopt and utilise the technology.
Trust and BIU:

Research has revealed a noteworthy affirmative correlation between trust and BIU. This implies that individuals who exhibit trust towards AI-based systems and technologies are more inclined to have the intention to use them (L. Chen et al., 2021; Venkatesh et al., 2012). The rationale for this association can be supported by the notion that trust plays a pivotal role in shaping an individual's assessment of the dependability, safety, and efficacy of a given technology, thereby influencing their behavioural inclination.

BIU and AU:

The correlation between Behavioural Intention to Use (BIU) and Actual Use (AU) has been extensively examined in various studies pertaining to the acceptance and utilisation of technology. The literature has consistently demonstrated a positive correlation between behavioural intention to use (BIU) and actual usage (AU) of artificial intelligence (AI)-based systems and technologies. This suggests that individuals who possess a strong intention to utilise such systems are more inclined to actively engage with them in practical settings (Eraslan Yalcin & Kutlu, 2019; Venkatesh et al., 2003). The justification for this association is rooted in the theoretical framework of planned behaviour, which posits that the intention to engage in a behaviour is a crucial determinant of its actual execution. According to Venkatesh et al. (2003), the presence of a robust intention to utilise a technology can act as a motivational catalyst, propelling individuals towards active adoption and engagement with the technology, ultimately leading to increased levels of effective usage. Furthermore, the realisation of their purpose via practical implementation reinforces their conviction in the utility and efficacy of the technology, thereby enhancing their dedication to sustained utilisation. Furthermore, the association between BIU and AU may be impacted by diverse additional factors within the UTAUT framework. The translation of behavioural intention to actual usage (BIU to AU) can be influenced by factors such as perceived performance expectancy and effort expectancy of artificial intelligence (AI)-based systems and technologies. According to Venkatesh et al. (2003), when users encounter favourable results and perceive the technology as user-friendly during their initial adoption, it strengthens their intention to use it and promotes sustained usage. Likewise, the impact of social elements, such as social influence and facilitating conditions, can also contribute to the conversion of Behavioural Intention to Use (BIU) into Actual Use (AU). The presence of supportive resources and positive social interactions can enhance individuals' self-assurance and ability to effectively utilise technology, as noted by Bu et al. (2021) and Venkatesh et al. (2003). It is noteworthy that extant research has consistently demonstrated a favourable association between Behavioural Intention to Use (BIU) and Actual Use (AU). However, it is imperative to acknowledge that the magnitude and character of this association may differ depending on the technological milieu, user demographics, and particular operationalizations of the Unified Theory of Acceptance and Use of Technology (UTAUT) framework. Further investigation and empirical analysis are required to thoroughly examine and substantiate the correlation between Behavioural Intention to Use (BIU) and Actual Usage (AU) within particular Artificial Intelligence (AI) systems and technologies.
In general, the Unified Theory of Acceptance and Use of Technology (UTAUT) model offers a valuable structure for comprehending the determinants that impact the adoption and utilisation of artificial intelligence (AI)-based systems and technologies by individuals. The UTAUT model's variables and dimensions exhibit coherence with both theoretical and empirical evidence, thereby offering significant perspectives for technology designers and developers, as well as organisations aiming to encourage technology adoption and utilisation.

2.6 Summary of Theoretical Review

Theoretical review is an essential aspect of empirical research as it establishes a robust theoretical basis and a framework for exploring the phenomenon under investigation. This review delved into the historical progression of technology adoption frameworks and identified the principal theories and models that have influenced our comprehension of technology adoption and utilisation throughout the years. The study reveals that the frameworks have undergone a transformation from their initial versions that emphasised individual-level aspects, such as perceived ease of use and usefulness, to more intricate and all-encompassing models that take into account social, cultural, and organisational factors, such as trust, facilitating conditions, and social influence. The Unified Theory of Acceptance and Use of Technology (UTAUT) is a highly recognised and empirically supported framework within the realm of technology adoption. Venkatesh et al. (2003) formulated the UTAUT framework with the aim of consolidating and expanding upon pre-existing models, in order to pinpoint the fundamental factors that influence the adoption and utilisation of technology by users. The UTAUT model comprises four essential factors, namely performance expectancy, effort expectancy, social influence, and facilitating conditions. This model has been widely applied across diverse settings and technological platforms. In order to overcome the constraints of UTAUT and broaden our comprehension of technology adoption and utilisation, a number of scholars have suggested various adaptations and expansions of the model. The incorporation of affective and emotional factors, such as hedonic motivation and attitude towards technology, and the examination of the role of trust and user involvement in the adoption process are among the considerations that are pertinent to this matter. Notwithstanding, the theoretical underpinnings and interconnections among said variables and dimensions are not always transparent, thereby necessitating additional empirical investigation to authenticate and enhance these models. The present review has identified a number of gaps and limitations in the extant theoretical literature pertaining to the adoption and utilisation of technology. The identified shortcomings encompass a failure to account for cultural and contextual variables that may impact the adoption of technology, a restricted emphasis on the stage following adoption and the significance of user satisfaction and continuance, and a disregard for the ethical and societal ramifications of technology adoption. The resolution of these deficiencies necessitates a comprehensive and interdisciplinary methodology towards the study of technology adoption, which takes into account the wider social, cultural, and ethical milieu within which technology is employed. The section on theoretical review establishes a robust groundwork for the empirical review and underscores the significance of comprehending the intricate and ever-changing character of technology adoption and utilisation. The section under consideration examines various theoretical models and frameworks that can serve as a valuable foundation for exploring the factors that influence
the adoption and utilisation of technology. However, it also underscores the necessity of conducting additional research to enhance and expand upon these models, as well as to address the deficiencies and omissions in the current body of literature.

2.7 Summary of Empirical Review

The empirical analysis has identified multiple factors that exert an influence on the adoption intention of ChatGPT among business professionals. The study revealed that various factors such as performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, trust, and behavioural intention to use are crucial determinants of adoption intention. The significance of these variables in forecasting adoption intention was consistently reinforced by empirical evidence from multiple studies. The aforementioned review has identified that the disposition towards artificial intelligence (AI) is a noteworthy forecaster of the intention to adopt it. Nevertheless, the empirical data pertaining to this variable exhibited incongruous results, as certain studies reported a positive correlation while others did not observe a statistically significant correlation. This implies that the inclination towards artificial intelligence (AI) may not serve as a conclusive forecaster of the intention to adopt it, and could be contingent on the particular usage context. An additional significant discovery highlighted in the review pertains to the intricate and diverse nature of the connections between variables and dimensions. Trust has the potential to act as a mediator in the association between performance expectancy and adoption intention. Additionally, the relationship between effort expectancy and adoption intention may be moderated by facilitating conditions. The aforementioned relationships underscore the significance of taking into account the interdependence of variables and dimensions in the anticipation of adoption inclination. The assessment additionally recognised various constraints and deficiencies within the current empirical body of literature. The majority of the examined research was cross-sectional in nature and utilised self-reported assessments, which could potentially be influenced by bias. Furthermore, the predominant focus of the research has been on individual-level determinants of adoption intention, with comparatively less emphasis on organisational and contextual factors. This empirical review presents a thorough examination of the present state of understanding concerning the adoption intention of ChatGPT among business professionals. The aforementioned review underscores the significance of various pivotal variables and dimensions while also pinpointing deficiencies and constraints in the extant body of literature. The present review offers a significant basis for forthcoming research endeavours, which can expand upon the current knowledge and promote our comprehension of the determinants that impact the intention to adopt.

3. MATERIALS & METHOD

3.1 Introduction

This chapter provides an overview of the variables, research hypotheses, research design process, data collection method, and statistical techniques that will be employed in the study. It sets the stage for the subsequent chapters, where the data will be analyzed and the hypotheses tested to gain insights into the
factors influencing the adoption intention of ChatGpt among Bangladeshi professionals. This chapter focusing on the variables and research hypotheses that form the foundation of the research. The chapter begins by introducing the Unified Theory of Acceptance and Use of Technology (UTAUT) as a conceptual framework used to understand the factors influencing technology adoption and use. The chapter presents the various constructs of the UTAUT model, including Attitude towards Artificial Intelligence (ATAI), Performance expectancy (PE), Effort expectancy (EE), Social influence (SI), Facilitating conditions (FC), Hedonic motivation (HM), Trust, Behavioral Intention to Use (BIU), and Actual use (AU). It emphasizes the interdependence of these constructs in shaping users' behavior towards technology adoption.

Following the conceptual framework, the chapter presents a series of research hypotheses that link these constructs to the Behavioral Intention to Use ChatGpt among professionals. Each hypothesis is discussed, providing background and justification based on previous research and literature. The research design process is then described, including the research approach (deductive), paradigm (positivism), and method (cross-sectional survey). The chapter also discusses the justification for using a structured online survey questionnaire as the data collection instrument, along with measures taken to ensure data quality and ethical considerations. Finally, the chapter outlines the data analysis process, which involves descriptive statistics, correlation analysis, and multiple regression analysis. It highlights the importance of these statistical techniques in examining the relationships between variables and testing the research hypotheses.

3.2 Variables

3.2.1 Conceptual Framework

The Unified Theory of Acceptance and Use of Technology (UTAUT) is a conceptual model used to understand the factors that influence the adoption and use of technology. The model includes the following constructs: Attitude towards Artificial Intelligence (ATAI), Performance expectancy (PE), Effort expectancy (EE), Social influence (SI), Facilitating conditions (FC), Hedonic motivation (HM), Trust (T), Behavioral Intention to Use (BIU), and Actual use (AU). The model suggests that the adoption and use of technology is influenced by the user's attitude towards the technology (ATAI), their perception of the technology's usefulness (PE), their perception of the effort required to use the technology (EE), the social influence on their decision to use the technology (SI), the facilitating conditions that enable the use of the technology (FC), the pleasure and enjoyment derived from using the technology (HM), and their trust in the technology. These factors together shape the user's behavioral intention to use the technology (BIU) and their actual use of the technology (AU). In the UTAUT model, each construct is interdependent and influences the user's behavior in relation to technology adoption and use. The model can be applied to various contexts and technologies to help understand the factors that influence technology adoption and use. The proposed model is visually represented in Fig. 1:

3.2.2 Research Hypothesis
3.2.2.1 The Linkage between Attitude towards Artificial Intelligence (ATAI) and Behavioral Intention to Use (BIU)

Attitude towards Artificial Intelligence (ATAI) can potentially impact the adoption of ChatGpt among professionals, as it represents a pre-existing mindset that encompasses values and is often elicited through a responsive expression towards an entity, location, or object. This psychological trait can influence one's actions and intentions and is closely linked to individual behavior and the attitude-behavior relationship in customers (Chatterjee, Rana, et al., 2021). According to Hewavitharana et al. (2021), attitudes are conceptualized as a unique feeling towards performing a particular behavior, either positively or negatively. Therefore, attitudes are believed to play a critical role in the actual intention to use a new technology such as an AI-integrated CRM system, which includes ChatGpt as a tool, as well as in use behavior (Balakrishnan et al., 2022; Chatterjee, Ghosh, et al., 2021; Cimperman et al., 2016; Ikumoro & Jawad, 2019). Based on this perspective, the following hypotheses have been formulated:

H1: Attitude towards Artificial Intelligence has positive effect on Behavioral Intention to Use of ChatGpt among professionals.

3.2.2.2 The Linkage between Performance expectancy (PE) and Behavioral Intention

According to (Venkatesh et al., 2003) Performance expectancy (PE) refers to an individual's belief that a system can enhance their job performance. This concept is closely linked with the perceived usefulness of a technology, as individuals anticipate that using the system will improve their ability to perform their job. PE is linked with the quality of job development and is based on the belief of employees that the use of AI will improve their performance within organizations (Chatterjee, Chaudhuri, et al., 2021). Venkatesh et al., (2003) have identified PE as the most influential factor for the Behavioral Intention of Use to adopt technology.

H2: Performance expectancy (PE) has positive effect on Behavioral Intention to Use of ChatGpt among professionals

3.2.2.3 The Linkage between Effort expectancy (EE) and Behavioral Intention

Effort expectancy (EE) is a significant determinant of technology acceptance, referring to the perceived ease of use associated with the system (Venkatesh et al., 2003). The construct of EE encompasses antecedents such as complexity and ease of use (Alsyouf, 2021; Balakrishnan et al., 2022; Dwivedi et al., 2016; Ooi & Tan, 2016), and in this study, it represents employees' beliefs about the ease of using AI in an organization. The concept of EE is consistent with the ease of use construct proposed in the diffusion of innovation (DoI) theory, defined as the degree of simplicity or difficulty in using AI in an organization (Alhwaiti, 2023; Bervell & Umar, 2017). Additionally, users’ individual behavioral characteristics influence their technology adoption (de Sena Abrahão et al., 2016; Khechine & Lakhal, 2018). Consistent with
previous research, EE has a positive impact on individuals' attitudes towards using technology (Dwivedi et al., 2019), leading to the formulation of the following hypotheses:

H3: Effort expectancy (EE) has positive effect on Behavioral Intention to Use of ChatGpt among professionals.

3.2.2.4 The Linkage between Social influence (SI) and Behavioral Intention

The degree to which an individual's social environment affects their acceptance of a technology is referred to as social influence, as stated by (Taherdoost, 2018). Social influence was one of the preserved constructs when UTAUT was refined into UTAUT 2 to explain voluntary use, according to (Venkatesh et al., 2012). Recent studies highlighted social influence as a significant precursor to an individual's behavioral intention to use a technology (Gao & Bai, 2014; Slade et al., 2015; Sobti, 2019). Therefore, we propose the following hypothesis:

H4: Social influence (SI) has positive effect on Behavioral Intention to Use of ChatGpt among professionals.

3.2.2.5 The Linkage between Facilitating conditions (FC) and Behavioral Intention

In the context of adoption intention of ChatGPT among Business Professionals, facilitation conditions (FC) refer to the extent to which individuals perceive that the technical infrastructure is in place to support the use of new technologies (Chatterjee, Ghosh, et al., 2021; Venkatesh et al., 2003). Previous research has shown that FC plays a significant role in determining the acceptance and adoption of new technologies and subsequently impacts usage behavior (Chao, 2019; Gu et al., 2021). When the technological infrastructure is user-friendly and supportive of employee usage, it becomes easier for them to use the AI (Venkatesh et al., 2003). As a result, employees' attitudes towards using the system are positively inclined when appropriate technological infrastructure is available (Lutfi, 2022). Based on these discussions, The study proposed the following hypotheses:

H5: Facilitating conditions (FC) has positive effect on Behavioral Intention to Use of ChatGpt among professionals.

3.2.2.6 The Linkage between Hedonic motivation (HM) and Behavioral Intention

Previous research demonstrated the importance of hedonic factors in influencing users' behavioral intentions towards adopting new technologies. Hedonic motivation is one of the key factors that influence the adoption and usage of new technologies (Venkatesh et al., 2003). Similarly Hedonic factors, such as enjoyment and excitement, are significant predictors of users' intention to use new technologies (Madigan et al., 2017). Therefore, it can be hypothesized that professionals who are motivated by
hedonic factors, such as enjoyment and excitement, are more likely to have a positive behavioral intention towards ChatGpt.

H6: Hedonic motivation (HM) has positive effect on Behavioral Intention to Use of ChatGpt among professionals.

3.2.2.7 The Linkage between Trust (T) and Behavioral Intention

Prior research indicated that trust is a critical factor in users' acceptance and adoption of new technologies. According to (Patil et al., 2020) trust is defined as the willingness of an individual to rely on another party in a situation involving risk. In the context of technology adoption, users' trust in a system or its provider can significantly impact their adoption behavior. (Venkatesh et al., 2003) found that trust is positively related to the adoption and use of new technologies, indicating that users are more likely to adopt a new system if they have a high level of trust in its reliability and security. Similarly, (Al-Saedi et al., 2020) found that users' trust in a system has a positive impact on their intention to use it. Therefore, The study hypothesize that professionals who trust ChatGpt's reliability and security are more likely to have a positive behavioral intention towards it.

H7: Trust (T) has a positive effect on Behavioral Intention to Use of ChatGpt among professionals.

3.2.2.8 The Linkage between Behavioral Intention to Use (BIU) and Actual Use (AU)

Venkatesh et al. (2003) demonstrated that behavioral intention is an accurate predictor of usage behavior, and it plays a crucial role in determining whether a specific action will be performed. Numerous studies have observed that individuals' behavioral intentions to adopt innovative technology positively influence their actual usage behavior (R. Hoque & Sorwar, 2017; Sobti, 2019). Behavioral intention is seen as an indicator of an individual's readiness to perform a specific behavior and is regarded as an immediate precursor to behavioral action (Alkhowaiter, 2022). Therefore, if employees demonstrate behavioral intention to use a new technology such as AI integrated ChatGpt, they are likely to show corresponding usage behavior to implement the system. This leads to the following hypothesis:

H8: Behavioral Intention to Use (BIU) has positive effect on Actual Use of ChatGpt among professionals.

3.2.2.3 Questionnaire Designing:

The questionnaire used in this study will be designed using two theoretical frameworks: the Unified Theory of Acceptance and Use of Technology (UTAUT) model. UTAUT is a widely used framework for explaining and predicting user acceptance and use of technology (Venkatesh, Morris, Davis, & Davis, 2003). The frameworks will be used to identify the key factors that influence the adoption intention of ChatGPT among Bangladeshi professionals. The questionnaire will consist of two sections. The first section will gather demographic information about the participants, such as Gender, Age, Highest level of
educational qualification, Designation, Organization Type, Industry sector, Year of Experience. The second section will include questions that measure the constructs of interest, including Attitude towards Artificial Intelligence (ATAI), Performance expectancy (PE), Hedonic motivation (HM), Trust (T), Effort expectancy (EE), Social influence (SI), Facilitating conditions, Behavioral Intention to Use (BIU), Actual Use (AU). Participants were asked to rate their agreement with each statement. The measuring items and their relevant sources were listed in Table 3.1.
<table>
<thead>
<tr>
<th>Factor</th>
<th>Items</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Attitude towards Artificial Intelligence (ATAI)</strong></td>
<td>ChatGpt enables my work to be more efficient.</td>
<td>(Chu et al., 2022)</td>
</tr>
<tr>
<td></td>
<td>Application of the ChatGpt will be more convenient.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>ChatGpt enables me to be more in control of my daily life</td>
<td></td>
</tr>
<tr>
<td></td>
<td>I hold a very positive attitude towards the use of ChatGPT.</td>
<td></td>
</tr>
<tr>
<td><strong>Performance expectancy (PE)</strong></td>
<td>I would find ChatGPT useful for my academic/professional work</td>
<td>(Escobar-Rodriguez et al., 2014; Khechine &amp; Lakhal, 2018; Thomas et al., 2013; Wan et al., 2020)</td>
</tr>
<tr>
<td></td>
<td>Using ChatGPT would enable me to accomplish tasks more quickly</td>
<td></td>
</tr>
<tr>
<td></td>
<td>The use of ChatGPT increases the efficiency of my professional and personal work</td>
<td></td>
</tr>
<tr>
<td><strong>Effort expectancy (EE)</strong></td>
<td>It is easy for me to learn how to use ChatGPT</td>
<td>(Escobar-Rodriguez et al., 2014; Khechine et al., 2014; Thomas et al., 2013; Wan et al., 2020)</td>
</tr>
<tr>
<td></td>
<td>My interaction with ChatGPT is clear and understandable</td>
<td></td>
</tr>
<tr>
<td></td>
<td>I find ChatGPT easy to use</td>
<td></td>
</tr>
<tr>
<td></td>
<td>I have no difficulty in using ChatGPT</td>
<td></td>
</tr>
<tr>
<td><strong>Social influence (SI)</strong></td>
<td>People who are important to me think that I should use ChatGPT</td>
<td>(Escobar-Rodriguez et al., 2014; Khechine et al., 2014; Thomas et al., 2013; Wan et al., 2020)</td>
</tr>
<tr>
<td></td>
<td>All of my friends and colleagues are using ChatGPT</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Using ChatGPT enhances my sense of worth in my community.</td>
<td></td>
</tr>
<tr>
<td><strong>Facilitating conditions</strong></td>
<td>I have the resources necessary to use ChatGpt (Internet, PC, International Credit card, other privileges Etc.)</td>
<td>(Escobar-Rodriguez et al., 2014; Khechine et al., 2014; Thomas et al., 2013; Venkatesh et al., 2012; Wan et al., 2020)</td>
</tr>
<tr>
<td></td>
<td>I have the hardware and software necessary to use ChatGPT</td>
<td></td>
</tr>
<tr>
<td></td>
<td>I have the knowledge necessary to use ChatGPT</td>
<td></td>
</tr>
</tbody>
</table>
### 3.3 Research Design Process:

In the research design process, several aspects needed to be considered, such as the research approach, paradigm, method, justification, type of data, time horizon, and study setting. In this study, the research design process involved the following:

#### 3.3.1 Research Approach:

The research approach used in this study was deductive. The deductive approach involved starting with a hypothesis or theory and testing it empirically using data (Woiceshyn & Daellenbach, 2018). The hypothesis was that several factors predicted the adoption intention of ChatGPT among Bangladeshi professionals.

#### 3.3.2 Research Paradigm:

The research paradigm used in this study was positivism. Positivism is a scientific approach to research that assumes knowledge can be discovered through objective, empirical observation, and experimentation. The use of a positivist paradigm ensured that the research was based on objective and empirical evidence (Antwi & Hamza, 2015).

#### 3.3.3 Research Method:

<table>
<thead>
<tr>
<th>Factor</th>
<th>Items</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hedonic motivation (HM)</td>
<td>Using ChatGPT is fun.</td>
<td>(Escobar-Rodríguez &amp; Carvajal-Trujillo, 2014; Escobar-Rodriguez et al., 2014; Venkatesh et al., 2012)</td>
</tr>
<tr>
<td></td>
<td>Using ChatGPT is enjoyable</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Using ChatGPT is very entertaining</td>
<td></td>
</tr>
<tr>
<td>Trust (T)</td>
<td>ChatGPT output is reliable for my professional or academic projects</td>
<td>(Escobar-Rodríguez &amp; Carvajal-Trujillo, 2014; Escobar-Rodriguez et al., 2014; Kim et al., 2011)</td>
</tr>
<tr>
<td></td>
<td>ChatGPT output is trustworthy</td>
<td></td>
</tr>
<tr>
<td>Behavioral Intention to Use (BIU)</td>
<td>I intend to continue using the ChatGPT for academic or professional reasons.</td>
<td>(Daughan &amp; Akkoyunlu, 2016; Tawafak et al., 2021; Wan et al., 2020; B. Wu &amp; Chen, 2017; Yan et al., 2021)</td>
</tr>
<tr>
<td></td>
<td>I plan to use ChatGPT for academic or professional reasons in the future</td>
<td></td>
</tr>
<tr>
<td></td>
<td>I will recommend other people to use ChatGPT</td>
<td></td>
</tr>
<tr>
<td>Actual Use (AU)</td>
<td>I prefer to use ChatGPT</td>
<td>(Escobar-Rodríguez &amp; Carvajal-Trujillo, 2014; San Martín &amp; Herrero, 2012; Venkatesh et al., 2012)</td>
</tr>
<tr>
<td></td>
<td>I like to use ChatGPT</td>
<td></td>
</tr>
</tbody>
</table>
The research method used in this study was a cross-sectional survey. A cross-sectional survey involves collecting data from a sample of individuals at a specific point in time. The use of a cross-sectional survey allowed for the collection of data on the factors that predicted the adoption intention of ChatGPT among Bangladeshi professionals at a specific point in time (Wang & Cheng, 2020).

### 3.3.4 Justification of Research Method:

The use of a cross-sectional survey as the research method had several advantages. It allowed for the collection of a large amount of data from a diverse group of participants in a relatively short period. It was also cost-effective and allowed for the measurement of several constructs simultaneously (Wang & Cheng, 2020).

### 3.3.5 Type of Data:

The type of data collected in this study was quantitative data. Quantitative data involves the collection of numerical data, which is then analyzed using statistical methods. The use of quantitative data allowed for the collection and analysis of large amounts of data necessary for determining the factors that predicted the adoption intention of ChatGPT among Bangladeshi professionals. Quantitative research methods: A synopsis approach (Apuke, 2017).

### 3.3.6 Time Horizon:

The time horizon for this study was cross-sectional. A cross-sectional study collects data at a specific point in time, and therefore, it has a cross-sectional time horizon (Wang & Cheng, 2020). The use of a cross-sectional time horizon allowed for the collection of data on the factors that predicted the adoption intention of ChatGPT among Bangladeshi professionals at a specific point in time.

### 3.3.7 Study Setting:

The study setting for this study was online. The survey was distributed through various online platforms, such as social media, email, and online forums. Conducting the study online was a cost-effective method and allowed for the collection of data from a large and diverse sample of Bangladeshi professionals, regardless of their geographical location.

### 3.4 Sampling Method

#### 3.4.1 Target Population:

The target population for this study was Bangladeshi professionals who were studying postgraduate programs in different universities in Bangladesh. This included individuals who were studying in fields such as information technology, finance, healthcare, education, and others.

#### 3.4.2 Sampling Frame:

The sampling frame for this study was a list of universities and educational institutions in Bangladesh offering postgraduate programs.
3.4.3 Sampling Technique:

The sampling technique for this study was stratified random sampling. Stratified random sampling involved dividing the population into strata based on the university they were studying in and then randomly selecting participants from each stratum (Howell et al., 2020). This technique ensured that the sample was representative of the target population.

3.4.4 Sample Size:

The sample size for this study was 350 participants. This sample size was determined using the sample size formula for cross-sectional studies, which takes into account the population size, expected prevalence of the outcome variable, and desired level of precision (Rutterford et al., 2015). A sample size of 350 participants was deemed sufficient to achieve a power of 0.8 with a 95% confidence level.

3.4.5 Sampling Units:

The sampling units for this study were individual professionals studying postgraduate programs in different universities in Bangladesh.

3.4.6 Inclusion Criteria:

The inclusion criteria for this study were as follows:

- Participants had to be Bangladeshi professionals studying postgraduate programs in different universities in Bangladesh.
- Participants had to have experience using or interacting with artificial intelligence technologies.
- Participants had to be proficient in English to complete the survey.

3.4.7 Exclusion Criteria:

The exclusion criteria for this study were as follows:

- Participants who did not meet the inclusion criteria.
- Participants who had a known cognitive impairment or mental illness that may have affected their ability to complete the survey.

3.5 Data Collection Method

3.5.1 Data Collection Instrument:

The data collection instrument for this study was a structured questionnaire survey. The survey questionnaire was designed based on the UTAUT model and included questions on the factors that predicted the adoption intention of ChatGPT among Bangladeshi professionals. The questionnaire utilized a 5-point Likert scale for responses.

3.5.2 Data Collection Procedure:
The data collection procedure for this study involved the following steps:

- Contacting the selected universities and obtaining permission to conduct the survey among their postgraduate students.
- Distributing the questionnaire survey online through email and university communication channels.
- Providing instructions for completing the questionnaire and ensuring that participants understood the purpose of the study and their rights as participants.
- Collecting informed consent from participants before they started the survey questionnaire.
- Collecting the completed survey questionnaires through an online survey platform.

3.5.3 Data Quality Control:

To ensure data quality, the following measures were taken:

- Piloting the survey questionnaire with a small group of participants to identify and address any issues with the questionnaire design or wording.
- Ensuring that the survey questionnaire was clear, concise, and easy to understand.
- Providing instructions for completing the survey questionnaire and ensuring that participants understood the purpose of the study and their rights as participants.
- Verifying the completeness and accuracy of the data collected before starting the data analysis.
- Ensuring that the data collected were stored securely and confidentially.

3.6 Data Analysis Process

3.6.1 Data Collection:

The data for this study were collected through a cross-sectional survey using an online questionnaire. The survey was distributed among Bangladeshi professionals studying postgraduate programs in different universities in Bangladesh. The survey included questions related to the factors that predicted the adoption intention of ChatGPT among Bangladeshi professionals.

3.6.2 Data Coding:

The data collected through the survey were coded using a numerical system. Each response to the questionnaire was assigned a numerical code, which was used for data entry and analysis.

3.6.3 Data Analysis:

The data analysis process involved the use of various statistical techniques to determine the factors that predicted the adoption intention of ChatGPT among Bangladeshi Business professionals. The data were analyzed using Structural equation Modeling.

3.7 Ethical Considerations
In conducting this study, several ethical considerations were taken into account:

- Informed consent was obtained from all participants before they started the survey questionnaire.
- Participants’ anonymity and confidentiality were ensured by collecting data without personally identifiable information and storing the data securely.
- Participants were informed about the purpose of the study, their rights as participants, and the voluntary nature of their participation.
- The study was conducted in accordance with ethical guidelines and regulations to protect the welfare and rights of the participants.

### 3.6.7 Reliability of the Measurements:

The reliability of the measurements was assessed using Cronbach’s alpha, which is a measure of internal consistency reliability. Cronbach’s alpha was calculated for each construct in the survey, including Attitude towards Artificial Intelligence (ATAI), Performance expectancy (PE), Hedonic motivation (HM), Trust (T), Effort expectancy (EE), Social influence (SI), Facilitating conditions, Task characteristics, Technology characteristics (TEC), Task–technology Fit (TTF), Behavioral intention, and Actual Use (AU). A Cronbach’s alpha value of 0.7 or higher indicated adequate internal consistency reliability for each construct.

<table>
<thead>
<tr>
<th>Cronbach's Alpha</th>
<th>Cronbach's Alpha Based on Standardized Items</th>
<th>N of Items</th>
</tr>
</thead>
<tbody>
<tr>
<td>.952</td>
<td>.954</td>
<td>9</td>
</tr>
</tbody>
</table>

The reliability statistics provided in the table show the measures of internal consistency for a set of items or questions in a survey or test. In this case, the Cronbach's Alpha coefficient is reported as .952, indicating a high level of internal consistency among the items. This coefficient ranges between 0 and 1, with values closer to 1 indicating higher reliability. Therefore, the value of .952 suggests that the items in the scale are highly reliable and consistently measure the construct of interest. Another measure of reliability mentioned is Cronbach's Alpha based on standardized items, which is reported as .954. This coefficient is calculated based on the standardized scores of the items. Standardizing the items involves transforming them to have a mean of 0 and a standard deviation of 1. This standardized version of Cronbach's Alpha provides an alternative assessment of reliability and is often used when the items in the scale have different scales or measurement units. The slightly higher value of .954 indicates that even after standardization, the items maintain a high level of internal consistency.

Overall, based on the reliability statistics presented, the scale or instrument in question demonstrates a high level of internal consistency, suggesting that it is a reliable tool for measuring the construct of interest.
4. RESULTS

4.1 Demographic Characteristics
Table 4.1
Demographic Characteristics of the Respondents

<table>
<thead>
<tr>
<th>Demographic Factors</th>
<th>Frequency</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Gender</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>265</td>
<td>75.7</td>
</tr>
<tr>
<td>Female</td>
<td>85</td>
<td>24.3</td>
</tr>
<tr>
<td><strong>Age</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>11–26 Years</td>
<td>207</td>
<td>59.1</td>
</tr>
<tr>
<td>27–42 Years</td>
<td>132</td>
<td>37.7</td>
</tr>
<tr>
<td>43–58 Years</td>
<td>11</td>
<td>3.1</td>
</tr>
<tr>
<td><strong>Highest level of Educational Qualification</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bachelor/Honors</td>
<td>200</td>
<td>57.1</td>
</tr>
<tr>
<td>Masters</td>
<td>146</td>
<td>41.7</td>
</tr>
<tr>
<td>PhD</td>
<td>4</td>
<td>1.1</td>
</tr>
<tr>
<td><strong>Current Employment Status</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Post Graduate Student</td>
<td>189</td>
<td>54.0</td>
</tr>
<tr>
<td>Entry-level employee</td>
<td>74</td>
<td>21.1</td>
</tr>
<tr>
<td>Mid-level employee</td>
<td>42</td>
<td>12.0</td>
</tr>
<tr>
<td>Senior-level employee</td>
<td>1</td>
<td>.3</td>
</tr>
<tr>
<td>Manager</td>
<td>8</td>
<td>2.3</td>
</tr>
<tr>
<td>Executive</td>
<td>36</td>
<td>10.3</td>
</tr>
<tr>
<td><strong>Organization Type</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Public</td>
<td>21</td>
<td>6.0</td>
</tr>
<tr>
<td>Private</td>
<td>329</td>
<td>94.0</td>
</tr>
<tr>
<td><strong>Industry sector</strong></td>
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<td></td>
</tr>
<tr>
<td>Manufacturing Industries</td>
<td>51</td>
<td>14.6</td>
</tr>
<tr>
<td>Agricultural Industry</td>
<td>5</td>
<td>1.4</td>
</tr>
<tr>
<td>Service Industry</td>
<td>245</td>
<td>70.0</td>
</tr>
<tr>
<td>Construction Industry</td>
<td>2</td>
<td>.6</td>
</tr>
<tr>
<td>Automotive Industry</td>
<td>29</td>
<td>8.3</td>
</tr>
</tbody>
</table>
The table presents the demographic characteristics of the respondents, providing valuable insights for the study. The sample size consisted of 350 participants, with 75.7% being male and 24.3% female. In terms of age, the majority fell within the 11–26 years range, accounting for 59.1% of the respondents, while 37.7% were aged between 27–42 years, and a smaller percentage (3.1%) were in the 43–58 years range. Regarding educational qualifications, 57.1% held a Bachelor/Honors degree, 41.7% had a Masters degree, and only 1.1% possessed a PhD. Current employment status revealed that 54.0% of respondents were postgraduate students, while entry-level employees accounted for 21.1%, mid-level employees for 12.0%, and senior-level employees for a negligible percentage (.3%). The majority of respondents worked in private organizations (94.0%) compared to public organizations (6.0%). The service industry was the most represented sector (70.0%), followed by manufacturing industries (14.6%) and the automotive industry (8.3%). The agricultural industry (1.4%), construction industry (0.6%), and other sectors (5.1%) were less represented. Experience with internet and computers was distributed relatively evenly, with 35.4% having less than 2 years of experience, 32.6% having 2–5 years, and 32.0% having more than 5 years. These comprehensive demographic insights provide a solid foundation for understanding the characteristics and perspectives of business professionals in relation to the adoption intention of ChatGPT, thereby contributing to the body of knowledge in this area.

### 4.2 Reliability Analysis
Table 4.2 presents the results of the reliability analysis and convergent validity assessment for the constructs in this study. The reliability analysis, conducted using Cronbach's alpha, measures the consistency between items within each construct. A Cronbach's alpha value above 0.7 indicates high reliability (Taber, 2018). In this study, all constructs demonstrated strong internal consistency, as indicated by Cronbach's alpha values exceeding 0.7. Furthermore, the study established convergent validity by examining the Average Variance Extracted (AVE) for each construct. AVE values greater than 0.5 are considered indicative of good convergent validity (Asmelash & Kumar, 2019). In this case, all constructs surpassed the threshold, confirming their ability to explain more than half of the variance in their respective observed indicators. These results validate the research instrument as reliable and valid for measuring the constructs of Actual Use (AU), Attitude Towards Artificial Intelligence (ATAI), Behavioral Intention to Use (BIU), Effort Expectancy (EE), Facilitating Conditions (FC), Hedonic Motivation (HM), Performance Expectancy (PE), Social Influence (SI), and Trust (T).

### 4.3 Path Analysis of The Structural Model
Table 4.3  
Results of path analysis

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Path coefficients</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>ATAI -&gt; BIU</td>
<td>0.188</td>
<td>Supported</td>
</tr>
<tr>
<td>PE -&gt; BIU</td>
<td>0.234</td>
<td>Supported</td>
</tr>
<tr>
<td>EE -&gt; BIU</td>
<td>-0.205</td>
<td>Supported</td>
</tr>
<tr>
<td>SI -&gt; BIU</td>
<td>0.086</td>
<td>Supported</td>
</tr>
<tr>
<td>FC -&gt; BIU</td>
<td>0.352</td>
<td>Supported</td>
</tr>
<tr>
<td>HM -&gt; BIU</td>
<td>-0.012</td>
<td>Not Supported</td>
</tr>
<tr>
<td>T -&gt; BIU</td>
<td>0.278</td>
<td>Supported</td>
</tr>
<tr>
<td>BIU -&gt; AU</td>
<td>0.898</td>
<td>Supported</td>
</tr>
</tbody>
</table>

In hypothesis testing, a common criterion is to assess whether the p-value associated with a path coefficient is below a predetermined significance level (such as 0.05 or 0.001). If the p-value is below the chosen threshold, it is considered statistically significant, indicating support for the hypothesis. Conversely, if the p-value is above the threshold, the hypothesis is not supported (Dul et al., 2020; McShane et al., 2019).

For the presented results, the path analysis of structural equation modeling (SEM) was conducted to analyze the proposed hypotheses. Table 5 displays the path coefficients and corresponding results. Out of the eight tested hypotheses, seven were supported, while one was not supported.

**H1: ATAI -> BIU**: The path coefficient of 0.188 indicates a positive relationship between Attitude Towards Artificial Intelligence (ATAI) and Behavioral Intention to Use (BIU). The hypothesis is supported.

**H2: PE -> BIU**: The path coefficient of 0.234 indicates a positive relationship between Performance Expectancy (PE) and BIU. The hypothesis is supported.

**H3: EE -> BIU**: The path coefficient of -0.205 suggests a negative relationship between Effort Expectancy (EE) and BIU. The hypothesis is supported.

**H4: SI -> BIU**: The path coefficient of 0.086 implies a weak positive relationship between Social Influence (SI) and BIU. The hypothesis is supported.

**H5: FC -> BIU**: The path coefficient of 0.352 implies a positive relationship between Facilitating Conditions (FC) and BIU. The hypothesis is supported.

**H6: HM -> BIU**: The path coefficient of -0.012 suggests a weak negative relationship between Hedonic Motivation (HM) and BIU. The hypothesis is not supported.
H7: T → BIU: The path coefficient of 0.278 suggests a positive relationship between Trust (T) and BIU. The hypothesis is supported.

H8: BIU → AU: The path coefficient of 0.898 signifies a strong positive relationship between BIU and Actual Use (AU). The hypothesis is supported.

Overall, the results indicate that most of the hypotheses were supported, highlighting the significant influence of factors such as ATAI, EE, FC, PE, SI, and T on BIU, and the strong relationship between BIU and AU. However, the hypothesis regarding HM and BIU did not receive support from the data.

Table 4.4
Path coefficient matrix

<table>
<thead>
<tr>
<th></th>
<th>AU</th>
<th>BIU</th>
</tr>
</thead>
<tbody>
<tr>
<td>ATAI</td>
<td>0.188</td>
<td></td>
</tr>
<tr>
<td>AU</td>
<td></td>
<td></td>
</tr>
<tr>
<td>BIU</td>
<td>0.898</td>
<td></td>
</tr>
<tr>
<td>EE</td>
<td>-0.205</td>
<td></td>
</tr>
<tr>
<td>FC</td>
<td>0.352</td>
<td></td>
</tr>
<tr>
<td>HM</td>
<td>-0.012</td>
<td></td>
</tr>
<tr>
<td>PE</td>
<td>0.234</td>
<td></td>
</tr>
<tr>
<td>SI</td>
<td>0.086</td>
<td></td>
</tr>
<tr>
<td>T</td>
<td>0.278</td>
<td></td>
</tr>
</tbody>
</table>

The matrix illustrates the path coefficients for the relationships between the constructs. The path coefficient represents the strength and direction of the relationship between two constructs. For example, the path coefficient of 0.898 between BIU and AU indicates a strong positive relationship between Behavioral Intention to Use (BIU) and Actual Use (AU).

ATAI → BIU: The path coefficient of 0.188 suggests a positive relationship between Attitude Towards Artificial Intelligence (ATAI) and Behavioral Intention to Use (BIU). However, since the coefficient is not statistically significant, it indicates that the relationship between ATAI and BIU may not be meaningful in this study.

EE → BIU: The path coefficient of -0.205 suggests a negative relationship between Effort Expectancy (EE) and Behavioral Intention to Use (BIU). However, since the coefficient is not statistically significant, it implies that there is no meaningful relationship between EE and BIU in this study.

FC → BIU: The path coefficient of 0.352 indicates a positive relationship between Facilitating Conditions (FC) and Behavioral Intention to Use (BIU). It suggests that favorable conditions or resources can
contribute to a higher intention to use ChatGPT.

HM -> BIU: The path coefficient of -0.012 suggests a weak negative relationship between Hedonic Motivation (HM) and Behavioral Intention to Use (BIU). However, since the coefficient is not statistically significant, it implies that there is no meaningful relationship between HM and BIU in this study.

PE -> BIU: The path coefficient of 0.234 indicates a positive relationship between Performance expectancy (PE) and Behavioral Intention to Use (BIU). This means that individuals who perceive greater benefits or usefulness from using artificial intelligence are more likely to have a higher intention to use it.

SI -> BIU: The path coefficient of 0.086 suggests a weak positive relationship between Social Influence (SI) and Behavioral Intention to Use (BIU). However, since the coefficient is not statistically significant, it implies that there is no meaningful relationship between SI and BIU in this study.

T -> BIU: The path coefficient of 0.278 indicates a positive relationship between Trust (T) and Behavioral Intention to Use (BIU). This means that individuals who have greater trust in artificial intelligence are more likely to have a higher intention to use it.

Overall, the interpretation of the path coefficients suggests that the most significant factor influencing the intention to use artificial intelligence is the individual's actual use of it (BIU -> AU). However, it is important to consider the non-significant coefficients and the limitations of the study when interpreting these results.

### 4.4 Discriminant validity

<table>
<thead>
<tr>
<th>Variables</th>
<th>ATAI</th>
<th>AU</th>
<th>BIU</th>
<th>EE</th>
<th>FC</th>
<th>HM</th>
<th>PE</th>
<th>SI</th>
<th>T</th>
</tr>
</thead>
<tbody>
<tr>
<td>ATAI</td>
<td>0.85</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AU</td>
<td>0.73</td>
<td>0.968</td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BIU</td>
<td>0.741</td>
<td>0.898</td>
<td>0.924</td>
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<td></td>
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<td></td>
</tr>
<tr>
<td>EE</td>
<td>0.701</td>
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<td>0.86</td>
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<td></td>
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<td>FC</td>
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<td>0.81</td>
<td></td>
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<tr>
<td>HM</td>
<td>0.639</td>
<td>0.604</td>
<td>0.593</td>
<td>0.677</td>
<td>0.619</td>
<td>0.919</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PE</td>
<td>0.797</td>
<td>0.775</td>
<td>0.741</td>
<td>0.708</td>
<td>0.71</td>
<td>0.733</td>
<td>0.917</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SI</td>
<td>0.733</td>
<td>0.648</td>
<td>0.679</td>
<td>0.708</td>
<td>0.635</td>
<td>0.637</td>
<td>0.664</td>
<td>0.891</td>
<td></td>
</tr>
<tr>
<td>T</td>
<td>0.722</td>
<td>0.728</td>
<td>0.722</td>
<td>0.724</td>
<td>0.629</td>
<td>0.645</td>
<td>0.734</td>
<td>0.825</td>
<td>0.924</td>
</tr>
</tbody>
</table>

The discriminant validity matrix presents the correlations between variables in the study, allowing us to assess the distinctiveness of each construct. The diagonal values represent the square root of the
average variance extracted (AVE) for each construct, while the off-diagonal values indicate the correlations between constructs. Based on the matrix, we can observe that all diagonal values (represented by the square roots of the AVE) are higher than the correlations between constructs. This suggests that each construct has a higher correlation with its own items than with items from other constructs, indicating discriminant validity. For example, the diagonal value for ATAI is 0.85, which is higher than the correlations between ATAI and other constructs (ranging from 0.639 to 0.797). Similarly, the diagonal value for AU is 0.968, indicating a higher correlation within the AU construct compared to correlations with other constructs (ranging from 0.599 to 0.775).

These findings support the discriminant validity of the measurement instrument, indicating that the constructs in the study are distinct and accurately measure their intended concepts. It provides confidence that the variables in the study are not measuring the same underlying construct and allows for meaningful interpretation of their relationships in subsequent analyses.

4.5: Outer Loading Matrix
<table>
<thead>
<tr>
<th></th>
<th>AU</th>
<th>ATAI</th>
<th>BIU</th>
<th>EE</th>
<th>FC</th>
<th>HM</th>
<th>PE</th>
<th>SI</th>
<th>T</th>
</tr>
</thead>
<tbody>
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<td>AU_1</td>
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</tr>
<tr>
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<td>0.937</td>
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<td>0.903</td>
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<td></td>
<td></td>
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<td>0.931</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
The outer loading values represent the relationships between the latent variables (AU, ATAI, BIU, EE, FC, HM, PE, SI, T) and their corresponding observed indicators or items. These values indicate the strength of the relationship between each latent variable and its indicators, with higher values indicating a stronger relationship. Here is the interpretation for each variable:

**AU (Actual Use):**

AU_1 and AU_2 have high outer loading values of 0.969 and 0.967, respectively. This indicates that these items strongly represent the latent variable AU, suggesting that they effectively capture the concept of actual use of ChatGPT among professionals.

**ATAI (Attitude Towards AI):**

ATAI_1, ATAI_2, ATAI_3, and ATAI_4 have high outer loading values of 0.865, 0.868, 0.784, and 0.877, respectively. These findings indicate that these items are good indicators of the latent variable ATAI, representing professionals' attitudes towards AI technologies, including ChatGPT.

**BIU (Behavioral Intention to Use):**

BIU_1, BIU_2, and BIU_3 have high outer loading values of 0.931, 0.924, and 0.919, respectively. These values indicate that these items effectively capture the concept of behavioral intention to use ChatGPT among professionals, representing the latent variable BIU.

**EE (Effort Expectancy):**

EE_1, EE_2, EE_3, and EE_4 have outer loading values of 0.875, 0.899, 0.866, and 0.797, respectively. These values suggest that these items are good indicators of the latent variable EE, representing professionals' Effort Expectancy associated with using ChatGPT.

**FC (Facilitating Conditions):**

FC_1, FC_2, FC_3, and FC_4 have outer loading values of 0.813, 0.781, 0.864, and 0.778, respectively. These values indicate that these items effectively represent the latent variable FC, which refers to the facilitating conditions for adopting and using ChatGPT, such as resource availability and technical support.

**HM (Hedonic Motivation):**
HM_1, HM_2, and HM_3 have outer loading values of 0.893, 0.927, and 0.935, respectively. These values indicate that these items effectively capture the concept of hedonic motivation, representing professionals' motivation to use ChatGPT for the enjoyment and pleasure it provides.

**PE (Performance Expectancy):**

PE_1, PE_2, and PE_3 have outer loading values of 0.943, 0.867, and 0.937, respectively. These values suggest that these items are good indicators of the latent variable PE, representing professionals' perception of ChatGPT's ease of use.

**SI (Social Influence):**

SI_1, SI_2, and SI_3 have outer loading values of 0.903, 0.836, and 0.931, respectively. These values indicate that these items effectively capture the concept of social influence, representing the impact of colleagues and peers on professionals' intention to use ChatGPT.

**T (Trust):**

T_1 and T_2 have outer loading values of 0.923 and 0.925, respectively. These values suggest that these items are good indicators of the latent variable T, representing professionals' trust in ChatGPT as a reliable and trustworthy tool.

### 4.6: Structural Equation Model Analysis

The structural equation model (SEM) analysis revealed important insights into the relationships among the variables in the study. The findings indicate that behavioral intentions to use (BIU) have a significant impact on actual usage (AU), with a strong path coefficient of 0.898. Additionally, BIU is influenced by attitude towards AI (ATAI), effort expectancy (EE), facilitating conditions (FC), hedonic motivation (HM), performance expectancy (PE), social influence (SI), and trust (T). These predictors collectively explain 69.8% ($R^2 = 0.698$) of the variance in BIU. Among them, facilitating conditions demonstrate the strongest positive influence (0.352) on BIU, followed by performance expectancy (0.234), trust (0.278), attitude towards AI (0.188), effort expectancy (0.205), and social influence (0.086). Furthermore, BIU strongly predicts AU with a path coefficient of 0.898. The overall model explains a substantial proportion of the variance in AU ($R^2 = 0.806$). The high factor loadings of the individual items within each construct confirm their effectiveness in representing their respective variables in the model. Overall, these findings emphasize the significance of facilitating conditions, performance expectancy, trust, attitude towards AI, effort expectancy, and social influence in shaping behavioral intentions and subsequent actual usage of ChatGPT.

### 5. FINDINGS

#### 5.1 Findings from Demographic Characteristics
The demographic characteristics of the respondents provide valuable insights into the study. The sample size of 350 participants consisted mostly of males (75.7%) and females (24.3%). In terms of age, the majority fell within the 11–26 years range (59.1%), followed by those aged between 27–42 years (37.7%), and a smaller percentage in the 43–58 years range (3.1%). Education-wise, 57.1% held a Bachelor/Honors degree, 41.7% had a Masters degree, and only 1.1% possessed a PhD. In terms of employment status, 54.0% were postgraduate students, 21.1% were entry-level employees, 12.0% were mid-level employees, and a negligible percentage (.3%) were senior-level employees. The majority of respondents worked in private organizations (94.0%) compared to public organizations (6.0%). The service industry was the most represented sector (70.0%), followed by manufacturing industries (14.6%) and the automotive industry (8.3%). Less represented sectors included the agricultural industry (1.4%), construction industry (0.6%), and other sectors (5.1%). In terms of experience with internet and computers, respondents were distributed relatively evenly, with 35.4% having less than 2 years of experience, 32.6% having 2–5 years, and 32.0% having more than 5 years. These findings highlight the diverse backgrounds and perspectives of the participants, providing a comprehensive understanding of the characteristics of business professionals in relation to the adoption intention of ChatGPT.

5.2 Findings from Reliability analysis:

The findings indicate that all constructs in the study demonstrate strong internal consistency and convergent validity. The reliability analysis, measured using Cronbach's alpha, reveals that each construct has a Cronbach's alpha value exceeding 0.7, indicating high reliability. This suggests that the items within each construct consistently measure the underlying concept they are intended to represent. Additionally, the study establishes convergent validity by examining the Average Variance Extracted (AVE) for each construct. The AVE values, which measure the amount of variance explained by the construct, exceed the threshold of 0.5 for all constructs. This indicates that each construct explains more than half of the variance in its respective observed indicators, confirming good convergent validity. These findings validate the research instrument used in the study as reliable and valid for measuring the constructs of Actual Use (AU), Attitude Towards Artificial Intelligence (ATAI), Behavioral Intention to Use (BIU), Effort Expectancy (EE), Facilitating Conditions (FC), Hedonic Motivation (HM), Performance Expectancy (PE), Social Influence (SI), and Trust (T). The robustness of the instrument enhances the credibility and integrity of the study's measurement and enables accurate assessment of the relationships among the variables.

5.3 Findings from Structural Equation Model

Based on the path analysis and structural equation model (SEM) analysis, the following findings can be derived:

Behavioral Intentions to Use (BIU) significantly influence Actual Usage (AU) of ChatGPT, with a strong positive relationship (path coefficient = 0.898). This implies that individuals who have higher intentions to use ChatGPT are more likely to actually use it.

Several factors significantly influence BIU:
- Attitude Towards Artificial Intelligence (ATAI) positively influences BIU (path coefficient = 0.188). Individuals with more positive attitudes towards AI are more likely to have higher intentions to use ChatGPT.

- Performance Expectancy (PE) positively influences BIU (path coefficient = 0.234). Individuals who perceive greater benefits and usefulness from using AI are more likely to have higher intentions to use ChatGPT.

- Effort Expectancy (EE) negatively influences BIU (path coefficient = -0.205). Higher perceived effort required for using ChatGPT leads to lower intentions to use it.

- Social Influence (SI) weakly and positively influences BIU (path coefficient = 0.086). Although the relationship is weak, individuals influenced by social factors are more likely to have higher intentions to use ChatGPT.

- Facilitating Conditions (FC) positively influence BIU (path coefficient = 0.352). Favorable conditions and available resources contribute to higher intentions to use ChatGPT.

- Hedonic Motivation (HM) does not significantly influence BIU (path coefficient = -0.012). There is no meaningful relationship between hedonic motivation and intentions to use ChatGPT.

- Trust (T) positively influences BIU (path coefficient = 0.278). Individuals with higher trust in ChatGPT are more likely to have higher intentions to use it.

The overall model explains a substantial proportion of the variance in AU ($R^2 = 0.806$), indicating that the factors influencing BIU have a strong impact on the actual usage of ChatGPT. The discriminant validity analysis confirms that each construct (ATAI, AU, BIU, EE, FC, HM, PE, SI, T) is distinct and accurately measures its intended concept. The correlations between constructs are lower than the diagonal values (square roots of AVE), indicating discriminant validity. These findings suggest that attitudes towards AI, perceived benefits and usefulness, perceived effort, social influence, facilitating conditions, and trust play significant roles in shaping individuals' intentions to use ChatGPT. These intentions, in turn, strongly influence the actual usage of ChatGPT. These insights can help in understanding the factors influencing the adoption and use of AI technologies like ChatGPT and can inform strategies to promote its acceptance and usage among professionals.

### 5.4 Summary of the Findings

The study investigated the adoption intention of ChatGPT among business professionals and provided valuable insights into various aspects of the topic. The findings are summarized as follows:

The sample consisted mostly of males (75.7%) and females (24.3%), with the majority falling within the age range of 11–26 years (59.1%). Education-wise, a significant portion held a Bachelor/Honors degree (57.1%) or a Masters degree (41.7%). In terms of employment status, the majority were postgraduate students (54.0%), followed by entry-level employees (21.1%). Private organizations (94.0%) were the main workplace, with the service industry (70.0%) being the most represented sector. The study demonstrated strong internal consistency and convergent validity. All constructs had Cronbach's alpha values exceeding
0.7, indicating high reliability. The constructs also exceeded the threshold of 0.5 for Average Variance Extracted (AVE), confirming good convergent validity. Respondents had a generally positive attitude towards ChatGPT, perceiving it as efficient, convenient, and useful for academic and professional work. User experience was positive, with respondents finding ChatGPT easy to use. Trust and reliability had moderate mean scores, while support availability received a relatively high mean score. Overall, respondents expressed an intention to continue using ChatGPT and recommend it to others. Attitude Towards Artificial Intelligence, Performance Expectancy, Trust, and Behavioral Intention to Use showed strong positive correlations with other constructs. Hedonic Motivation and Trust had a moderate positive correlation, while Effort Expectancy and Actual Use had a moderate positive correlation. These correlations indicate the significant influence of attitudes, expectations, motivations, and social factors on the intention to use and actual use of ChatGPT. The regression model revealed that Behavioral Intention to Use, Performance Expectancy, Trust, Effort Expectancy, Facilitating Conditions, and Attitude Towards Artificial Intelligence significantly predicted Actual Use. Behavioral Intention to Use was the strongest predictor. Attitude Towards Artificial Intelligence, Hedonic Motivation, and Social Influence did not have significant effects on Actual Use in this analysis. BIU strongly influenced AU, with several factors significantly influencing BIU. Attitude Towards Artificial Intelligence, Performance Expectancy, Facilitating Conditions, and Trust had positive effects on BIU, while Effort Expectancy had a negative effect. Social Influence weakly influenced BIU, and Hedonic Motivation did not significantly influence BIU. The overall model explained a substantial proportion of the variance in AU. The findings suggest that attitudes, expectations, motivations, and social factors are significant predictors of the intention to use and actual use of ChatGPT. Factors such as Performance Expectancy, Trust, Effort Expectancy, Facilitating Conditions, and Behavioral Intention to Use play crucial roles in influencing the actual usage behavior. These insights can inform strategies to promote the adoption and usage of ChatGPT among business professionals.

6. DISCUSSION AND CONCLUSIONS

6.1 Discussion:

The discussion of the findings from the study on the adoption intention of ChatGPT among business professionals provides insights into the factors influencing the use of AI technologies and their implications for practitioners and researchers. Firstly, the demographic characteristics of the respondents indicate that the sample consisted of a diverse group of business professionals. The majority of participants were young adults, suggesting that the younger generation is more receptive to adopting AI technologies. The high percentage of individuals with bachelor's and master's degrees highlights the importance of education in shaping attitudes towards technology adoption. The predominance of males in the sample may suggest potential gender disparities in the adoption of AI technologies, which could be explored further in future research. The reliability analysis establishes the robustness of the research instrument used in the study. The high Cronbach's alpha values indicate that the constructs reliably measure the intended concepts. This finding enhances the credibility of the study's measurement and
ensures the consistency of the results obtained. The structural equation model (SEM) analysis provides a comprehensive understanding of the relationships between constructs and their impacts on actual usage. The significant influence of behavioral intentions to use on actual usage underscores the importance of individuals’ intentions in driving their adoption behavior. Attitude towards AI, performance expectancy, facilitating conditions, and trust were found to positively influence behavioral intention to use. However, effort expectancy did not have a significant positive impact on behavioral intention to use. This suggests that minimizing perceived effort required to use AI systems may be crucial for fostering higher intentions to use. Additionally, the weak effect of social influence on behavioral intention to use implies that while social factors may have some influence, they may not be as strong as other factors in driving adoption behavior. Overall, the findings contribute valuable insights into the adoption intention and actual usage of ChatGPT among business professionals. These insights can inform practitioners and developers in designing interventions to enhance adoption and usage. Focusing on factors such as perceived performance benefits, trust-building mechanisms, reducing perceived effort, and creating favorable conditions can facilitate wider acceptance and effective utilization of AI technologies in academic and professional contexts. Further research can delve into specific demographic factors, explore gender disparities, and investigate the role of individual

6.2 Conclusion:

In conclusion, this study Predicting the adoption intention and actual use of ChatGPT among Business Professionals. The findings provide valuable insights into the adoption process and have implications for the design and implementation of ChatGPT in educational and professional contexts. The results supported the hypotheses and revealed several key findings. Firstly, respondents generally had a positive attitude towards ChatGPT, perceiving it as efficient, convenient, and useful for their academic and professional work. They found it easy to use with clear interactions, although there were some concerns about the entertainment aspect and trustworthiness of the system. The correlation analysis showed that attitudes, expectations, motivations, and social factors significantly predicted the intention to use and actual use of ChatGPT. Positive attitudes towards artificial intelligence were associated with higher performance expectations, indicating that individuals with a positive attitude expected better performance from ChatGPT. Performance expectations, in turn, influenced hedonic motivation, suggesting that the belief in improved performance led to a sense of pleasure derived from using ChatGPT. Trust was strongly correlated with social influence, indicating that as trust in ChatGPT increased, so did its impact on social influence. This suggests that individuals were more likely to adopt ChatGPT when they perceived it as trustworthy and when they observed others using and endorsing it. Effort expectancy showed a moderate positive correlation with actual use, indicating that the easier ChatGPT was to use, the more likely it was to be adopted and utilized. Regression analysis revealed that behavioral intention to use ChatGPT was the strongest predictor of actual use. Factors such as performance expectancy, trust, effort expectancy, and facilitating conditions also significantly influenced actual use. However, attitude towards artificial intelligence, hedonic motivation, and social influence did not directly impact actual use. The structural equation model analysis confirmed the construct validity of the observed indicators, indicating a strong relationship between the observed variables and their
corresponding latent constructs. Overall, these findings contribute to our understanding of the adoption process of ChatGPT among Business Professionals. They highlight the importance of attitudes, expectations, motivations, and social factors in predicting adoption intention and actual use. The results can guide the design and development of ChatGPT, focusing on improving factors such as performance expectancy, trust, and ease of use to encourage widespread adoption. It is important to note that this study had limitations, such as the sample composition and generalizability to other populations. Further research is needed to validate and expand upon these findings. Nonetheless, this study provides valuable insights for researchers, practitioners, and developers interested in understanding and promoting the adoption of AI-based chat systems like ChatGPT.

DECLARATIONS

Statement regarding potential competing interests: The authors declare no competing interests

Statement of Ethics Approval: I, Md Mehedi Hasan Emon, principal investigator of the study titled “Predicting Adoption Intention of ChatGPT- A Study on Business Professionals of Bangladesh,” hereby affirm that the research project has received ethical approval from the Faculty of Business Administration, AIUB on May 2023.

REFERENCES


**Figures**
Figure 1

Conceptual Model

Figure 2
Figure 5.1: Structural Equation Model

Supplementary Files

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