A STUDY ON FACTORS AFFECTING BEHAVIOURAL INTENTION TOWARDS USING AI CHATBOTS AMONG STUDENTS' PERSPECTIVES IN A PRIVATE UNIVERSITY

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Group 1

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BY

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A final year project submitted in partial fulfilment
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APRIL 2024

DECLARATION

We hereby declare that:

(1) This undergraduate FYP is the end result of our own work and that due acknowledgement has been given in the references to ALL sources of information be they printed, electronic, or personal.

(2) No portion of this FYP has been submitted in support of any application for any other degree or qualification of this or any other university, or other institutes of learning.

(3) Equal contribution has been made by each group member in completing the FYP.

(4) The word count of this research report is 17,109.

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This dissertation is dedicated to:

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For guided us throughout the completion of this research study.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
BI	Behavioural Intention
CAV	Coefficient Alpha Value
DV	Dependent Variable
EE	Effort Expectancy
HC	Highest Contribution
HT	Habit
HEIs	Higher Education Institutions
IV	Independent Variable
INFO	Informativeness
PE	Performance Expectancy
SI	Social Influence
SPSS	Statistical Package for Social Science
UTAR	Universiti Tunku Abdul Rahman
UTAUT2	Unified Theory of Acceptance and Use of Technology 2

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PREFACE

Final year project is a compulsory subject for Bachelor of Business Administration (Honours) students taken to graduate. The topic of this study is "A study on factors affecting behavioural intention towards using AI Chatbots among students' perspectives in a private university". This study is conducted because AI is our 21st century trend and a lot of industries are adopting into their field. It is significant to study universities suitable to adopt this new AI and what factors will affect the student behavioural intention towards using AI Chatbots.

Universities student is the future talent in developing countries. This is fundamental for a developing country. A big change starting from the beginning can let the entire process move smoothly and well-planned. However, in some of the universities in certain foreign country are restricted students adopt AI Chatbots in academics. But somehow many fields of industry are adopting this new technology in their workplace smoothly and excellently. Thus, this research provides a more comprehensive understanding of the factors that affect student behavioural intention toward using AI Chatbots in a private university.

In short, this research can outline the five independent variables which are performance expectancy, effort expectancy, social influence, habit, and informativeness that may influence student behavioural intention toward using AI Chatbots. This research is perceived to be advantageous for future studies.

ABSTRACT

The aim of conducting this research project is to study the factors that affecting behavioural intention towards using AI Chatbots among students' perspectives in a private university. The factors that may influence student behavioural intention toward using AI Chatbots include performance expectancy, effort expectancy, social influence, habit, and informativeness. The researchers focus on a private university which is UTAR in both campuses which are Kampar and Sungai Long. In this research, we collected 357 questionnaires from the students at both UTAR campuses successfully and analysed them through Statistical Package for the Social Sciences (SPSS) for the pilot study and full study. Pearson Correlation Coefficient Analysis and Multiple Regression Analysis are used to test the significant relationship between the independent variables (performance expectancy, effort expectancy, social influence, habit, and informativeness) and dependent variable (behavioural intention). Based on this research, performance expectancy emerges as the most influential independent variable among the four others, significantly affecting behavioural intention towards using AI Chatbots among students' perspectives in private university, as it has the highest unstandardised coefficients of beta value, namely 0.451. In addition, this study incorporates an additional independent variable alongside UTAUT2 model, namely informativeness. The inclusion of informativeness in this research study is novel, as no prior studies have explored this aspect in the related topic. In conclusion, all the independent variables (performance expectancy, effort expectancy, social influence, habit, and informativeness) are found to be having a positive significant relationship with the dependent variable (behavioural intention). Lastly, a summary of the major findings, implications of the research, limitations of the research, and some recommendations are indicated in this study.

Keywords: Behavioural Intention, Performance Expectancy, Effort Expectancy, Social Influence, Habit, Informativeness

CHAPTER 1: RESEARCH OVERVIEW

1.0 Introduction

Artificial intelligence (AI) conversation has gained considerable prominence in the present times. AI Chatbots play a pivotal role in education by augmenting student understanding and fostering self-directed learning enthusiasm. Hence, it is imperative for researchers to undertake a study aimed at examining the factors affecting behavioural intention (BI) towards using AI Chatbots among students' perspectives in a private university, which is Universiti Tunku Abdul Rahman (UTAR). The research background is introduced in this chapter along with the problem statement, research purpose, research questions, hypotheses, significance, chapter structure, and summary.

1.1 Research Background

1.1.1 The Development of Higher Education in Malaysia

In recent decades, the progress of Malaysia's higher education system has been noteworthy. It has witnessed a surge in student enrolment, gained international recognition for research and institutional quality, and emerged as a favoured choice for global students. These achievements underscore the commitment of the nation's academic community, backing from the private sector, and substantial government funding (Ministry of Education Malaysia, 2015). Nonetheless, the Ministry of Education recognizes the necessity for continuous adaptation to remain at the forefront of worldwide developments. The rise of transformative technologies like robotics, the Internet of Things, and automated knowledge work is anticipated to reshape society and commerce. A fundamental reimagining of higher education and institutions is imperative to equip Malaysian youth for this rapidly evolving future. In response, the Ministry introduced the Malaysia Education Blueprint 2015-2025 (Higher Education) in 2013. This comprehensive plan, crafted over two years, integrates insights from local and international education experts, university leadership, and the general public. It serves as an internally driven roadmap to empower Malaysia's progression towards achieving high-income status.

Accordingly, the Ministry's primary aim is to elevate Malaysia's higher education system to global prominence, fostering competitiveness in the international economy. The Malaysia Education Blueprint for Higher Education seeks to build on past achievements and bring about significant changes, with key goals including:

1. Cultivating an entrepreneurial mindset among students, encouraging job creation.
2. Balancing traditional academia with technical and vocational training.
3. Embracing technology for personalized learning and tangible outcomes.
4. Shifting to a more balanced regulatory model for public and private institutions.
5. Ensuring financial sustainability by reducing reliance on government funds and involving all stakeholders.

Apart from other industries, education constitutes a significant portion of Malaysia's fiscal expenditure, representing an increase of 0.93% from RM50.4 billion in 2021 to RM52.6 billion in 2022 (Luther, 2020). In the 2023 budget, the education sector received the largest allocation of RM55.2 billion, RM2.6 billion more than in 2022, and accounted for 14.22% of the total 2023 budget (Kementerian Kewangan, 2023). The revenue from the service sectors has increased from RM435.9 billion to RM 460.0 billion in the fourth quarter of 2020 to 2021 (Ministry of Economy Department of Statistics Malaysia Official Portal, 2021; Ministry of Economy Department of Statistics Malaysia Official Portal, 2022).

1.1.2 The Rise of Artificial Intelligence in Higher Education

In recent years, the convergence of AI systems and AI Chatbots in academia has attracted much attention and interest (Kooli, 2023). AI technologies have the potential to drastically alter research and educational practices by automating time-consuming and repetitive tasks, developing content, assisting with data analysis, evaluating student performance and assignments, and developing entirely new paradigms for learning and assessment (Kooli, 2023; Hien et al., 2018). Nevertheless, the application of AI Chatbots in the academic field is not devoid of obstacles and disputes.

The use of AI Chatbots in higher education has the potential to change the learning process completely. These AI Chatbots offer multifaceted benefits that encompass enhanced productivity, streamlined communication, personalized learning assistance, and reduced ambiguity in interactions (Sandu & Gide, 2019). Particularly within the context of fostering teaching and learning, AI Chatbots serve as invaluable companions that curate content, adapt to students' individual needs and pace, and stimulate collaborative dialogues, reflective thinking, and facilitate learning motivation (Molnár & Szüts, 2018; Yin et al., 2021). Notably, integrating AI Chatbots into higher education has demonstrated efficacy in improving students' mental health, self-learning capabilities, and stress management (Kamita et al., 2019). Overcoming issues of delayed response, AI Chatbots facilitate continuous access to learning resources, thereby bolstering academic achievement and self-efficacy (Hwang & Chang, 2021; Almahri et al., 2020). In addition, AI Chatbots empower learners to take charge of their education at their own pace (Wang et al., 2021). Besides, students interacting with AI Chatbots outperformed those under traditional instruction, underscoring the value of these AI-driven companions in higher education. Notably, students' satisfaction stems from the AI Chatbots' instantaneous feedback and interaction, effectively circumventing delays that might hinder the learning process (Essel et al., 2022). According to Rahim et al. (2022), AI Chatbots provide both students and university staff with a swift and cost-effective means to access information efficiently. Essel et al. (2022) emphasize that AI Chatbots offer an interactive approach that facilitates ongoing student engagement, enabling them to ask questions pertaining to specific subjects. According to Almahri et al. (2020), students' motivation has been boosted by AI Chatbots, as AI Chatbots often serve as engaging and inventive educational tools that captivate their attention."

In the field of education, one of the major ethical issues raised by the use of AI Chatbots concerns the privacy rights of students and teachers. According to Shwetarani (2023), the main challenge faced by the education industry is the ethical concern issue which is learners misuse AI Chatbots in terms of data privacy, security, and data provided by AI Chatbots. One of the primary causes of privacy infringement is excessive exposure of personal information on online platforms. Although sensitive personal data and information are protected by existing laws and standards, data access and security violations by AI-driven technological corporations have increased privacy concerns. (Stahl & Wright, 2018; Murphy, 2019). Even when consent processes are designed to be protective and reduce privacy concerns, many people offer consent without taking into consideration the extent of the information they share, such as language usage, ethnic identification, biographical information, and location metadata (Remian, 2019). This uninformed sharing of information effectively diminishes individuals' autonomy and privacy safeguards. In other words, as AI Chatbots reduce introspection and independent thinking, people's capacity for autonomy could weaken. Another ethical issue is monitoring and tracking systems that gather specific data on the preferences and behaviours of students and teachers. AI Chatbots monitoring systems use algorithms and machine learning models to monitor users' present activity as well as to forecast their future preferences and behaviour (Regan & Jesse, 2019).

Besides, there are significant numbers of users who do not use this AI Chatbots software as it has been introduced recently worldwide (Yang & Evans, 2019). Nowadays, AI is growing rapidly due to globalization, especially with the introduction of virtual agent AI Chatbots to help organisations provide better service to customers. However, Higher Education Institutions (HEIs) are unprepared for adoption of this new technology in their education field. BI towards using AI Chatbots is subjectively influenced by performance expectancy (PE), effort expectancy (EE), social influence (SI), habit (HT), and informativeness (INFO). Therefore, researchers have conducted a study regarding the factors affecting the BI of students towards using AI Chatbots. If these factors have a positive relationship towards students' BI in using AI Chatbots, it gives a reference for HEIs to adopt AI Chatbots for academic purposes.

In this era of modernization, AI Chatbots became popular globally in late November 2022. However, AI Chatbots have existed in the world since 1960 and are called ELIZA, which was created by Joseph Weizenbaum. There are lots of AI Chatbots developed between the evolution from ELIZA to ChatGPT, including PARRY, which was constructed by American psychiatrist Kenneth Colby in 1972, and others such as SIRI, Dr. Sbaitso, Jabberwacky, SmarterChild, Artificial Linguistic Internet Computer Entity (A.L.I.C.E.), Google Now or Google Assistant, Cortana, and Alexa (Ina, 2022). However, researchers can see that each of the AI Chatbots acts for different function, which has shown in Table 1(Abdullahi, 2023).

1.1.3 Background of the Private Institution

Table 1

Different types of AI Chatbots

No.	Types of AI Chatbots	Best use for the function
1.	Bing Chat Enterprise	Organisations in the Microsoft ecosystem
2.	ChatGPT	Versatility and advanced chat generative AI features
3.	OpenAI Playground	Customizability
4.	Perplexity AI	Finding information on the internet
5.	YouChat	Students and researchers
6.	Chatsonic	Individuals in the creative industries
7.	Google Bard	Brainstorming ideas
8.	Socrates.ai	Internal knowledge-base management
9.	HuggingChat	Developers
10.	Jasper	Marketing and sales team

Source: Abdullahi, A. (2023, September 14). 10 Best AI Chatbots 2023. EWEEK. https://www.eweek.com/artificial-intelligence/best-ai-chatbots/

In this research, researchers opted for UTAR as a representative among the private universities. The establishment of UTAR started with the story of Kolej Tunku Abdul Rahman (KTAR) in 1964 and opened for the first intake of students in 2002 that offered eight-degree courses (Introduction - Universiti Tunku Abdul Rahman, n.d.). According to Sharif Study (2022), UTAR holds a Quacquarelli Symonds (QS) World University Ranking 2023 within the range of 801-850 and an Asia University Ranking 2023 of 174. Today, UTAR offers an extensive array of 138 academic programmes from foundation studies, undergraduate and postgraduate, catering to a student population exceeding 21,000 across its two campuses in Kampar and Sungai Long (Introduction - Universiti Tunku Abdul Rahman, n.d.).

Moreover, UTAR holds a well-established status and has been granted the certification of self-accreditation. UTAR possesses the privilege of this designation, allowing them to independently design and introduce academic programmes through their respective Senates, without involving the Malaysia Qualifications Agency (MQA). UTAR has the qualification to conduct trial implementations within their campuses, gaining approval from their respective managements without the need for engagement from MQA; meanwhile, it is expected to carry out its own programme accreditation more efficiently and effectively (Self-Accreditation Malaysia Qualifications Agency, n.d.). Therefore, UTAR stands as a representative entity for the research outcomes. According to the Department of Quality Assurance (n.d.), UTAR's academic programmes receive MQA Provisional Accreditation upon initiation. This accreditation indicates that the programme has satisfied the essential MQA prerequisites for commencing its operations.

Given this autonomy, the study's focus on AI Chatbots adoption gains significance across HEIs. If the results are able to be carried out, all the universities can test run for their university approval from their management without waiting for involvement from MQA (Self-Accreditation Malaysia Qualifications Agency, n.d.).

1.2 Problem Statement

AI is a significant driver behind the current wave of technical innovation and economic change, which is radically altering how people learn. In 2022, the emergence of the AI Chatbot "ChatGPT" has propelled AI to the forefront and become a new trend for the future. In the modern age, the conventional education system grapples with challenges such as crowded classrooms, insufficient personalized attention for students, diverse learning paces and preferences, and difficulties in keeping pace with technological advancements. In response, AI Chatbots are gaining prominence as a viable solution to tackle these issues effectively (Labadze et al., 2023).

Therefore, studying the factors affecting students' BI in using AI Chatbots is crucial because it enables researchers to pinpoint obstacles and enablers affecting students from using AI Chatbots. This comprehension aids educators, developers, and policymakers in tackling hurdles and capitalize on prospects to foster AI technology acceptance and integration within educational contexts. Furthermore, universities are pivotal hubs for readying students for a job market where AI technologies are increasingly available. Grasping students' BI toward AI Chatbots can guide the crafting of educational programs to enhance students' digital literacy, technical proficiency, and adaptiveness. Moreover, AI Chatbots are both current and future trends. Embracing AI Chatbots during university education can also enhance students' competitiveness when seeking employment, as nearly every industry strives to integrate this technology. This adoption could give students a competitive advantage upon graduation, as they will be equipped with skills and experience relevant to a rapidly evolving job market. Besides, universities have the opportunity to leverage insights gained from research to optimize educational practices through the integration of AI Chatbots. For instance, these AI Chatbots can seamlessly integrate into learning management systems, offering tailored assistance, addressing student inquiries, facilitating communication, and delivering prompt feedback. By comprehending BI, educators can adeptly customize these interventions to suit the specific needs of students. Additionally, by understanding more about students' BI in using AI Chatbots, university management can plan strategically for academic development processes, training, or courses.

AI Chatbots can foster a learning environment by granting access to educational materials whenever needed, providing tailored explanations according to each student's requirements, and establishing a non-judgmental space for inquiries, thus assisting students significantly in their educational journey. This level of independence aligns with modern educational methods that advocate for self-directed learning, which enhances student motivation, involvement, and academic achievements (William, 2010). Essentially, it enables learners to interact with software autonomously, eliminating the necessity for traditional classrooms or instructors (Shawar and Atwell, 2007). Students benefit from immediate answers to queries and support in navigating complex subjects at their own speed.

In education, students utilise AI Chatbots for various purposes, such as assignments, tutorials, and acquiring additional knowledge to enhance academic performance (Mallow, 2023). However, AI Chatbots present potential challenges, such as their database information not being updated in real time. For example, ChatGPT's data only extends until January 2022, meaning the information it generates is not the latest. This limitation affects users' information retrieval and profoundly impacts students' willingness to use AI Chatbots (Gupta, 2023). If users seek to acquire new knowledge through AI Chatbots, real-time information may not have a significant impact on them, but if users want to know the latest information, it becomes impractical. Additionally, the quality (performance) of information provided by AI Chatbots is also a critical concern affecting student BI, directly influencing users' confidence and satisfaction and directly impacting BI (Gupta, 2023). In this research study, researchers have used four factors (PE, EE, SI, and HT) from the UTAUT2 model and one additional factor (INFO) to study the factors affecting the student's BI to use AI Chatbots.

PE is closely tied to the attributes of students or users utilising AI Chatbots. When students anticipate positive outcomes from AI Chatbots, the perceived usefulness of information or trust depends on users' attributes (Melián-González et al., 2019). However, the evolution of AI Chatbots has introduced challenges, particularly in the education sector. Some students may misuse the AI Chatbots function, resort to free essay writing, cheating on assignments or assessments generated by AI Chatbots. Consequently, several universities, including the Los Angeles Unified School District in the US, Imperial College London, and the University of Cambridge in the UK, restrict the use of AI for academic purposes (Heaven, 2023). If students utilize AI Chatbots effectively, it has the potential to enhance their academic performance. When they encounter a new topic at school, they can delve deeper into their understanding by utilising AI Chatbots as a supplementary learning tool (Heaven, 2023).

In addition, EE is influenced by the ease of use of AI Chatbots, although more accurate results may necessitate a subscription to premium versions, such as ChatGPT Pro (Ortiz, 2023). The interplay of PE and EE contributes to SI, as the advantages of AI Chatbots, when widely disseminated in society, shape students' BI in adopting these tools (Melián-González et al., 2019).

Due to PE and EE, both factors collectively influence SI, affecting the adoption of AI Chatbots. As society disseminates the advantages of AI Chatbots, it impacts students' BI toward using them (Melián-González et al., 2019). However, a notable concern arises regarding privacy issues. When users pose questions to AI Chatbots, there is a potential problem related to plagiarism, primarily when students use them for assignments or other tasks. Therefore, the widespread use of AI Chatbots may shape users' behaviour, particularly since many universities permit students to utilize AI Chatbots. To address the plagiarism issue and prevent non-original work, universities are advised to invest in a Turnitin account (Hern, 2022).

In short, it is crucial for researchers to study the factors affecting students' BI to use AI Chatbots. In the Malaysian education context, many researchers have applied the Technology Acceptance Model (TAM) to explore students' intention to adopt AI Chatbots, as seen in studies such as Keong (2022) and Algerafi et al. (2023), which predominantly focused on postgraduate students, such as Rahim et al. (2022). Additionally, previous Malaysian research study, such as that conducted by Al-Emran et al. (2024), has focused on students' adoption of AI Chatbots in knowledge-sharing, rather than specifically focusing on BI. This study aims to fill a gap in the context of Malaysian university environments by utilising the latest technology acceptance and use model, namely the UTAUT2 Model, and by focusing on undergraduate students, who exhibit significant differences from postgraduate students in terms of the learning process, course requirements, academic workload, and complexity, among other factors. Additionally, this study introduces a new IV, INFO. INFO is deemed crucial in affecting students' BI when using AI Chatbots. This is because INFO will directly impact students' perceptions regarding the trustworthiness and reliability of AI Chatbots. Students tend to trust and depend on AI Chatbots that consistently deliver accurate and relevant information. The inclusion of INFO enhances the meaningfulness of this research study by enabling a more comprehensive examination of whether the informational content of AI Chatbots directly affects students' BI to use them. By considering INFO alongside the UTAUT2 model, researchers can better elucidate the factors affecting students' BI towards using AI Chatbots. This enhancement in methodology allows for a more nuanced understanding of the relationship between the INFO of AI Chatbots and students' BI to use AI Chatbots, thereby enriching the insights gained from this research.

Furthermore, university management can leverage insights gained from this research to better understand students and tailor study plans to meet current trends and incorporate new learning methods. In short, this research study will further enhance understanding and knowledge regarding the factors affecting students' BI in using AI Chatbots.

1.3 Research Objectives

1.3.1 General Objective

This research aims to explore and investigate the factors affecting the BI towards using AI Chatbots among students' perspectives in a private university. The relationship between five independent variables which include PE, EE, SI, HT, and INFO will be examined with the dependent variable, the BI towards using AI Chatbots.

1.3.2 Specific Objectives

1. To investigate whether there is a significant relationship between performance expectancy and the behavioural intention of students towards using AI Chatbots.
2. To investigate whether there is a significant relationship between effort expectancy and the behavioural intention of students towards using AI Chatbots.
3. To investigate whether there is a significant relationship between social influence and the behavioural intention of students towards using AI Chatbots.
4. To investigate whether there is a significant relationship between habit and the behavioural intention of students towards using AI Chatbots.

5. To investigate whether there is a significant relationship between informativeness and the behavioural intention of students towards using AI Chatbots.

1.4 Research Questions

1. How does performance expectancy affect the behavioural intention of students towards using AI Chatbots?
2. How does effort expectancy affect the behavioural intention of students towards using AI Chatbots?
3. How does social influence affect the behavioural intention of students towards using AI Chatbots?
4. How does habit affect the behavioural intention of students towards using AI Chatbots?
5. How does informativeness affect the behavioural intention of students towards using AI Chatbots?

1.5 Hypotheses of the Study

H1: There is a significant relationship between performance expectancy and the behavioural intention of students towards using AI Chatbots.
H2: There is a significant relationship between effort expectancy and the behavioural intention of students towards using AI Chatbots.
H3: There is a significant relationship between social influence and the behavioural intention of students towards using AI Chatbots.
H4: There is a significant relationship between habit and the behavioural intention of students towards using AI Chatbots.
H5: There is a significant relationship between informativeness and the behavioural intention of students towards using AI Chatbots.

1.6 Significance of the Study

1.6.1 Theoretical Contribution

AI communication has gained rapid prominence and popularity over time. In the Fourth Industrial Revolution era, educators have the flexibility to employ traditional classrooms or online platforms, using technological tools like AI Chatbots (Mendoza et al., 2020). However, global acceptance of AI Chatbots adoption in education varies; while some institutions like the London School of Economics have embraced it, others such as Imperial College, Queen Mary University of London, and King's College London remain hesitant (Williams, 2023). Despite a growing interest in AI Chatbots adoption in non-HEI contexts, the readiness of most HEIs to adopt AI Chatbots remains limited (Rahim et al., 2022). This research area, exploring AI Chatbots adoption within the HEIs context, is relatively novel and less explored in the realm of information systems, and notably, this topic remains unexplored within Malaysian universities (Williams, 2023).

The validity and reliability of the information provided by AI Chatbots, as well as the practicality and alignment with customers' expectations, have emerged as crucial considerations. This is particularly relevant in the context of providing accurate answers to students. While existing research has extensively explored AI Chatbots and individual intentions across various industries such as medicine, product and service industries, banking, and e-commerce, there is a gap in research focused on Higher Education Institutions (HEIs) in Malaysia. Therefore, this research aims to identify and evaluate how the independent variables, PE, EE, SI, HT, and INFO will affect the DV, the BI of students towards using AI Chatbots.

This study makes a unique contribution to the theoretical landscape by examining AI Chatbots adoption among students in Malaysian universities, extending beyond the UTAUT2 model. While some researchers have investigated variables such as PE, EE, SI, and HT collectively in one study, this research further incorporates INFO. This addition allows for a deeper understanding of the topic, providing a more comprehensive framework for future research purposes. By integrating INFO, this study presents a richer framework that captures the factors influencing students' perspectives on AI Chatbots adoption. This integration reveals intricate relationships between traditional adoption aspects and these novel dimensions, thereby broadening the discourse on AI Chatbots in education and informing technology integration strategies.

1.6.2 Practical Contribution

This research is also useful for HEIs in identifying the factors that affect the adoption of AI Chatbots among students. It is helpful for educators to consider whether AI Chatbots should be banned or allowed to be used by students in completing their tasks, assignments, or even tests. Moreover, researchers or students who conduct research related to the area of the BI of students towards using AI Chatbots may benefit from this study as well. They will have a general knowledge of the relevant research area and may use these findings as a reference, providing them with effective and reliable information.

This is significant for researchers to study factors affecting BI towards using AI Chatbots among students' perspectives in a private university. Therefore, by observing this research data, universities' management can learn more about the younger generation's mindset regarding their BI towards using AI Chatbots in the university context.

1.7 Chapter Layout

Chapter 1: Introduction

Highlights the research background, research objectives and questions, hypotheses, problem statement, significance of the study, chapter layout, and conclusion.

Chapter 2: Literature Review

Discussion of the underlying theory, relevant theoretical framework and model, proposed research conceptual framework, review of literature, and hypotheses development.

Chapter 3: Research Methodology

Discussion of research design, sampling design, research instrument, data collection methods, data processing, measurement scales, and data analysis.

Chapter 4: Research Results

The survey was conducted using Google Forms, and the data collected will be interpreted through SPSS software.

Chapter 5: Conclusion and Discussion

Summarise the results and findings, discussion of theoretical and managerial implications, limitations of research study, and recommendations for future study.

1.8 Conclusion

This chapter has highlighted the problem statement, and research background including the significance of the BI of students towards using AI Chatbots. The independent and dependent variables have been structured and research questions as well as hypotheses have been mentioned in this chapter.

CHAPTER 2: LITERATURE REVIEW

2.0 Introduction

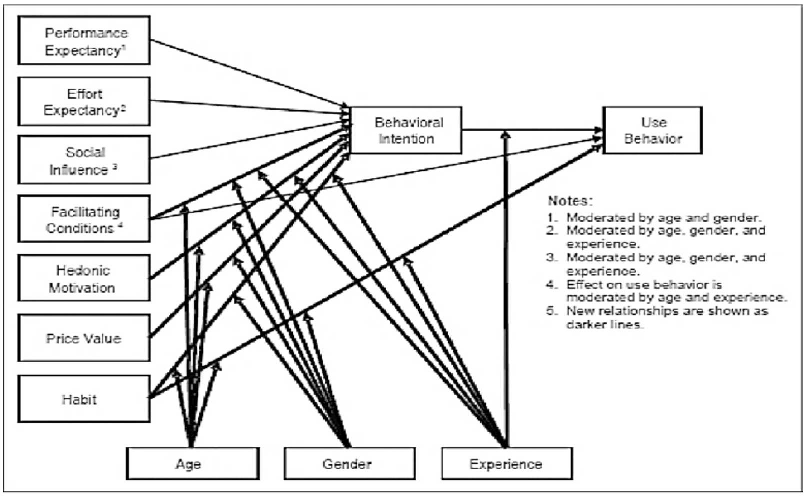
Chapter 2 objective is to relate the theories and review the literature. Two variables which are dependent (BI) and independent (PE, EE, SI, HT, and INFO) have been studied by researchers. Based on findings from the literature or journal articles, the relationship between IV and DV will be explained. Furthermore, the theoretical model and hypothesis design will be carried on in this chapter as well.

2.1 Underlying Theory

2.1.1 Unified Theory of Acceptance and Use of Technology 2 (UTAUT2)

Figure 1

Theoretical Model of UTAUT2



Source: Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, *36*(1), 157-178.

The unified theory of acceptance and use of technology 2 (UTAUT2), shown in Figure 1, stands out as a contemporary and highly effective theory concerning technology acceptance. This theory builds upon its predecessor, the unified theory of acceptance and use of technology (UTAUT), introduced by Venkatesh et al. in 2003. UTAUT was a culmination of eight prominent theories related to technology acceptance, namely the Theory of Reasoned Action (TRA); the Technology Acceptance Model (TAM); the Innovation Diffusion Theory (IDT); the Theory of Planned Behaviour (TPB); the Model of Perceived Credibility (PC); the Social Cognitive Theory (SCT); the Motivational Model (MM) and a hybrid model combining constructs from TPB and TAM (Almahri et al., 2020; Kulak et al., 2019). UTAUT2 has been refined to be applicable in both professional and consumer settings.

Put differently, UTAUT2 is constructed by building upon the foundational theory of the Technology Acceptance Model (TAM) and integrating additional factors. TAM, devised by Fred D. Davis in 1985, incorporates the Theory of Reasoned Action (TRA) within its framework. TRA asserts that the adoption of technology is guided by cognitive processes with the objective of maximizing technological utility. Within TAM, the spotlight is on two key domains, namely the perceived ease of use and the perceived usefulness of the technology, both of which impact the intention to utilize the system (Muchran & Ahmar, 2018).

Venkatesh et al. (2003) outlined that UTAUT presented four primary elements that impact the intention and usage of information technology (IT), namely PE, EE, FC, and SI. Despite UTAUT's broad recognition, Venkatesh et al. integrated three additional components, namely hedonic motivation (HM), price value (PV), and HT, thereby expanding UTAUT into its evolved form, UTAUT2. To differentiate these two models, UTAUT is an employee forced or moderated to accept the changes using the technology, while UTAUT2 is an employee forced to accept the change and behave towards the technology (Almahri et al., 2020; Tamilmani et al., 2021).

PE refers to the extent to which individuals rely on a system such as AI Chatbots, enabling them to enhance their performance in the task. EE can be defined as the level of simplicity in utilising the system. SI means the degree to which an individual influences others to use the new system. FC refers to the extent to which individuals are persuaded to use the new system by organisational and technical infrastructure. HM is the enjoyment of fun while using technology. PV refers to the cost and pricing structure that may influence consumers' technology use. HT is the degree an individual is motivated by learning to automatically perform a behaviour to use the information system (Almahri et al., 2020).

In brief, researchers employ the UTAUT2 framework due to its capacity to offer a more thorough comprehension of the elements impacting the perspective of Malaysian university students towards AI Chatbots usage. Besides, these enhancements render UTAUT2 more flexible and attuned to the intricate technological environment of the present day, resulting in a more intricate grasp of user actions and viewpoints. Consequently, UTAUT2 is favoured due to its more inclusive structure, which effectively tackles the intricate aspects of technology acceptance. This renders it particularly appropriate for studying the BI of Malaysian university students regarding the adoption of AI Chatbots.

2.2 Review of the Literature

2.2.1 Dependent Variable – Behavioural Intention Towards Using AI Chatbots

BI, signifying the likelihood of users utilising AI Chatbots, is closely tied to attitudes towards these AI Chatbots. Predicting a customer's stance toward AI Chatbots allows researchers to anticipate their intention to use them (Gümüş

& Çark, 2021). Users who perceive sufficient resources and capabilities tend to show a more positive inclination towards embracing AI Chatbots. In other words, individuals who trust in the effectiveness of AI Chatbots, such as their performance, INFO, and usefulness, are more likely to adopt and utilize them (Wong et al., 2015).

Understanding the factors influencing the acceptance and adoption of AI Chatbots is crucial, given their potential benefits across diverse sectors such as education, transportation, and mental health care (Ramu et al., 2022; Xia et al., 2020; Doraiswamy et al., 2019). Therefore, comprehending what encourages users to accept, use, purchase, or try these AI Chatbots becomes essential (Turner et al., 2010; Sohn and Kwon, 2020; Schmidt et al., 2021; Taddeo and Floridi, 2018).

The BI in adopting AI Chatbots signifies the willingness of users to engage with these technological solutions. The correlation between attitudes towards AI Chatbots and users' BI is evident. By gauging a customer's BI, one can predict their attitude toward utilising AI Chatbots (Eeuwen, 2021). Users who have confidence in the availability of ample resources and efficient infrastructure demonstrate a more positive inclination toward embracing AI Chatbots.

2.2.2 Independent Variables 1 - Performance Expectancy

PE indicates the level at which users believe that utilising technology will bring them advantages when engaging in specific activities (Melián-González et al., 2019). Advanced technologies allow users to simplify their tasks, enhance efficiency, or even create new job opportunities, providing numerous advantages and profoundly impacting various aspects. The rapid development of advanced technology may raise concerns about its proper usage; users should correctly utilize technology and adhere to ethical guidelines to gain maximum benefits from the technology itself. Ultimately, it may lead to job satisfaction or high-quality job performance. Venkatesh et al. (2003) interpreted PE as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance". It also can be defined as the ability of students to get the exact answers or adequate information generated by AI Chatbots, thus enhancing their academic performance.

Different researchers have seen the dimensions used to measure PE varied. Huang and Kao (2015) highlighted that PE is constructed by perceived usefulness, relative advantage, extrinsic motivation, and job fit. Other researchers proposed that the indicators for PE are primarily determined by perceived usefulness, job fit, relative advantage, intrinsic and extrinsic motivation, and outcome expectations (Onaolapo & Oyewole, 2018; Martins et al., 2021). Many researchers have emphasized that PE is critical in determining the adoption and usage of Information Technology (Huang & Kao, 2015; Onaolapo & Oyewole, 2018; Almaiah et al., 2019). According to the research by Almahri et al. (2020), there is a significant between PE and BI in using AI Chatbots among students in United Kingdom (UK) universities. The research shows that PE will significantly influence the BI for the adoption of technology (Dakduk et al., 2018). Morosan and DeFranco (2016) suggest that PE is the highest determiner of intentions. Based on Lian (2015); Baptista and Oliveira (2015) studies, PE has non-significant relationships with intentions. Therefore, PE has been one of the IVs used to examine how it influences students' BI towards using AI Chatbots.

2.2.3 Independent Variables 2 - Effort Expectancy

EE refers to how effortlessly users can utilize technology (Melián-González et al., 2019). Within the framework of adopting technology, EE is also one of the critical factors for examining technology usage behaviour and BI (Huang & Kao, 2015; Almaiah et al., 2019). Venkatesh et al. (2003) define EE as "the degree of ease associated with the use of the system". Ghalandari (2012) highlighted that EE stems from the concept that connections exist between the exertion invested in tasks, the outcomes attained through that exertion, and the rewards gained due to the exertion. In this study, EE refers to the perceived ease with which university students believe they can interact with AI Chatbots and obtain assistance without significant mental or physical effort. The use of AI Chatbots among university students is directly associated with EE. This is because the use of AI Chatbots among university students is likely to be affected by the complexity of collecting relevant information quickly. Consequently, should university students recognize the high level of simplicity in utilising the AI Chatbots for academic purposes, they may not abstain from employing them.

EE consists of some criteria, such as complexity, perceived ease of use, and ease of use, and these criteria seem to be connected with the use of information technology (Huang & Kao, 2015; Martins et al., 2021). The concept of EE and its underlying variable have demonstrated significance in multiple research studies, establishing their role as a predictor of user intention to embrace novel technology (Almahri et al., 2020). Many researchers have widely used EE to examine whether it has a significant relationship with BI towards using AI Chatbots in the area of Internet banking (Arenas Gaitán et al., 2015), public transport (Kuberkar & Singhai, 2020), insurance industry (de Andrés-Sánchez & Gené-Albesa, 2023), and tourism industry (Melián-González et al., 2019). However, some previous studies such as Melián-González et al. (2019); Morosan and Defranco (2016); Oliveira et al. (2016); Fadzil (2018); Tano & Gidumal (2019) indicate that there is a negative correlation between the EE and the BI to use AI Chatbots. The results obtained by other researchers, such as Venkatesh et al., 2003; Costello & Osbome, 2005; and Zhou et al., 2010 indicate that the impact of EE on BI is significant and positive. Therefore, EE has been one of the IVs used to examine how it influences the BI of students towards using AI Chatbots.

2.2.4 Independent Variables 3 - Social Influence

SI pertains to the extent to which consumers believe that influential individuals support the use of a specific technology (Melián-González et al., 2019). Venkatesh et al. (2003) define SI as "the degree to which an individual perceives that important others believe he or she should use the new system". In this study, SI refers to the impact of peers, instructors, and friends on students' decisions to adopt AI Chatbots, reflecting the sway of others' opinions. In other words, colleagues' opinions and behaviors are likely to influence the student's decision on whether or not to use AI Chatbots. University students often look for direction from their fellow students and social groups. When these peers express favourable support for or start using AI Chatbots, it establishes a perception of what's socially accepted and trustworthy. According to Davis (1985), individuals might choose to engage in actions aligned with a referent's perspective, not due to the referent's direct influence but rather because the actions resonate with the individual's own beliefs.

There are a total of three constructs in SI, including subjective norms, social factors, and image (Huang & Kao, 2015; Martins et al., 2021). Numerous studies have extensively investigated the notions of SI and substantiated its impact on moulding users' behaviours. In fact, this construct has been examined in the usage of personal computing (Thompson et al., 1991), web-based learning (Raman & Don, 2013), mobile payment (Morosan & DeFranco, 2016), mobile applications (Tak & Panway, 2017), and online games (Xu, 2014). Similarly, this factor can also shape the inclination to utilize AI Chatbots. Previous researchers have found that the BI in adopting AI Chatbots was significantly influenced and positively affected by SI (Zhou et al., 2010; Raman & Don, 2013; Almahri et al., 2020). In this regard, university students tend to commit to using AI Chatbots for academic purposes frequently if they experience positive reinforcement when engaging with AI Chatbots. To align with the previous research, SI has been one of the IVs to examine how it influences the BI of students towards using AI Chatbots, and it was expected to have a positive impact on university students' using AI Chatbots.

2.2.5 Independent Variables 4 – Habit

HT can be explained as the extent to which a person carries out a behaviour automatically due to past learning (Limayem et al., 2007). Similarly, Kim and Malhotra (2005) equate with automatic behaviour. There are two distinct approaches to operationalizing HT. Firstly, HT is treated as behaviours that have been performed previously (Kim & Malhotra, 2005). Secondly, HT is assessed by the extent to which individuals view a behaviour as occurring automatically (Limayem et al., 2007). Limayem et al. (2007) employed prior usage as a predictor of HT. Similarly, Kim and Malhotra (2005) considered individuals' experience with target technologies when investigating the impact of HT on technology use. Fishbein and Ajzen (2005) also highlight that feedback from past experiences influences beliefs and subsequently future behaviour. In this context, HT is a perceived concept reflecting past experiences' outcomes. Regarding the translation of habitual actions into prior usage, Kim and Malhotra (2005) discovered that past usage strongly predicts future technology use. Despite objections to solely reducing HT manipulation to past use (Ajzen, 2002), some studies, like the work of Limayem et al. (2007), have taken a survey-based and perception-oriented approach to measuring HT. This method of measuring HT has demonstrated a direct impact on technology use, surpassing the influence of intention, and can mediate the connection between intention and technology use meaning that intention becomes less crucial as HT strengthens (Limayem et al., 2007). The construction of HT can be examined from three perspectives, namely past behaviour, reflexive behaviour, and personal experience (Limayem et al., 2007). In this study, HB refers to the automatic integration of AI Chatbots into students' academic routines due to consistent and repetitive use.

Research on HT intentions and habitual usage behaviour indicates that HT is a significant predictive factor in driving behavioural changes in technology usage (Venkatesh et al., 2012; Webb et al., 2008; Kim et al., 2007). Almahri et al. (2020) have found that the BI in adopting AI Chatbots was significantly influenced by HT, which is similar to the research done by Merhi et al. (2019). However, according to Dakduk et al. (2018), the factor of HT is only considered a relevant determinant of BI when it is moderated by experience, age, and gender. Similar to the research conducted by Raman and Don (2013), Fadzil, (2018) shows that HT and BI towards using technology have a negative relationship.

2.2.6 Independent Variables 5 – Informativeness

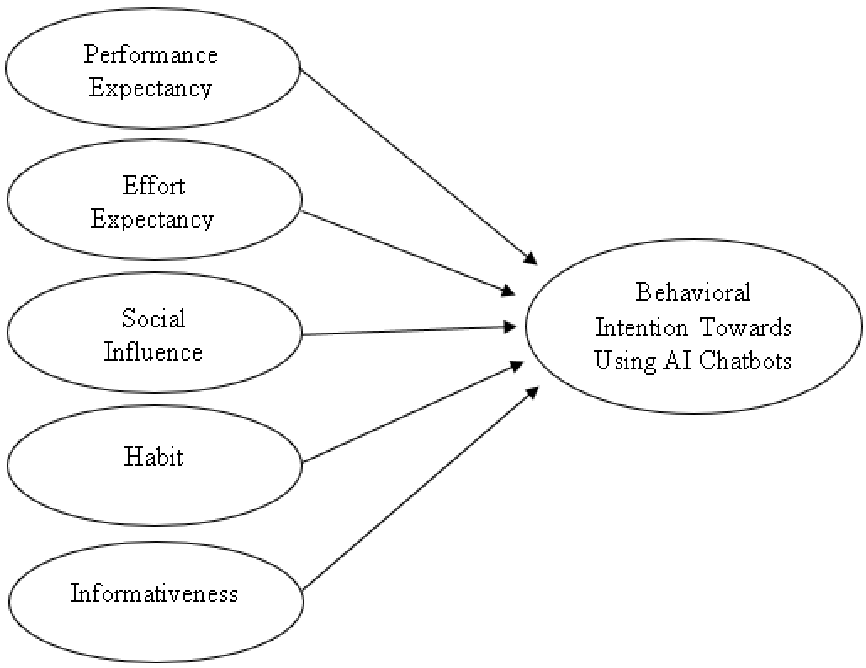
INFO pertains to how valuable the information provided on a website is perceived to be (Hsieh et al., 2021). This information should be relevant to helping users accomplish their tasks. As defined by Rotzoll and Haefner (1990), INFO pertains to a company's ability to furnish sufficient information enabling people to make well-informed decisions. Pavlou et al. (2007) approached INFO as a perceptual concept gauged through self-reported measures. Essentially, this notion is more associated with a sender's capacity to effectively capture the customer's attention, empowering them to thoughtfully evaluate the adoption of conveyed information and messages (Lee & Hong, 2016). In this study, INFO refers to the perception that AI Chatbots provide accurate, relevant, and valuable information to students, enhancing their understanding and aiding in their academic pursuits. The dimensions of INFO include believability, completeness, appropriate amount, accessibility, and timeliness (Kahn et al., as cited in Hsieh et al., 2021).

Numerous scholars have emphasized that INFO plays a pivotal role in determining the acceptance and utilization of IT, spanning across various domains. According to findings by Dinh and Park (2023), utilitarian motivation (INFO) significantly influences individuals' intention to use the mentioned Chatbot service. As Jan et al. (2023) indicated, INFO plays a positive role in shaping BI towards using text-based Chatbots. In line with DeLone and McLean's work (1992), INFO is identified as a critical aspect of AI Chatbots in creating a favourable experience that contributes to user satisfaction. The INFO provided by the AI Chatbots holds excellent importance, necessitating accuracy, relevance, and value. When AI Chatbots fail to understand the user and provide inaccurate information, accuracy and reliability are compromised, resulting in a negative user experience (Trivedi, 2019; Xu et al., 2017). Thus, INFO emerges as a pivotal factor in determining the adoption of AI Chatbots.

2.3 Proposed Conceptual Framework

Figure 2

Conceptual Framework Model



Source: Developed for the research

In this research, researchers focus on five key independent variables, namely PE, EE, SI, HT, and INFO. The first four variables are adapted from the UTAUT2 model, while INFO is introduced to enhance the understanding of students' BI toward adopting AI Chatbots. The conceptual framework, outlined in Figure 2, intricately incorporates these five independent variables. This framework, a synthesis of UTAUT2 elements, aims to illuminate the complex interplay of factors influencing students' BI toward AI Chatbots. The relationships between these five IVs and the DV are considered significant. It is hypothesized that these variables collectively exert a positive influence on students' BI toward using AI Chatbots. As these variables increase, the corresponding increase in the DV signifies the growing BI of students to adopt AI Chatbots. For instance, if students perceive AI Chatbots as informative tools enhancing their academic experience, their likelihood of integrating these technologies into their academic pursuits is expected to rise.

2.4 Hypothesis Development

2.4.1 The relationship between performance expectancy and the behavioural intention of students towards using AI Chatbots.

PE refers to the degree of reliance individuals place on a system to improve their performance in a given task (Terblanche & Kidd, 2022).

In the context of higher education, Rahim et al. (2022) found a significant link between PE and students' BI to use AI Chatbots. This underscores how perceptions of technology performance directly impact students' willingness to engage with it. Utilising the UTAUT2 Model, researchers examined this relationship concerning customer relationship management (CRM) adoption in higher education settings. Emphasizing the importance of users' perceptions regarding technology adoption within the community, they establish a connection between PE and users' emotions when employing AI Chatbots (Yablonsky & Petersburg, 2017; Almahri et al., 2020). This notion is reinforced by Almaiah et al. (2019), who expect prompt and accurate responses when interacting with AI Chatbots.

Furthermore, PE has exhibited a positive influence on the adoption of diverse technologies, such as social media, digital voice assistants, mobile services, mobile banking, and service-oriented Chatbots (Borrero et al., 2014; Kasilingam, 2020; Kim et al., 2019; Kuberkar & Singhal, 2020; Melián-González et al., 2019; Shan & Lu, 2009; Wagner et al., 2019; Yu, 2012; Emon et al., 2023). Notably, PE serves as a predictor of the intention to use technology in Qatar and the USA, as supported by Almahri et al. (2020) and El-Masri & Tarhini (2017). On the other hand, AI Chatbots have a few drawbacks that may diminish their usefulness. Generally, Chatbots are unable to address complex situations or problems (Vassilakopoulou et al., 2023). In these cases, the initial interaction with the AI Chatbots is deemed a waste of time and diminishes its usability (de Sá Siqueira et al., 2023). In specific conditions, the use of AI Chatbots may adversely affect the perception of service, highlighting an obvious disadvantage, namely their inherent lack of empathy (Vassilakopoulou et al., 2023). Therefore, the hypothesis is proposed.

H1: There is a significant relationship between performance expectancy and the behavioural intention of students towards using AI Chatbots.

2.4.2 The relationship between effort expectancy and the behavioural intention of students towards using AI Chatbots.

According to Almahri et al. (2020), EE can be explained as the level of simplicity in utilising the system. BI to use AI Chatbots is significantly influenced by EE, which is also compatible with the findings of other studies (Raman & Don, 2013; Venkatesh et al., 2003; Venkatesh et al., 2012; Zhou et al., 2010). Previous study results (Rahim et al., 2022) indicate that the tendency of users to adopt new technologies is substantially predicted by EE and associated implicit variables. As expected, PE and EE are significant elements in adopting AI Chatbots, and this has a favourable impact on the adoption of AI Chatbots by university students. However, outcomes that require further research and don't provide immediate pleasure may considerably impact user intention in terms of technology easiness (Terblanche & Kidd, 2022).

For instance, a study by El-Masri and Tarhini (2017) showed that whereas EE is insignificant in the USA research, it is significant in Qatar research. Moreover, authors in other research have also identified that individuals are inclined to use an application when they perceive it as user-friendly (Davis et al., 1989). Past research has consistently shown a positive correlation between EE and BI in various domains, including web-based learning, mobile banking, health information technology, and even in the context of service-oriented Chatbots (Chiu & Wang, 2008; Shan & Lu, 2009; Kijsanayotin et al., 2009; Kuberkar & Singhal, 2020). Since the higher education field and other fields show the relationship and support.

Nevertheless, there is a broad consensus that AI Chatbots technology has not yet advanced enough to enable seamless interaction in many contexts. AI Chatbots often provide users with confusing responses, affecting their perception of the system's usability and usefulness and negatively impacting their acceptance (Andrade & Tumelero, 2022). Some prominent issues in this context include a phobia of technological robots, which has significantly impacted users' BI and availability towards robots (Rajaobelina et al., 2021). Furthermore, the fact that AI Chatbots cannot capture voice tones or specific conversation directions further limits their performance in actual interactions (Tep et al., 2021). In general, the above shortcomings lead to frequent errors in actual interaction with robots (Xing et al., 2022). This problem hinders their ease of use (de Sá Siqueira et al., 2023) and explains why more than half of all interactions with robots fail to complete (Tep et al., 2021). Therefore, the hypothesis is proposed.

H2: There is a significant relationship between effort expectancy and the behavioural intention of students towards using AI Chatbots.

2.4.3 The relationship between social influence and the behavioural intention of students towards using AI Chatbots.

SI refers to whether an individual is influenced by others to use the new system. According to Rahim et al. (2022), SI is one of the critical factors determining students' BI in adopting AI Chatbots. Studies have shown that SI has a favourable effect on students' desire (BI) to implement AI Chatbots in universities for engagement. It appears that social impact positively influences students' BI to utilize AI Chatbots by increasing daily commitment to AI Chatbots use.

Moreover, studies in other fields have also found that SI significantly impacts users' BI toward using AI Chatbots in mobile banking, smartphones, and service AI Chatbots (Terblanche & Kidd, 2022). This phenomenon is closely tied to an individual's perception of their image or standing within an organization (Moore & Benbasat, 2001). Various research endeavours have established the importance of SI as a substantial predictor of the intention to adopt the technology. This holds true for domains such as mobile banking, smartphone applications, and AI service Chatbots (Yu, 2012; Tak & Panwar, 2017; Kim et al., 2019; Kuberkar & Singhal, 2020; Melián-González et al., 2019). Since more studies in other fields have been applied, further research is needed to explore the relationship between SI and the BI of university students in the education field.

Despite AI Chatbots becoming a common feature in assisting users, a considerable number of individuals still harbour reservations about engaging with them (Van Pinxteren et al., 2020). Notwithstanding this scepticism, robust commercial interest remains in AI Chatbots technology, primarily due to its acknowledged advantages. It is widely recognized that peers' viewpoints, such as friends or family, can shape people's perceptions and BI toward emerging technology, given the inherent human tendency to seek validation from valued individuals (Venkatesh et al., 2003). Similarly, while AI-powered technologies present numerous favorable outcomes, a widespread societal perception exists that AI entails various risks. Instances of concern involve fears that multinational corporations could exploit AI to accumulate unchecked influence and power, apprehensions about artificial intelligence surpassing human intelligence and posing a threat to humanity, and privacy-related issues (Stahl, 2021). Therefore, the hypothesis is proposed.

H3: There is a significant relationship between social influence and the behavioural intention of students towards using AI Chatbots.

2.4.4 The relationship between habit and the behavioural intention of students towards using AI Chatbots.

HT refers to the extent to which an individual is motivated by learning to automatically perform behaviour to use the information system. Rahim et al. (2022) stated that their study proved that HT greatly impacted university students' BI toward using AI Chatbots. The BI to utilize AI Chatbots technology is significantly influenced by HT, which is consistent with findings from other studies such as Venkatesh et al. (2012), Raman & Don (2013), and Merhi et al. (2019). El-Masri and Tarhini (2017) discovered that HT in Qatar and the USA's research is a predictor of BI toward using technology (Rahim et al., 2022). Authors like Venkatesh et al. (2012) and Laumer et al. (2019) have discussed the dual perspectives of HT, either as an illustration of a past action or as a recurring pattern. The UTAUT2 model asserts that HT yields both a direct and an indirect influence on technology usage. Following a preceding study conducted by Almahri et al. (2020), evidence was presented that the BI of university students engaging with AI Chatbots is favorably impacted by HT. Consequently, the current study endeavours to assess the relevance of the HT construct in empirical inquiries concerning students' adoption of AI Chatbots within the context of higher education institutions (Almahri et al., 2020). Therefore, the hypothesis is developed.

H4: There is a significant relationship between habit and the behavioural intention of students towards using AI Chatbots.

2.4.5 The relationship between informativeness and the behavioural intention of students towards using AI Chatbots.

INFO refers to how well users believe virtual agents can provide accurate data. By applying AI Chatbots, users trust the information provided in AI Chatbots in terms of accuracy, which affects students' BI towards using the system (Li & Mao, 2015). It portrays the sensation of users being knowledgeable about a specific service, encompassing its technical functionalities and the probable encounter linked with its utilization. Researchers also found that INFO, in terms of the richness of information provided by virtual agents, will also affect students' BI towards the adoption system (Yen & Chiang, 2020).

Apart from that, researchers approach INFO from different perspectives. Pasadeos (1990) discovered that newspaper advertisements tend to be more informative compared to radio and television advertisements. This is attributed to radio primarily focusing on relaxation, while television tends to emphasize entertainment and advertising. However, newspapers offer a wide range of useful and accurate information. Therefore, by applying this research, students can obtain information from AI Chatbots similar to how they acquire it from friends or family. Implementing this concept and adopting AI Chatbots can help overcome informational challenges. When AI Chatbots are capable of providing quality information, it will positively influence students' BI towards using AI Chatbots.

Researchers have also found that in previous research studies about utilitarian gratification, it is most similar to INFO, which satisfies individual utility needs and also includes information seeking (Papacharissi & Mendelson, 2010). Historically, delivering details about products, services, or brands has been acknowledged as a fundamental role that AI Chatbots fulfill in the realm of marketing communication. An illustrative example can be seen in the domain of luxury branding, where customers expressed satisfaction with Gucci's AI Chatbots. These AI Chatbots were valued for their capability to offer beneficial personalized information and foster valuable interactions with individual customers (Dinh & Park, 2023). The hypothesis below is developed because this IV has been studied less in the research field. Therefore, in this research, researchers apply the same concept as previous studies and apply it to higher education.

H5: There is a significant relationship between informativeness and the behavioural intention of students towards using AI Chatbots.

2.5 Conclusion

This chapter discussed the literature review and journal articles regarding the factors affecting the BI of students toward using AI Chatbots. The conceptual framework has been constructed and the hypotheses as well as the relationship between the variables are supported by the previous research.

CHAPTER 3: METHODOLOGY

3.0 Introduction

Chapter 3 gives a general idea regarding data processing, construct measurement, research design and instruments, data collection methods, sampling design, and data analysis in evaluating variables, which include PE, EE, SI, HT, and INFO towards the BI of students to adopt AI Chatbots.

3.1 Research Design

For this research, researchers opted for a quantitative research method over a qualitative approach. This decision was driven by the subjective nature of qualitative research, which typically involves physical interviews and observations, making it time-consuming and costly. Qualitative methods often observe specific groups of individuals in specific situations, limiting their generalizability. In contrast, quantitative research involves distributing surveys to the target population, providing accurate measurements in controlled environments. Additionally, quantitative research methods offer higher external validity compared to qualitative methods. Moreover, quantitative research is necessary to produce results that can be reproduced and validated (Lowhorn, 2007). Therefore, researchers directly adopted quantitative research methods for this study (George, 2023).

Furthermore, researchers chose a causal research design for this study. The objective of causal research is to examine cause-and-effect relationships between the DV (students' BI towards using AI Chatbots) and IVs (PE, EE, SI, HT, and INFO). Additionally, this research employed a cross-sectional approach, wherein researchers distributed questionnaires and collected data from targeted respondents.

3.2 Data Collection Methods

Data collection is the process of analysing data with the goal of study aligned with validation. This data collection can help researchers identify future trends and targeted population preferences for the study. Therefore, it is essential that researchers get reliable data from multiple relevant sources to strengthen the study. Data collection methods can be distributed into two main groups, namely primary and secondary data collection techniques (Sekaran & Bougie, 2016). Ajayi (2017) has highlighted that primary data are those that the researcher collects first-hand data, such as surveys and opinion polls from individuals and conducting experiments. In contrast, secondary data are those that have already been gathered or created by other researchers, such as government information available on the website.

In this research, researchers obtained both primary and secondary data using a combination of methods. This approach was adopted because secondary data alone might contain inaccurate or incomplete information gathered by previous researchers. By combining both primary and secondary data, researchers aimed to ensure a more comprehensive and accurate dataset for the study.

3.2.1 Primary Data

The questionnaire has been selected as this research's primary data collection method. Researchers utilized a hybrid approach, distributing questionnaires online through social media via Google Forms and physically distributing questionnaires to UTAR students from both Sungai Long and Kampar campuses.

Researchers opted for questionnaire distribution because it enables the direct collection of data and information from individuals, resulting in more accurate and reliable data. By gathering responses, researchers gain insights into participants' feelings and needs regarding the issue at hand. Additionally, primary data methods allow researchers to collect information from a wide range of populations with diverse experiences and backgrounds related to AI Chatbots adoption.

This method facilitated a deeper understanding of students' BI toward using AI Chatbots, enabled data collection within a short period, and proved to be less costly. Moreover, it allowed researchers to target a wider audience, as highlighted by Reja et al. (2003).

3.2.2 Secondary Data

Secondary data that researchers obtain is from online material such as Google Scholar and journal articles to support research with a more accurate and wide view of doing research towards this research.

Secondary data enables researchers to access databases, facilitating comparisons with information from previous studies. This can be particularly beneficial for obtaining reliable information, especially from credible sources such as government websites and large-scale research publications. Additionally, secondary data can complement primary data collection methods, enhancing the overall reliability and accuracy of the study's results.

3.3 Sampling Design

3.3.1 Target Population

The target population of this research will be degree students from UTAR Kampar and Sungai Long campuses. UTAR is well-established and holds self-accreditation status from MCQ Malaysia (Self-Accreditation Malaysia Qualifications Agency, n.d.). Following the completion of this research, management can consider adopting AI Chatbots in education strategies. Researchers can assist management in gaining a better understanding of Malaysian private universities' students' BI and attitudes toward using AI Chatbots. Additionally, this study's data can support and strengthen decision-making processes.

UTAR offers more than 100 programmes, making it impractical for researchers to target all UTAR students in each programme. Business and IT are recognized as the two largest programme clusters at UTAR, comprising 10 Business courses and 8 Information Technology courses approved by MCQ Malaysia, respectively. Therefore, Business and IT students will serve as representatives for all UTAR students across both campuses."

3.3.2 Sampling Frame and Sampling Location

This study covers a private university, UTAR, encompassing both the Kampar and Sungai Long campuses. Table 2 shows the locations and targeted populations for each Business and Information Technology course, the two largest programme clusters at UTAR. These two groups of students will represent all UTAR students.

Table 2

Targeted population and sampling location

Business Courses			
No.	**Programmes**	**Number of Students**	**Campus Location**
1.	Bachelor of Business Administration (Honours)	376	Kampar
2.	Bachelor of Business Administration (Honours) Banking and Finance	371	
3.	Bachelor of Business Administration (Honours) Entrepreneurship	143	
4.	Bachelor of Business Administration (Honours) Healthcare Management	44	
5.	Bachelor of Business Administration (Honours) in Logistics and Supply Chain Management	270	
6.	Bachelor of Business Administration (Honours) Retail Management	31	
7.	Bachelor of Business Administration (Honours) Risk Management	31	
8.	Bachelor of Business Administration (Honours) Tourism Destination Marketing	9	
9.	Bachelor of Marketing (Honours)	381	
10.	Bachelor of International Business (Honours)	400	Sungai Long
Total		2,056	

Information Technology Courses			
1.	Bachelor of Computer Science (Honours)	944	Kampar
2.	Bachelor of Information Systems (Honours) Business Information Systems	217	
3.	Bachelor of Information Systems (Honours) Digital Economy Technology	96	
4.	Bachelor of Information Systems (Honours) Information Systems Engineering	326	
5.	Bachelor of Information Technology (Honours) Communications and Networking	267	
6.	Bachelor of Information Technology (Honours) Computer Engineering	68	
7.	Bachelor of Information Technology (Honours) Industrial Intelligent Systems	3	
8.	Bachelor of Science (Honours) Software Engineering	562	Sungai Long
Total		2,483	

Source: Developed for the research

3.3.3 Sampling Element

Respondents were classified based on age, education level, and AI Chatbots experience. Besides that, respondents will be asked about their BI towards using AI Chatbots, PE, EE, SI, HT, and INFO.

Targeted respondents should meet the following criteria:

1. Students must be from UTAR.
2. Students must be a Degree holder.
3. Students had prior experience in using AI Chatbots.

3.3.4 Sampling Techniques

Sampling techniques have two elements which are probability and non-probability (Turner, 2020). Probability sampling is the method where every component has an equal chance to be selected and has a full list of the targeted respondents. Non-probability sampling is a technique that doesn't provide a way to evaluate the probability that every component of the population will be represented in the sample.

In this study, researchers choose the judgment sampling approach, which is a non-probability sampling. It may benefit researchers to select a representative sample for qualitative research because it is time and cost-effective. This is because questionnaires will be distributed accordingly to collect the data, which will be helpful and meaningful for the researcher. This sampling strategy was developed with the assumption that the suggested sample elements represent the target population and are most likely to help achieve the study's primary goals. Besides, researchers do not choose probability sampling because a full name list for each course student in UTAR is needed, and all the students have an equal chance to be selected. However, researchers can only get an estimated total number of university students. Therefore, researchers use non-probability sampling instead of probability sampling.

Moreover, the adoption of AI Chatbots in the HEI context is still new in Malaysia, and there are a small number of experienced or non-experienced university students who use AI Chatbots developed and adopted for academic administration purposes. Therefore, researchers have chosen the judgment sampling approach in this research. The judgment sampling approach does not require the full list of target respondents, and it will filter out the criteria of the participants. It will give more accurate information about the study by identifying the suitable targeted respondent (Rahim et al., 2022).

3.3.5 Sampling Size

The total number of students pursuing Business or Information Technology courses at both the UTAR Sungai Long and Kampar campuses is 4,539. The research requires a sample size of 357 students (see Appendix 1). This study was conducted using Google Forms and physical distribution methods, and the responses yielded a 100% response rate, with researchers collecting 357 valid questionnaires.

3.4 Research Instrument

The questionnaire was used as the primary research method.

3.4.1 Questionnaire Design

Questionnaires are generated in a close-ended form. According to Reja et al. (2003), closed-ended questions only allow the respondent to choose from the available options, making it easier for respondents to answer and increasing their willingness compared to open-ended questions. Section A comprises filter questions, while Section B focuses on the demographic profile. Sections C, D, E, F, G, and H involve the measurement of DV and IVs, utilising a five-point Likert scale rating method.

3.4.2 Pilot Studies

Questionnaires were distributed to 50 respondents in compliance with two conditions, namely students from both UTAR campuses and, at the same time, those who have prior experience in using AI Chatbots. The questionnaire's respondents gave their unrestricted consent to fill out the Google form.

While conducting the pilot study, researchers sent the questionnaire via Google form to respondents through social media and followed up by sending messages to remind them on 22 November 2023. After one week, researchers collected back the data and ran data analysis for the pilot study on 28 November 2023.

After successfully collecting the data from target respondents, the data collected was analysed using SPSS software to measure the questionnaire's reliability. The internal consistency of variables has also been analysed by researchers based on the Rule of Thumb of Cronbach's Coefficient Alpha (see Table 3).

Table 3

The Rule of Thumb of Cronbach's Coefficient Alpha

Cronbach's Coefficient Alpha (α) Value	Strength of Association
Less than 0.60	Poor reliability
0.60 to 0.70	Fair reliability
0.70 to 0.80	Good reliability
0.80 to 0.95	Excellent reliability

Source: Zikmund, W. G., Babin, B. J., Carr, J. C., & Griffin, M. (2013). Business Research Methods (9th ed.). New York: South-Western/Cengage Learning.

Table 4

Summary of Reliability Test Result (Pilot Study)

	Items	Cronbach's Coefficient Alpha	Strength of Reliability
Dependent Variable:			
Behavioral Intention	8	0.850	Excellent
Independent Variable:			
PE	5	0.866	Excellent
EE	4	0.794	Good
SI	5	0.833	Excellent
Habit	4	0.871	Excellent
Informativeness	4	0.763	Good

Source: Developed for the research

Table 4 shows the pilot test results for this research. The highest reliability value among all of the other variables is HT (0.871), followed by PE (0.866), SI (0.833), EE (0.794), and INFO (0.763). Apart from that, the Coefficient Alpha value for the dependent variable, the BI of students from UTAR towards using AI Chatbots, is 0.850. All the values are above 0.70, meaning all the variables have good and excellent reliability. In short, the questionnaire is reliable and appropriate. Therefore, the research has proceeded on a larger scale of respondents.

3.5 Construct Measurement

3.5.1 Nominal Scale

There are three questions in Section A used on a nominal scale which are question 2 (programme), question 3 (experience), and question 4 (types of AI Chatbots). While two questions in section B are question 1 (gender) and question 3 (ethnic group).

1. Gender

[ ] Male [ ] Female

3.5.2 Ordinal Scale

There are two questions in Section A that use an ordinal scale, which are question 1 (education level) and question 5 (frequency). Two questions in Section B of the questionnaire that used ordinal scale are question 2 (age) and question 4 (year of study).

2. Age

[ ] 17 and below [ ] 21-23

[ ] 18-20 [ ] 24 or older

3.5.3 Interval Scale

According to Boone and Boone (2012), the Likert-scale method is mainly used to analyse the interval measurement scale. In this research questionnaire, all the questions from section C onwards are categorized as interval scales. The researchers have set a five-point Likert scale in the questionnaire.

1= Strongly disagree
2= Disagree
3= Neutral
4= Agree
5= Strongly agree

No.	Questions	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
1.	I believe AI Chatbots is very easy to learn by beginner.	1	2	3	4	5

3.5.4 Origin of Measure of Construct

The operational definition of the key construct is used in the current study (see Table 5).

Table 5

Operational Definition of the Key Construct

Variables	Items	Construct Measurement	Sources
Behavioural Intention	8	• I believe AI Chatbots is very easy to learn by beginner. • I am willing to learn the experience of AI Chatbots from others. • I am willing to learn the case of AI Chatbots from the internet. • I am happy to share my AI Chatbots experience with others. • I will use AI Chatbots to solve problems related to my academic query.	Adopted and adapted from Rahim, Lahad, Yusof & Al-Sharafi (2022); An, Chai, Li, Zhou, Shen, Zheng & Chen (2023); Chatterjee & Bhattacharjee (2020)

		• I will recommend others to use AI Chatbots for academic matters. • I intend to use AI Chatbots in learning or teaching in the future. • I plan to use AI Chatbots frequently.	
Performance Expectancy	5	• I find AI Chatbots to be useful in my daily life. • Using AI Chatbots enables me to accomplish task more quickly. • Using AI Chatbots increases my productivity. • Using AI Chatbots increases my chances of achieving academic related information that is important to me. • The use of AI Chatbots will improve my academic performance.	Adopted and adapted from Chua, Rezaei, Gu, Oh & Jambulingam (2018); Venkatesh, Morris, Davis & Davis (2003); Rahim, A. lahad, Yusof & Al-Sharafi (2022); Onaolapo & Oyewole (2018)
Effort Expectancy	4	• Learning to operate AI Chatbots is easy for me. • My interaction with AI Chatbots would be clear and understandable. • It would be easy for me to become skillful at using AI Chatbots.	Adopted and adapted from Venkatesh, Morris, Davis & Davis (2003); Onaolapo & Oyewole (2018)

		• I do not require much technical expertise to effectively use AI Chatbots.	
Social Influence	5	• People who are important to me think that I should use AI Chatbots. • People who influence my behavior think that I should use AI Chatbots. • I would use chatbots because a proportion of my friends use AI Chatbots. • Using AI Chatbots will be a status symbol in my social networks. (e.g., friends, and family) • In general, university has supported use of AI Chatbots for academic purposes.	Adopted and adapted from Chua, Rezaei, Gu, Oh & Jambulingam (2018); Rahim, A. lahad, Yusof & Al-Sharafi (2022); Venkatesh, Morris, Davis & Davis (2003); Bilquise, Ibrahim & Salhieh (2023)
Habit	4	• The use of AI Chatbots has become a habit for me. • Using AI Chatbots has become natural to me. • I am addicted to using AI Chatbots. • I must use AI Chatbots.	Adopted and adapted from Venkatesh, Thong & Xu (2012)

Informativeness	4	• AI Chatbots provide timely information. • AI Chatbots are a convenient source of information. • AI Chatbots supply complete information for my question. • AI Chatbots supply relevant information for my question.	Adopted and adapted from Alalwan (2018)

Source: Developed for the research

3.6 Data Processing

Data processing involves converting gathered data into valuable information that is practical and aligned with specific goals. The process of data processing holds significant importance as it enhances outcomes, and reliability, and boosts efficiency.

3.6.1 Data Checking

Researchers checked the questionnaire to ensure that there were no grammatical errors and consistent with the research purpose before the distribution process. Therefore, researchers are able to collect accurate responses from the respondents.

3.6.2 Data Editing

Data editing is a vital step in reviewing whether there are any errors, omissions, or ambiguous answers, and these issues will be solved by re-editing the items in the questionnaire to ensure that the final results are accurate and valid.

3.6.3 Data Coding

Data coding involves using the numeric code on the questions which are required by the SPSS software to facilitate the data input. For example, the question regarding gender is coded as "1" for male, "2" for female. Similarly, all the questions were coded in a similar way.

3.6.4 Data Transcribing

The SPSS software will be used to transcribe the collected data into variables for further processing.

3.6.5 Data Cleaning

According to Rahm and Do (2000), data cleaning involves identifying and removing errors and discrepancies within data, aiming to enhance the overall data quality. While data cleaning may appear laborious, it serves as a crucial initial phase preceding any data analysis and should be allotted sufficient time using SPSS software (Njeri-Otieno, 2022).

3.7 Data Analysis

In this step, SPSS software was selected and used to transform the research data into simple and useful information.

3.7.1 Descriptive Analysis

Loeb et al. (2017) highlighted that descriptive analysis is crucial to almost every research project as it plays a vital role in providing a clearer picture for researchers, identifying research questions, and generating hypotheses. All the data collected will be transformed in an understandable manner and interpreted based on frequency distribution or percentage distribution using a bar graph, histogram, or pie chart.

3.7.2 Scale Measurement

Reliability refers to how consistent a measurement is within itself (Zikmund et al., 2013). Tavakol and Dennick (2011) have highlighted that Cronbach's alpha had commonly been used as an index of reliability. It has been widely used in research projects that consist of multiple-item measures of a particular topic or concept (Tavakol & Dennick, 2011). The rules of thumb used to determine the reliability of independent variables and dependent variables are shown in Table 3.

According to Zikmund et al. (2013), the coefficient alpha value range between 0.80 to 0.95 is considered to have very good reliability or excellent reliability. Besides, when the coefficient alpha ranges between 0.70 to 0.80, it shows a good reliability on the scale quality. Furthermore, a scale with a coefficient alpha value between 0.60 to 0.70 indicates fair reliability, when the coefficient alpha is less than 0.60, the scale has poor reliability.

3.7.3 Inferential Analysis

Inferential analysis refers to the method that empowers researchers to summarise the properties of the population based on a sample. This analytical approach encompasses tools like the Pearson Correlation Coefficient and Multiple Linear Regression, which aid in exploring connections between independent variables and the dependent variable.

3.7.3.1 Pearson Correlation Coefficient Analysis

Schober et al. (2018) highlighted that correlation is commonly used to analyse the relationship between two variables. Testing the association between independent and dependent variables by using the Pearson Correlation Coefficient may provide some insight into the significance, strength, and direction of the relationship (Schober et al., 2018).

3.7.3.2 Multiple Linear Regression Analysis

Multiple Linear Regression is a technique used to examine the relationship between one DV with more than one IV (Uyanik & Güler, 2013).

3.8 Conclusion

This chapter mainly focuses on how researchers conduct analysis in the research methodology, elements such as construct measurement, sampling designs, data collection methods, data processing, and analysis have been discussed. The analysis results based on the data collected from respondents have been disclosed in the following chapter.

CHAPTER 4: DATA ANALYSIS

4.0 Introduction

This chapter analyses the data collected from the UTAR students in the Kampar and Sungai Long campuses. All the data being analysed have been displayed in diagrams and tables. The results have provided more understanding about the relationship between IV and DV to the respondents.

4.1 Descriptive Analysis

In the descriptive analysis, researchers employ basic visual aids like bar charts, pie charts, and tables to present and analyse the gathered data succinctly. This facilitates a clear comprehension of the demographic characteristics of the respondents, offering a straightforward overview.

4.1.1 Respondent Demographic Profile

Information pertaining to the demographic characteristics of survey respondents, including gender, age, ethnic group, and year of study, has been systematically gathered.

4.1.1.1 Gender

Table 6

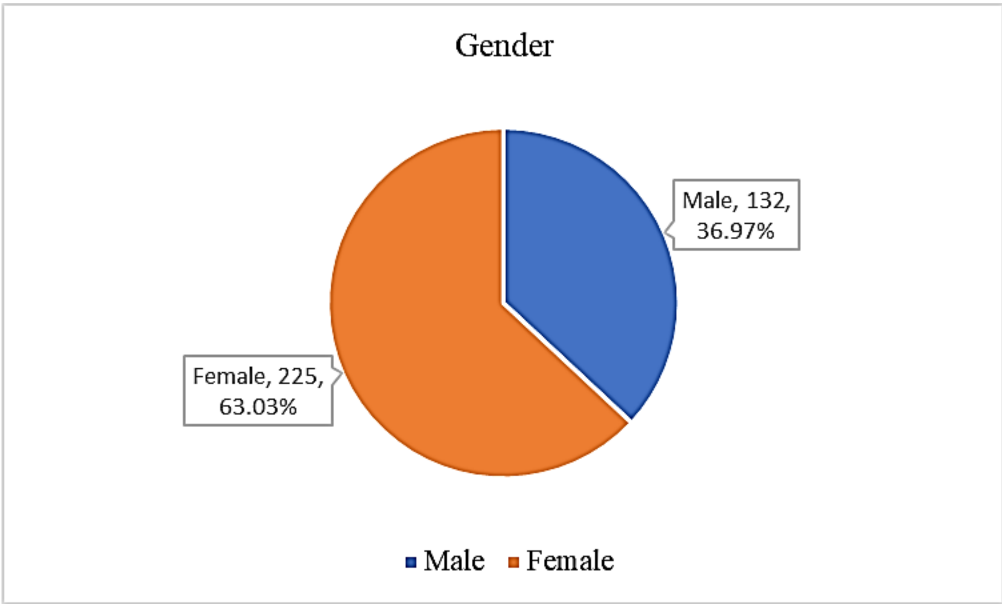
Respondent's Gender

Gender	Frequency	Percentage (%)	Cumulative Frequency	Cumulative Percentage (%)
Male	132	36.97	132	36.97
Female	225	63.03	357	100.00

Source: Developed for the research

Figure 3

Statistic of Respondent's Gender



Based on Table 6, Figure 3, out of the 357 respondents, 36.97% (132 respondents) are male, while 63.03% (225 respondents) are female.

4.1.1.2 Age

Table 7

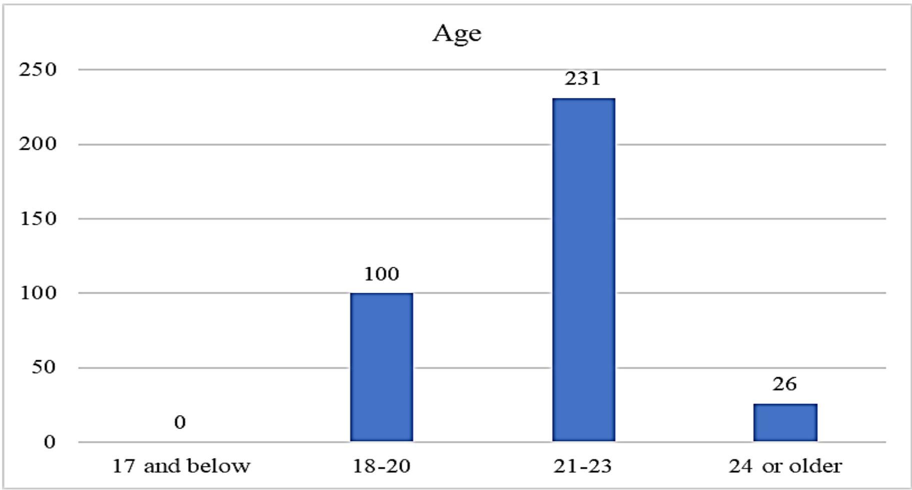
Respondent's Age

Age	Frequency	Percentage (%)	Cumulative Frequency	Cumulative Percentage (%)
17 and below	0	0.00	0	0.00
18 - 20	100	28.01	100	28.01
21 - 23	231	64.71	331	92.72
24 or older	26	7.28	357	100.00

Source: Developed for the research

Figure 4

Statistic of Respondent's Age



The respondents' ages were categorized into groups, as presented in Table 7 and Figure 4. Among the 357 total respondents, 28.01% (100 respondents) were in the 18-20 years age group, 64.71% (231 respondents) were in the 21-23 years age group, and 7.28% (26 respondents) were 24 years old or older. Importantly, no respondents aged 17 and below participated in this research survey.

4.1.1.3 Ethnic Group

Table 8

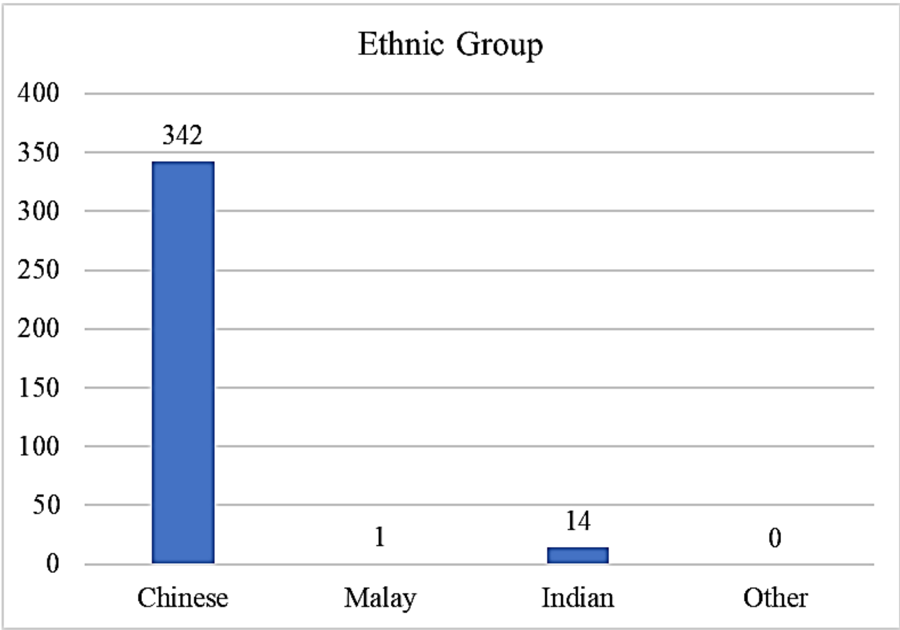
Respondent's Ethnic Group

Ethnic Group	Frequency	Percentage (%)	Cumulative Frequency	Cumulative Percentage (%)
Chinese	342	95.80	342	95.80
Malay	1	0.28	343	96.08
Indian	14	3.92	357	100.00
Other	0	0.00	357	100.00

Source: Developed for the research

Figure 5

Statistic of Respondent's Ethnic Group



The respondents' ethnicity is classified into four distinct groups, as illustrated in Table 8 and Figure 5. Among the 357 UTAR students' respondents, 95.80% (342 respondents) identify as Chinese, 0.28% (1 respondent) as Malay, and 3.92% (14 respondents) as Indian.

4.1.1.4 Year of Study

Table 9

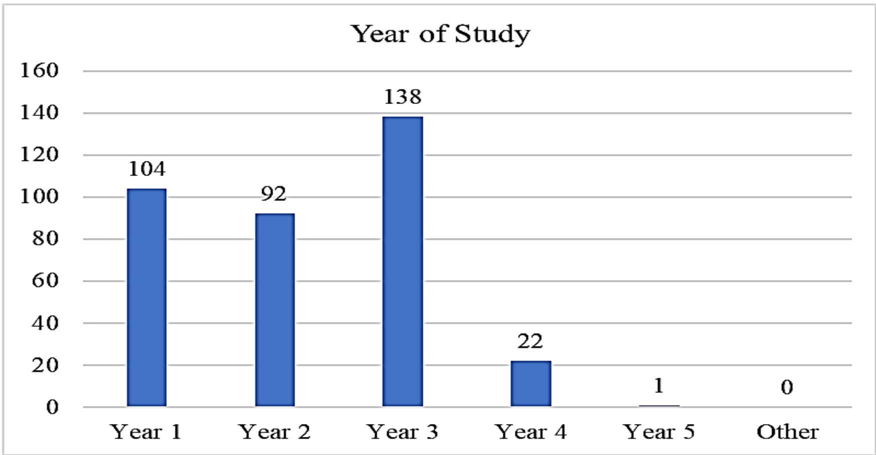
Respondent's Year of Study

Year of Study	Frequency	Percentage (%)	Cumulative Frequency	Cumulative Percentage (%)
Year 1	104	29.13	104	29.13
Year 2	92	25.77	196	54.90
Year 3	138	38.66	334	93.56
Year 4	22	6.16	356	99.72
Year 5	1	0.28	357	100.00
Other	0	0.00	357	100.00

Source: Developed for the research

Figure 6

Statistic of Respondent's Year of Study



Examining Table 9 and Figure 6 shows that 29.13% (104 respondents) out of the 357 total respondents are Year 1 students, 25.77% (92 respondents) represent Year 2, the majority at 38.66% (138 respondents) fall under Year 3, and a smaller proportion of 6.16% (22 respondents) are Year 4 students. Notably, only 0.28% (1 respondent) are categorised as Year 5 students.

4.1.2 Central Tendencies Measurement of Construct

4.1.2.1 Behavioural Intention

Table 10
Central Tendency Measurement for Behavioural Intention

Question	Statement	Mean	Standard Deviation	Mean Ranking	Standard Deviation Ranking
BI 1	I believe AI Chatbots is very easy to learn by beginner.	4.22	0.825	8	5
BI 2	I am willing to learn the experience of AI Chatbots from others.	4.17	0.792	6	7
BI 3	I am willing to learn the case of AI Chatbots from the internet.	4.12	0.81	3	6
BI 4	I am happy to share my AI Chatbots experience with others.	4.08	0.898	2	2
BI 5	I will use AI Chatbots to solve problems related to my academic query.	4.21	0.787	7	8
BI 6	I will recommend others to use AI Chatbots for academic matters.	4.13	0.833	5	4
BI 7	I intend to use AI Chatbots in learning or teaching in the future.	4.12	0.849	4	3
BI 8	I plan to use AI Chatbots frequently.	3.87	1.007	1	1

Source: Developed for this research

Table 10 outlines the central tendencies in measuring BI. BI1 has the highest mean value of 4.22, indicating widespread agreement among respondents. Following closely are BI5 (4.21), BI2 (4.17), BI6 (4.13), BI7 (4.12), BI3 (4.12), BI4 (4.08) and BI8 with the lowest mean of 3.87. Additionally, BI8 exhibits the highest standard deviation at 1.007, followed by BI4 (0.898), BI7 (0.849), BI6 (0.833), BI1 (0.825), BI3 (0.810), BI2 (0.792) and finally, BI5 (0.787), with the least standard deviation, signifying stronger agreement on the statement.

4.1.2.2 Performance Expectancy

Table 11
Central Tendency Measurement for Performance Expectancy

Question	Statement	Mean	Standard Deviation	Mean Ranking	Standard Deviation Ranking
PE 1	I find AI Chatbots to be useful in my daily life.	4.02	0.891	1	1
PE 2	Using AI Chatbots enables me to accomplish task more quickly.	4.27	0.765	5	5
PE 3	Using AI Chatbots increases my productivity.	4.23	0.798	4	4
PE 4	Using AI Chatbots increases my chances of achieving academic related information that is important to me.	4.13	0.838	3	3
PE 5	The use of AI Chatbots will improve my academic performance.	4.04	0.862	2	2

Source: Developed for this research

Moving to Table 11, it presents central tendencies in PE. PE2 has the highest mean (4.27), indicating widespread agreement among respondents. Following in sequence, PE3 (4.23), PE4 (4.13), PE5 (4.04), and PE1 with the lowest mean of 4.02. In terms of standard deviation, PE1 has the highest value at 0.891, followed by PE5 (0.862), PE4 (0.838), PE3 (0.798), and PE2 (0.765) with the lowest standard deviation, indicating more uniform agreement.

4.1.2.3 Effort Expectancy

Table 12

Central Tendency Measurement for Effort Expectancy

Question	Statement	Mean	Standard Deviation	Mean Ranking	Standard Deviation Ranking
EE 1	Learning to operate AI Chatbots is easy for me.	4.14	0.795	4	4
EE 2	My interaction with AI Chatbots would be clear and understandable.	4.07	0.810	2	3
EE 3	It would be easy for me to become skilful at using AI Chatbots.	4.07	0.814	3	2
EE 4	I do not require much technical expertise to effectively use AI Chatbots.	3.97	0.961	1	1

Source: Developed for this research

Table 12 displays central tendencies for EE. EE1 leads with the highest mean of 4.14, indicating widespread agreement. EE3 (4.07), EE2 (4.07), and EE4 tie for the lowest mean at 3.97. Examining standard deviations, EE4 has the highest value at 0.961, followed by EE3 (0.814), EE2 (0.810), and EE1 (0.795) with the lowest standard deviation, suggesting stronger agreement.

4.1.2.4 Social Influence

Table 13

Central Tendency Measurement for Social Influence

Question	Statement	Mean	Standard Deviation	Mean Ranking	Standard Deviation Ranking
SI 1	People who are important to me think that I should use AI Chatbots.	3.64	1.052	2	2
SI 2	People who influence my behavior think that I should use AI Chatbots.	3.74	1.024	3	3
SI 3	I would use chatbots because a proportion of my friends use AI Chatbots.	3.81	1.024	5	4
SI 4	Using AI Chatbots will be a status symbol in my social networks. (e.g., friends, and family)	3.53	1.207	1	1
SI 5	In general, university has supported use of AI Chatbots for academic purposes.	3.8	1.023	4	5

Source: Developed for this research

Turning to Table 13, it presents central tendencies in SI. SI3 leads with the highest mean (3.81), indicating widespread agreement among respondents. Sequentially, SI5 (3.80), SI2 (3.74), SI1 (3.64), and SI4 with the lowest mean of 3.53. Regarding standard deviation, SI4 has the highest value at 1.207, followed by SI1 (1.052), SI2 (1.024), SI3 (1.024), and SI5 (1.023) with the lowest standard deviation, suggesting more uniform agreement.

4.1.2.5 Habit

Table 14
Central Tendency Measurement for Habit

Question	Statement	Mean	Standard Deviation	Mean Ranking	Standard Deviation Ranking
HT 1	The use of AI Chatbots has become a habit for me.	3.61	1.090	3	3
HT 2	Using AI Chatbots has become natural to me.	3.79	1.026	4	4
HT 3	I am addicted to using AI Chatbots.	3.35	1.239	2	2
HT 4	I must use AI Chatbots.	3.25	1.295	1	1

Source: Developed for this research

Table 14 presents central tendencies in HT. HT2 has the highest mean at 3.79, indicating widespread agreement, followed by HT1 (3.61), HT3 (3.35), and HT4, with the lowest mean of 3.25 follow in sequence. Examining standard deviations, HT4 has the highest value at 1.295, followed by HT3 (1.239), HT1 (1.090), and HT2 (1.026) with the lowest standard deviation, signifying stronger agreement.

4.1.2.6 Informativeness

Table 15
Central Tendency Measurement for Informativeness

Question	Statement	Mean	Standard Deviation	Mean Ranking	Standard Deviation Ranking
INFO 1	AI Chatbots provide timely information.	3.73	1.039	1	1
INFO 2	AI Chatbots are a convenient source of information.	4.09	0.863	4	3
INFO 3	AI Chatbots supply complete information for my question.	3.80	0.992	2	2
INFO 4	AI Chatbots supply relevant information for my question.	3.96	0.855	3	4

Source: Developed for this research

Table 15 provides central tendencies in INFO. INFO2 leads with the highest mean (4.09), indicating widespread agreement. INFO4 (3.96), INFO3 (3.80), and INFO1, with the lowest mean of 3.73, follow in sequence. Notably, INFO1 has the highest standard deviation at 1.039, followed by INFO3 (0.992), INFO4 (0.863), and INFO2 (0.855) with the lowest standard deviation, indicating more consistent agreement.

4.2 Scale Measurement

4.2.1 Reliability Test

By utilising the SPSS Software (Version 25), the reliability of the results from 357 sets of questionnaires can be assessed.

Table 16

Cronbach's Alpha Reliability Test

Question	Cronbach's Alpha Value	Number of Items
Dependent Variable:		
BI	0.874	8
Independent Variable:		
PE	0.876	5
EE	0.781	4
SI	0.863	5
HT	0.880	4
INFO	0.824	4

Source: Developed for the research

After running the SPSS result from 357 set response data, it can be concluded that the questionnaires were reliable. Table 16 shows the outcomes for each variable. Firstly, the Coefficient Alpha Value (CAV) for the DV (BI) is 0.874, while other IVs (PE, EE, SI, HT, and INFO) show the value of 0.876, 0.781, 0.863, 0.880, and 0.824 respectively. According to the Alpha Cronbach Value shown in Table 17, researchers can conclude that CAV for UTAR students is within the excellent and acceptable reliability, which is within the range of 0.71 - 0.80 and the range of good of 0.81 - 0.90.

Table 17

The Alpha Cronbach Value

Alpha Cronbach Value	Interpretation
0.91 - 1.00	Excellent
0.81 - 0.90	Good
0.71 - 0.80	Good and Acceptable
0.61 - 0.70	Acceptable
0.01 - 0.60	Not Acceptable

Source : Cortina, J. M. (1993). What is coefficient alpha? An examination of theory and applications. *Journal of applied psychology, 78* (1), 98.

4.3 Inferential Analysis

4.3.1 Pearson Correlation Analysis

Table 18 outlines the guidelines for interpreting the strength of a Pearson Correlation Coefficient and its coefficient ranges.

Table 18

Rule of Thumb for Interpreting the Strength of a Correlation Coefficient

Coefficient Range	Strength
±0.91 to ±1.00	Very Strong
±0.71 to ±0.90	High
±0.41 to ±0.70	Moderate
±0.21 to ±0.40	Small but Definite Relationship
±0.00 to ±0.20	Slight, Almost Negligible

Source : Hair, Jr., Money, A. H., Samouel, P., & Page, M. (2007). Research methods for business. Chichester. West Sussex: John Wiley & Sons, Inc.

4.3.1.1 Performance Expectancy with Behavioural Intention (Hypothesis 1)

H0: There is no significant relationship between performance expectancy and the behavioural intention of students towards using AI Chatbots.

H1: There is a significant relationship between performance expectancy and the behavioural intention of students towards using AI Chatbots.

Table 19

Correlations between Performance Expectancy with Behavioural Intention

		Behavioural Intention
Performance Expectancy	Pearson Correlation	0.783
	Significant (2-tailed)	<0.000
	N	357

Source: Generated from SPSS Software (Version 25)

In Table 19, a positive correlation coefficient indicates a direct relationship between PE and BI in UTAR students. The correlation coefficient of PE is 0.783, signifying that as PE increases, BI also rises. The correlation coefficient value of 0.783 falls within the range of ±0.71 to ±0.90. Consequently, the relationship between PE and BI is high and significant, as evidenced by the p-value (<0.000), which is less than the alpha value (0.05).

4.3.1.2 Effort Expectancy with Behavioural Intention (Hypothesis 2)

H0: There is no significant relationship between effort expectancy and the behavioural intention of students towards using AI Chatbots.
H1: There is a significant relationship between effort expectancy and the behavioural intention of students towards using AI Chatbots.

Table 20

Correlations between Effort Expectancy with Behavioural Intention

		Behavioural Intention
Effort Expectancy	Pearson Correlation	0.723
	Significant (2-tailed)	<0.000
	N	357

Source: Generated from SPSS Software (Version 25)

Examining the outcomes in Table 20, a positive correlation coefficient suggests a positive relationship between EE and BI. The correlation coefficient for EE is 0.723, illustrating that higher levels of EE correspond to increased BI. With a correlation coefficient of 0.723 falling within the range of ±0.71 to ±0.90, the relationship between EE and BI is deemed high and significant, supported by a p-value (<0.000) below the alpha value (0.05).

4.3.1.3 Social Influence with Behavioural Intention (Hypothesis 3)

H0: There is no significant relationship between social influence and the behavioural intention of students towards using AI Chatbots.
H1: There is a significant relationship between social influence and the behavioural intention of students towards using AI Chatbots.

Table 21
Correlations between Social Influence with Behavioural Intention

		Behavioural Intention
Social Influence	Pearson Correlation	0.602
	Significant (2-tailed)	<0.000
	N	357

Source: Generated from SPSS Software (Version 25)

Table 21 results demonstrate a positive correlation between SI and BI, as indicated by the positive correlation coefficient. SI has a correlation coefficient of 0.602, implying that heightened perceived SI aligns with increased BI. Both correlation coefficients fall within the coefficient range of ±0.41 to ±0.70, and this relationship is deemed moderate and significant, as the p-value (<0.000) is below the alpha value (0.05).

4.3.1.4 Habit with Behavioural Intention (Hypothesis 4)

H0: There is no significant relationship between habit and the behavioural intention of students towards using AI Chatbots.
H1: There is a significant relationship between habit and the behavioural intention of students towards using AI Chatbots.

Table 22
Correlations between Habit with Behavioural Intention

		Behavioural Intention
Habit	Pearson Correlation	0.547
	Significant (2-tailed)	<0.000
	N	357

Source: Generated from SPSS Software (Version 25)

Analysing Table 22, a positive correlation coefficient signifies a connection between HT and BI. The correlation coefficient for HT is 0.547, suggesting that a stronger HT corresponds to higher BI. Within the coefficient range of ±0.41 to ±0.70, the relationship between HT and BI is considered moderate and significant, with a p-value (<0.000) below the alpha value (0.05).

4.3.1.5 Informativeness with Behavioural Intention (Hypothesis 5)

H0: There is no significant relationship between informativeness and the behavioural intention of students towards using AI Chatbots.
H1: There is a significant relationship between informativeness and the behavioural intention of students towards using AI Chatbots.

Table 23

Correlations between Informativeness with Behavioural Intention

Business Courses		Behavioural Intention
Informativeness	Pearson Correlation	0.558
	Significant (2-tailed)	<0.000
	N	357

Source: Generated from SPSS Software (Version 25)

From the findings in Table 23, a positive correlation coefficient highlights a positive relationship between INFO and BI. The correlation coefficient for INFO is 0.558, indicating that increased INFO is associated with higher BI. With a correlation coefficient falling within the range of ±0.41 to ±0.70, the relationship between INFO and BI is moderate and significant, supported by a p-value (<0.000) below the alpha value (0.05).

4.3.2 Multiple Linear Regression Analysis

Table 24

Analysis of Variance

ANOVA						
	Model	Sum of Squares	df	Mean Square	F	Sig.
1	Regression	92.364	5	18.473	142.576	<0.000
	Residual	45.477	351	0.130		
	Total	137.841	356			

Source: Generated from SPSS Software (Version 25)

Based on Table 24, the p-value (<0.000) is below the alpha value (0.05), indicating that the F-statistic is significant. The model used in this study effectively describes the relationship between the DV and IV. Therefore, all the IVs (PE, EE, SI, HT, INFO) are significant in explaining the variance in BI.

Table 25

R-square Value's Model Summary

Model Summary				
Model	R	R-Square	Adjusted R-Square	Std. Error of the Estimate
1	0.819	0.670	0.665	0.35995

Source: Generated from SPSS Software (Version 25)

The R-value is the correlation coefficient between DV and IV taken together. Based on Table 25, the value of the correlation coefficient (R-value) for this study is 0.819. This is a positive and high correlation between DV (BI) and IV (PE, EE, SI, HT, and INFO).

Table 26

Rule of Thumb for Interpreting the Strength of a Correlation Coefficient

R-squared Value	**Strength**
Less than 0.3	None or very weak
0.3 to 0.5	Weak or low
0.5 to 0.7	Moderate
More than 0.7	Strong

Source : Moore, D. S., Notz, W. I, & Flinger, M. A. (2013). The basic practice of statistics (6th ed.). New York, NY: W. H. Freeman and Company. Page (138).

The R-square indicates the percentage of how the IV (PE, EE, SI, HT, and INFO) can explain the variations in the DV (BI). Based on Table 25, the R-square value for the study was 0.670 or 67%. As a result, the R-square value falls under the range of 0.5 to 0.7, indicating a moderate correlation coefficient (see Table 26). However, the remaining 33.0% as other additional variables that are important in interpreting BI unexplained in this study.

Table 27

The Estimate of Parameter

Coefficients						
	Model	Unstandardized Coefficients		Standard Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	0.837	0.129		6.468	<0.000
	PE	0.451	0.045	0.493	10.012	<0.000
	EE	0.264	0.046	0.280	5.689	<0.000
	SI	0.036	0.036	0.050	1.014	0.311
	HT	0.059	0.027	0.095	2.171	0.031
	INFO	<0.000	0.036	<0.000	<0.000	1.000

Source: Generated from SPSS Software (Version 25)

Regression Equation:

Y = a + b1X1 + b2X2 + b3X3 + b4X4 + b5X5

Where,

Y = Behavioural Intention

X1 = Performance Expectancy

X2 = Effort Expectancy

X3 = Social Influence

X4 = Habit

X5 = Informativeness

a = the intercept

b = the slope (coefficient of Xn)

Multiple Regression Equation

BI = 0.837 + 0.451 (PE) + 0.264 (EE) + 0.036 (SI) + 0.059 (HT) -0.00000946 (INFO)

Highest Contribution (HC)

The IV that demonstrates the most significant contribution to the variation of the DV (BI), is PE. This conclusion is drawn from the unstandardised coefficients of beta values, where PE exhibits the highest value (0.451) if compared to other IVs (EE, SI, HT, and INFO). Consequently, it can be asserted that PE stands out as the most influential factor in explaining BI within the scope of this study. In other words, PE makes the most robust and unique contribution to elucidating the variance in the DV (BI), even when accounting for the influence of all other predictor variables in the model.

Second-Highest Contribution

EE is the second-HC among 5 IV to the DV because the beta value (under unstandardised coefficients) for this IV is the second largest (0.264). This indicates that EE makes the second strongest unique contribution in explaining the variation in DV (BI) when the variance explained by all other predictor variables in the model. EE emerges as the second-highest contributor compared to other IVs (PE, SI, HT, and INFO) to the DV (BI). Consequently, it can be inferred that EE makes the second-strongest and distinctive contribution in explaining the variance observed in the DV (BI), even when accounting for the impact of all other predictor variables in the model.

Third-Highest Contribution

The IV demonstrating the third-HC to the variation of the DV (BI), is HT. This determination is derived from the unstandardised coefficients of beta values, with HT displaying the third-highest value (0.059) if compared to other IVs (PE, EE, SI, and INFO). Consequently, it can be asserted that HT makes the third strongest and distinctive contribution in explaining the variance observed in the DV (BI), even when accounting for the impact of all other predictor variables in the model.

Fourth Highest Contribution

SI is identified as the fourth-HC among the five IVs to the DV (BI). This determination is based on the beta value (under unstandardised coefficients), with SI presenting the fourth-highest value (0.036) compared to the other IV (PE, EE, HT, and INFO). This implies that SI makes the fourth-strongest and distinct contribution in explaining the variation observed in the DV (BI), even considering the impact of all other predictor variables in the model.

Lowest Contribution

The IV that contributes the least to the variation of the DV (BI), is INFO. This determination is based on the beta value (under unstandardised coefficients), with INFO exhibiting the lowest value (-0.00000946) among the four IVs considered (PE, EE, SI, and HT). Consequently, it can be stated that INFO is the least influential factor in explaining BI in this study. This implies that INFO makes the smallest contribution to elucidating the variation in the DV (BI) when the variance explained by all other predictor variables in the model is controlled for.

4.4 Conclusion

In summary, this chapter encompasses the distribution, collection, meticulous analysis, and detailed explanation of the administered questionnaire. Additionally, it includes the computation and presentation of the standard deviation and mean score, coupled with a scale measurement to ascertain the questionnaire survey's reliability. The outcomes of the Multiple Linear Regression Analysis and Pearson Correlation Coefficient conducted through SPSS software elucidate the associations between the five IVs (PE, EE, SI, HT, and INFO) and the DV (BI).

CHAPTER 5: DISCUSSION, CONCLUSION AND IMPLICATION

5.0 Introduction

The last chapter offers a comprehensive summary, presenting an overview of the statistical analyses, encompassing both descriptive and inferential approaches. Additionally, valuable insights regarding the key discoveries will be expounded upon. Furthermore, the researchers have discussed the limitations inherent in this study and offer recommendations for future researchers.

5.1 Summary of Statistical Analysis

This chapter included an in-depth exploration of the outcomes derived from both the descriptive and inferential analyses conducted in the preceding chapter. Researchers have provided a comprehensive summary to offer a cohesive overview of the findings.

5.1.1 Summary of Descriptive Analysis

Table 28

Summary of Descriptive Analysis

Variable	Frequency	Percentage (%)	Cumulative Frequency	Cumulative Percentage (%)
Gender				
Male	132	36.97	132	36.97
Female	225	63.03	357	100
Age Group				
17 and below	0	0	0	0
18-20	100	28.01	100	28.01
21-23	231	64.71	331	92.72
24 or older	26	7.28	357	100
Ethnic Group				
Chinese	342	95.8	342	95.8
Malay	1	0.28	343	96.08
Indian	14	3.92	357	100
Other	0	0	357	100
Year of Study				
Year 1	104	29.13	104	29.13
Year 2	92	25.77	196	54.9
Year 3	138	38.66	334	93.56
Year 4	22	6.16	356	99.72
Year 5	1	0.28	357	100
Other	0	0	357	100

Source: Developed for the research

Based on Table 28, the research survey encompassed a cohort of 357 respondents, with gender distribution revealing that 36.97% or 132 respondents were male, and females constituted 63.03% or 225 respondents. In terms of age demographics, a significant proportion fell within the 21-23 age range, accounting for 64.71% or 231 respondents, followed by the 18-20 age category at 28.01% or 100 respondents, and the 24 or older age range at 7.28% or 26 respondents. It is noteworthy that no respondents fell below the age of 17. Ethnically, the preponderance of respondents identified as Chinese (95.80% or 342 respondents), followed by Indian (3.92%, or 14 respondents) and Malay (0.28%, or 1 respondent). The academic distribution indicated a predominant presence in Year 3 (38.66%, or 138 respondents), followed by Year 1 (29.13%, or 104 respondents), Year 2 (25.77%, or 92 respondents), Year 4 (6.16%, or 22 respondents), and Year 5 (0.28%, or 1 respondent). These findings collectively afford a comprehensive insight into the survey participants' demographic characteristics and academic profiles.

5.1.2 Summary of Inferential Analysis

5.1.2.1 Reliability Test

Data from 357 respondents was used and run for the reliability test. Although most variables are more than 0.8, IV (EE) is 0.781, slightly lower than others. The highest CAV is HT, followed by PE, BI, SI, INFO, and EE. The ranking can be viewed in Table 29.

Table 29

Cronbach's Alpha Reliability Test

Question	Cronbach's Alpha Value	Number of Items	Ranking
Dependent Variable:			
BI	0.874	8	3
Independent Variable			
PE	0.876	5	2
EE	0.781	4	6
SI	0.863	5	4
HI	0.88	4	1
INFO	0.824	4	5

Source: Developed for the research

5.1.2.2 Pearson Correlation Coefficient Analysis

The Pearson Correlation Coefficient test in Chapter 4 shows that there is a positive and significant relationship between the IVs (PE, EE, SI, HT, and INFO) and DV (BI) because of the positive value of the correlation coefficient. The respective R-values for each IV are PE (0.783), EE (0.723), SI (0.602), HT (0.547), and INFO (0.558). Therefore, when the IVs (PE, EE, SI, HT, and INFO) are high, DV (BI) is also high.

The correlation coefficients of the PE and EE under coefficients range from ±0.71 to ±0.90. Therefore, the relationship is high. The remaining variables fall under coefficients ranging from ±0.41 to ±0.70. Hence, the relationship is moderate. The relationship between the IVs (PE, EE, SI, HT, INFO) and DV (BI) are significant as the p-value (<0.000) is less than the alpha value (0.05).

5.1.2.3 Multiple Linear Regression Analysis

Upon deeper examination of each IV, notable differences in their effects emerge. The F-statistic indicates significance, given the p-value (<0.000) is lower than the alpha value of 0.05. Specifically, PE and EE demonstrate p-values of <0.000, while SI and INFO exhibit insignificance with p-values of 0.311 and 1.000, respectively. Additionally, HT shows a marginally significant relationship with a p-value of 0.031.

This implies that the relationships between PE, EE, and HT towards BI are significant, whereas SI and INFO demonstrate insignificant relationships towards BI. This finding aligns with existing literature suggesting that students may exhibit a greater tendency for self-management of learning, thereby reducing the influence of their close friends or peers on BI (Wang et al., 2009). The lack of significance in the relationship between SI and students' BI towards using AI Chatbots may be influenced more by personal perceptions than external social pressures. While SI can play a role in shaping BI, students are not exposed to external influences if they are primarily driven by their own perceptions and attitudes (BI) toward AI Chatbots or if students view AI Chatbots as tools for personal help or academic support, rather than something popular or socially acceptable. In short, students' use of AI Chatbots is mainly driven by their own cognition of AI Chatbots and their own BI.

Moreover, the reliance on AI Chatbots for INFO might discourage students from engaging in self-directed learning efforts. If AI Chatbots provide inaccurate information or advice, it could potentially hinder students' learning progress (Labadze et al., 2023). When AI Chatbots are unable to obtain accurate and up-to-date information, or the information and responses they provide are inaccurate, students may perceive the AI Chatbots as incapable of offering meaningful assistance or as untrustworthy. For example, ChatGPT's latest information is only available until January 2022. As a result, students may not consider AI Chatbots a valuable source of information or may be unable to provide the help or guidance they need. This leads to an insignificant relationship between INFO and students' BI to use AI Chatbots.

The R-square value of 0.670 indicates that the independent variables (PE, EE, SI, HT, and INFO) collectively explain 67.0% of the variance in the dependent variable (BI). In general, for this study, all the IVs are significant relationship with DV.

5.2 Discussion of Major Findings

Researchers have identified the outcomes for each hypothesis developed based on the results from SPSS. The IVs and DV are deemed to be a positive relationship when the r-value is a positive sign, while the p-value can be used to determine whether to accept or reject the research hypothesis. When the p-value is less than 0.05, the alternate hypothesis (H1) will be accepted, and the null hypothesis (H0) will be rejected. Table 30 is the summary between the IVs and DV.

Table 30

The Summary of Pearson's Correlation Coefficient and Multiple Linear Regression for the Independent Variables and Behavioural Intention

	Hypothesis	Results	Outcomes
H1	There is a significant relationship between performance expectancy and the behavioural intention of students towards using AI Chatbots.	r-value = 0.783	Supported
		p-value = <0.000	
		(p-value) = <0.000	
H2	There is a significant relationship between effort expectancy and the behavioural intention of students towards using AI Chatbots.	r-value = 0.723	Supported
		p-value = <0.000	
		(p-value) = <0.000	
H3	There is a significant relationship between social influence and the behavioural intention of students towards using AI Chatbots.	r-value = 0.602	Supported
		p-value = <0.000	
		(p-value) = 0.311	
H4	There is a significant relationship between habit and the behavioural intention of students towards using AI Chatbots.	r-value = 0.547	Supported
		p-value = <0.000	
		(p-value) = 0.031	
H5	There is a significant relationship between informativeness and the behavioural intention of students towards using AI Chatbots.	r-value = 0.558	Supported
		p-value = <0.000	
		(p-value) = 1.000	

Source: Developed for the research

5.2.1 Hypothesis 1: Performance Expectancy with Behavioural Intention

The finding indicates that PE significantly influences BI, aligning with the findings of previous research conducted by Rahim et al. (2022). Based on the Gatzioufa and Saprikis (2022) study and Sitthipon et al. (2022) findings further confirm the critical role of PE in shaping user BI. A study by Gatzioufa and Saprikis (2022) found that PE significantly impacts users' intention to use AI Chatbots, highlighting the critical factors in performance and accuracy when users decide to use these AI Chatbots. This suggests that a higher level of PE in AI Chatbots directly influences whether users are inclined to adopt the technology. Similarly, Sitthipon et al. (2022) further confirmed that PE has a significant impact on an individual's BI to use AI Chatbots. The findings highlight the importance of PE in the user decision-making process, revealing that users will include PE as one of the important considerations when considering whether to use AI Chatbots.

5.2.2 Hypothesis 2: Effort Expectancy with Behavioural Intention

In research, EE plays a critical predictive role in user acceptance of new technologies (Emon et al., 2023). In particular, EE positively impacts university students' willingness to adopt AI Chatbots in the future. This may indicate that university students are more willing to embrace and adopt the new technology when they believe that using AI Chatbots is relatively easy and doesn't require too much effort. This is consistent with Alalwan et al. (2017), who point out that EE involves users' expected perception of the ease of use of a technology platform or the effort required to use it. Thus, the EE positively influences user BI, further emphasizing EE's importance in users' adoption decisions for new technologies. The hypothesis of this study makes a critical point that EE will influence user BI toward AI Chatbots. If users expect relatively little effort when using a new technology, they may be more inclined to accept and adopt it (Ragheb et al., 2022).

5.2.3 Hypothesis 3: Social Influence with Behavioural Intention

Earlier studies on AI Chatbots have revealed that SI can influence users' BI to use AI Chatbots in diverse ways. Favourable SI, for example, can improve users' perceptions of the effectiveness and user-friendliness of AI Chatbots, simultaneously reducing perceived risks and obstacles to adoption (Mogaji et al., 2021; Terblanche & Kidd, 2022). Conversely, adverse SI may instigate scepticism and apprehension regarding the efficacy and dependability of AI Chatbots, fortifying resistance to change (Conrad et al., 2015). Various sources, including friends, family, colleagues, experts, influencers, and online reviews, can serve as origins of SI (Fu et al., 2020). Concerns about the potential misuse of AI Chatbots, such as disseminating misinformation, biased content, or harmful recommendations, can also contribute to negative SI. The widespread and swift global acceptance and utilization of AI Chatbots post their official launch indicate that SI is perceived to positively influence its adoption (Saini, 2023).

5.2.4 Hypothesis 4: Habit with Behavioural Intention

According to the findings, HT has a positive impact on the students' BI in adopting AI Chatbots. Previous research has indicated that HT directly and indirectly influences technology usage (Rahim et al., 2022). This study reveals that HT positively influences university students' BI to adopt AI Chatbots. The HT of using AI Chatbots among students can be noticeably predicted, suggesting that as the frequency of technology use increases, students are more likely to consider it as one of the choices for customer service solutions. The influence of this HT aligns with the conclusions of prior research, which stated that HT has a positive impact on the BI when using AI Chatbots (Almahri & Bell, 2020). When using AI Chatbots becomes routine, HT becomes an additional driving force, increasing the BI to use this technology (Fadzil, 2018). Besides, previous study emphasizes the significance of BI in the use of AI Chatbots, indicating that students intend to use AI Chatbots when needed, and they hold a positive attitude towards utilising AI Chatbots to explore their intentions and usage (Rahim et al., 2022).

5.2.5 Hypothesis 5: Informativeness with Behavioural Intention

According to Dehghani et al. (2016), INFO is a crucial variable in defining a user's intention to use AI Chatbots. For AI Chatbots, offering clear, useful information contributes to building trust in users regarding this technology. This, in turn, makes users more inclined to choose AI Chatbots and maintain long-term loyalty. In addition, INFO promotes user interaction with AI Chatbots. When users feel AI Chatbots are able to promote valuable information, they are more likely to engage, seek additional knowledge from AI Chatbots, and try out related AI products and services (Wang et al., 2020). In short, INFO plays a crucial role in shaping user intent towards AI Chatbots. By offering valuable, accurate, and clear information, it enhances users' understanding and trust in AI Chatbots, influencing their willingness to purchase and adopt AI solutions (Hameed et al., 2022).

5.3 Implication of the Study

5.3.1 Theoretical Implications

The research suggests that the framework is relevant within an educational setting, specifically focusing on a private university in Malaysia. The study identifies five key factors influencing students' BI towards using AI Chatbots. The empirical evidence gathered in this research underscores the significance of these dimensions. Notably, all IVs employed in the study exhibit a noteworthy correlation with BI. The model proves its relevance following rigorous testing, as the IVs demonstrate a capacity to explain a substantial variation in the DV.

After reviewing several research papers, researchers observed a limited mention of IV, which was INFO in existing studies. Consequently, researchers contribute to the literature by introducing an additional IV to this study, enhancing the research framework and providing valuable insights for this study and future research.

5.3.2 Managerial Implications

The managerial implications of this study indicate that developers should concentrate on enhancing the PE and EE of AI Chatbots. Drawing upon previous literature such as Al-Emran et al. (2024) and Ashfaq et al. (2020), researchers recommend developers ensure that AI Chatbots furnish users with responses rich in information and of high quality, all the while simplifying and streamlining user workflows. In the deployment of AI Chatbots across diverse settings, policymakers should take into consideration HT factors. For example, student users may be more susceptible to the influence of positive prior experience on self-regulated learning. Policymakers can modify their implementation strategies to enhance the student's BI towards this technology and understand these HT factors (Tian et al., 2021). Moreover, privacy concerns emerge as pivotal factors in accepting AI Chatbots (De Cosmo et al., 2021). Developers and decision-makers must safeguard user privacy by adhering to ethical standards, such as maintaining the confidentiality and security of user information. It is also crucial to inform users about the confidentiality and security measures implemented by AI Chatbots, fostering trust and BI. Through the enhancement of PE, EE, SI, HT, and INFO, AI Chatbots like ChatGPT can be developed and implemented to optimise student's BI to use AI Chatbots.

Universities can potentially enhance student learning experiences by offering talks, seminars, or training sessions focused on integrating AI chatbots, such as ChatGPT, into academic pursuits. An et al. (2022) highlight the importance of adopting, rather than merely imitating, information when utilizing AI chatbots in educational settings. The findings of this study can serve as a catalyst for UTAR management to consider incorporating AI chatbots into their strategic planning for the future. The positive response data from participants underscores the value of AI chatbots for all related parties. UTAR management can leverage this information to implement AI chatbots within the academic framework, integrating them into the curriculum and relevant policies. To facilitate student adoption of AI Chatbots, UTAR management could offer classes to educate students on effectively utilizing AI chatbots or provide them with complimentary AI chatbot accounts. By taking these steps, UTAR can harness the potential of AI chatbots to enhance student learning experiences and stay at the forefront of technological advancement in education.

As a conclusion, the five factors in this study (PE, EE, SI, HT, and INFO) can affect the BI of university students toward using AI Chatbots. This research has significant ramifications because it provides a guideline for the management of universities to consider whether to propose the implementation of AI Chatbots in academic fields in future.

5.4 Limitations of Study

This study countered some of the limitations of the time-consuming to collect data from private and public universities in Malaysia due to each university being located in a different state. Therefore, the study has narrowed down instead of focusing on all Malaysian universities, where researchers targeted a private university focusing on two biggest programme clusters to represent all UTAR students.

During the first stage of collecting data for the whole study, getting high responses from targeted individuals is very difficult. This is because the questionnaire was distributed through online platforms such as Google form links to all targeted respondents. Furthermore, most students chose to ignore the messages as they were unwilling and lacked interest in the study or did not know the purpose and reason for completing this research. When researchers were focused on distributing the research survey through the online platform, only around 80 responses were collected within two weeks. In this regard, researchers have planned to distribute the research survey physically by showing QR codes to respondents. As a result, the survey responses have dramatically increased within several days to a number of 300 responses. Therefore, researchers have adopted both methods when distributing the research survey to targeted respondents.

Moreover, in this study, researchers only focus on 5 IVs. This is based on past studies and found that these 5 IVs are most relevant for student BI on these AI Chatbots. On the other hand, researchers have found that some of the responses did not fulfil the requirements of this study, which will decrease the number of respondents in this study. Hence, researchers took the initiative to go to the UTAR Sungai Long campus and request assistance from the Faculty General Office of both FAM and LKC FES in terms of distributing the research survey to targeted respondents through webmail or other platforms.

5.5 Recommendations for Future Research

This research encountered several limitations during the study. Here, researchers have provided recommendations and advice to all future researchers who are further researching or planning to conduct a similar study. Future researchers can expand their research to focus on more public and private universities in Malaysia. This can broaden the view of different types of university students, and the results will be more diversified and representative of the perspectives of Malaysian university students.

In this research, researchers overcame the limitation and found that the physical distribution of questionnaires was more effective than online distribution. Although researchers must attend the campuses to find targeted respondents physically, it allows researchers to understand the respondent's opinions through communication. Besides, conducting a physical collection of responses may reduce respondents' uncertainty or unwillingness, where researchers can do a short briefing about this research. As a result, it can attract the participant's attention to answer the research questionnaire. Therefore, it can be said that future researchers can adopt both methods to distribute questionnaires but should focus more on physical distribution instead of online distribution to increase effectiveness.

As the study only focused on 5 IVs, future researchers were suggested to add more IVs into their research, such as hedonic motivation, past experiences, and others. Therefore, various results and views can be obtained from different angles of IVs. Simply put, it allows researchers to view from different perspectives accurately. Lastly, future researchers can collaborate with targeted universities to help distribute questionnaires to the targeted students. It will save time and get the real targeted students to distribute the survey link or questionnaires more effectively, such as using networking, like requesting a lecturer to help find students to participate.

5.6 Conclusion

This research study has demonstrated that the independent variables (PE, EE, SI, HT, and INFO) significantly impact students' BI toward using AI Chatbots. These findings highlight the importance of these variables in shaping students' intentions regarding AI Chatbots usage. Besides, researchers have provided valuable recommendations for future studies to enhance the understanding of factors influencing BI toward AI Chatbots among students. The primary objectives of this research have been achieved, and the findings are not only beneficial to the educational sector but can also be applied to different contexts. In this research, PE is the most influential factor affecting students' BI toward AI Chatbots. However, it is crucial to recognize that the determinants of BI may evolve, reflecting the changing needs of students. Future researchers are encouraged to conduct in-depth analyses to ascertain the extent of these factors in various academic settings and identify emerging trends in student preferences. In light of this comparative research between UTAR students, future studies should delve deeper into understanding the nuanced variations in the factors affecting BI toward AI Chatbots within these distinct academic disciplines. Such analyses will contribute to a more comprehensive understanding of how specific variables may influence students' attitudes and BI in UTAR courses, offering tailored insights for educational institutions and stakeholders aiming to cater to the diverse needs of their student populations.

REFERENCES

Ajayi, V. O. (2017). Primary sources of data and secondary sources of data. *Benue State University*, *1*(1), 1-6.

Ajzen, I. (2002). Residual effects of past on later behavior: Habituation and reasoned action perspectives. *Personality & Social Psychology Review, 6*(2), 107-122. https://doi.org/10.1207/S15327957PSPR0602_02

Al-Emran, M., AlQudah, A. A., Abbasi, G. A., Al-Sharafi, M. A., & Iranmanesh, M. (2024). Determinants of using AI-based chatbots for knowledge sharing: evidence from PLS-SEM and fuzzy sets (fsQCA). *IEEE Transactions on Engineering Management.* 1-16. http://dx.doi.org/10.1109/TEM.2023.3237789

Alalwan, A. A., Dwivedi, Y. K., & Rana, N. P. (2017). Factors influencing adoption of mobile banking by Jordanian bank customers: Extending UTAUT2 with trust. *International Journal of Information Management*, *37*(3), 99-110. https://doi.org/10.1016/j.ijinfomgt.2017.01.002

Alalwan, A. A. (2018). Investigating the impact of social media advertising features on customer purchase intention. *International journal of information management*, *42*, 65-77. https://doi.org/10.1016/j.ijinfomgt.2018.06.001

Algerafi, M. A., Zhou, Y., Alfadda, H., & Wijaya, T. T. (2023). Understanding the factors influencing higher education students' intention to adopt artificial intelligence-based robots. *IEEE*, *11,* 99752-99764. http://dx.doi.org/10.1109/ACCESS.2023.3314499

Almahri, F. A. J., Bell, D., & Merhi, M. (2020). Understanding student acceptance and use of Chatbots in the United Kingdom universities: A structural equation modelling approach. *6th International Conference on Information Management (ICIM),* 284-288. https://doi.org/10.1109/ICIM49319.2020.244712

Almaiah, M. A., Alamri, M. M., & Al-Rahmi, W. (2019). Applying the UTAUT model to explain the students' acceptance of mobile learning system in higher education. *Ieee Access, 7,* 174673-174686. https://doi.org/10.1109/ACCESS.2019.2957206

An, X., Chai, C. S., Li, Y., Zhou, Y., Shen, X., Zheng, C., & Chen, M. (2022). Modeling English teachers' behavioral intention to use artificial intelligence in middle schools. *Education and Information Technologies, 28*(5), 5187-5208. https://doi.org/10.1007/s10639-022-11286-z

Andrade, I. M., & Tumelero, C. (2022). Increasing customer service efficiency through artificial intelligence chatbot. *Revista de Gestão, 29*(15-16), 238–251. http://dx.doi.org/10.1108/REGE-07-2021-0120

Arenas Gaitán, J., Peral Peral, B., & Ramón Jerónimo, M. (2015). Elderly and internet banking: An application of UTAUT2. *Journal of Internet Banking and Commerce, 20 (1), 1-23.* http://hdl.handle.net/11441/57220

Ashfaq, M., Yun, J., Yu, S., & Loureiro, S. M. C. (2020). I, Chatbot: Modeling the determinants of users' satisfaction and continuance intention of AI-powered service agents. *Telematics and Informatics, 54*, 1-17.

https://doi.org/10.1016/j.tele.2020.101473

Baptista, G., & Oliveira, T. (2015). Understanding mobile banking: The unified theory of acceptance and use of technology combined with cultural moderators. *Computer in Human Behavior, 50*, 418-430. https://doi.org/10.1016/j.chb.2015.04.024

Bilquise, G., Ibrahim, S., & Salhieh, S. E. M. (2023). Investigating student acceptance of an academic advising chatbot in higher education institutions. *Education and Information Technologies*, 1-26. https://doi.org/10.1007/s10639-023-12076-x

Boone Jr, H. N., & Boone, D. A. (2012). Analyzing likert data. *The Journal of extension*, *50*(2), 48. https://doi.org/10.34068/joe.50.02.48

Borrero J. D., Yousafzai S. Y., Javed U., Page K. L. (2014). Expressive participation in Internet social movements: Testing the moderating effect of technology readiness and sex on student SNS use. *Computers in Human Behavior, 30, 39–49.* https://doi.org/10.1016/j.chb.2013.07.032

Chatterjee, S., & Bhattacharjee, K. K. (2020). Adoption of artificial intelligence in higher education: A quantitative analysis using structural equation modelling. *Education and Information Technologies*, *25*, 3443-3463. https://doi.org/10.1007/s10639-020-10159-7

Chiu C. M., Wang E. T. (2008). Understanding Web-based learning continuance intention: The role of subjective task value. *Information and Management, 45(3), 194–201.* https://doi.org/10.1016/j.im.2008.02.003

Chua, P. Y., Rezaei, S., Gu, M. L., Oh, Y., & Jambulingam, M. (2018). Elucidating social networking apps decisions: Performance expectancy, effort expectancy and social influence. *Nankai Business Review International*, *9*(2), 118-142. https://doi.org/10.1108/NBRI-01-2017-0003

Costello, A.B. and Osborne, J.W. (2005), "Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis", Practical Assessment Research & Evaluation, Vol. 10 No. 7, pp. 1-9. https://doi.org/10.7275/jyj1-4868

Conrad, M. K., Upadhyaya, S., Joa, C. Y., & Dowd, J. (2015). Bridging the divide: Using UTAUT to predict multigenerational tablet adoption practices. *Computers in Human Behavior, 50*, 186-196. https://doi.org/10.1016%2Fj.chb.2015.03.032

Cortina, J. M. (1993). What is coefficient alpha? An examination of theory and applications. *Journal of Applied Psychology*, *78*(1), 98.

Dakduk, S., Santalla-Banderali, Z., & Van Der Woude, D. (2018). Acceptance of blended learning in executive education. *Sage Open*, *8*(3), https://doi.org/10.1177/2158244018800647

Davis F. D., Bagozzi R. P., Warshaw P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science, 35(8), 982–1003.* https://doi.org/10.1287/mnsc.35.8.982

Davis, F. D. (1985). *A technology acceptance model for empirically testing new end-user information systems: Theory and results* (Doctoral dissertation, Massachusetts Institute of Technology). http://hdl.handle.net/1721.1/15192

de Andrés-Sánchez, J., & Gené-Albesa, J. (2023). Explaining policyholders' chatbot acceptance with an Unified Technology Acceptance and Use of Technology-Based Model. *Journal of Theoretical and Applied Electronic Commerce Research*, *18*(3), 1217-1237. https://doi.org/10.3390/jtaer18030062

de Cosmo, L. M., Piper, L., & Di Vittorio, A. (2021). The role of attitude toward chatbots and privacy concern on the relationship between attitude toward mobile advertising and behavioral intent to use chatbots. *Italian Journal of Marketing*, *2021*, 83-102. https://doi.org/10.1007/s43039-021-00020-1

de Sá Siqueira, M. A., Müller, B. C. N., & Bosse, T. (2023). When do we accept mistakes from chatbots? The impact of human-like communication on user experience in chatbots that make mistakes. *International Journal of Human-Computer Interaction*, 1-11. https://doi.org/10.1080/10447318.2023.2175158

Dehghani, M., Niaki, M. K., Ramezani, I., & Sali, R. (2016). Evaluating the influence of YouTube advertising for attraction of young customers. *Computers in Human Behavior, 59*, 165-172. https://doi.org/10.1016/j.chb.2016.01.037

Department of Quality Assurance. (n.d.). Retrieved November, 2023, from https://dqa.utar.edu.my/MOE-MQA-Approvals--and--Accreditation.php

Delone, W., & McLean, E. (1992). Information systems success: The quest for the dependent variable. *Journal of Management Information, 3*(4), 60-95. https://doi.org/10.1287/isre.3.1.60

Dinh, C.-M., & Park, S. (2023). How to increase consumer intention to use Chatbots? An empirical analysis of hedonic and utilitarian motivations on social presence and the moderating effects of fear across generations. *Electronic Commerce Research.* https://doi.org/10.1007/s10660-022-09662-5

Doraiswamy, P. M., London, E., Varnum, P., Harvey, B., Saxena, S., Tottman, S., Campbell, P., Ibanez, A. F., Manji, H., & Al Olama, M. A. A. S. (2019). Empowering 8 billion minds: Enabling better mental health for all via the ethical adoption of technologies. *NAM perspectives*. https://doi.org/10.31478/201910b

Eeuwen, M, V. (2021). *Mobile conversational commerce: messenger chatbots as the next interface between businesses and consumers*. UNIVERSITY OF TWENTE. https://essay.utwente.nl/71706/1/van%20Eeuwen_MA_BMS.pdf

El-Masri, M., & Tarhini, A. (2017). Factors affecting the adoption of e-learning systems in Qatar and USA: Extending the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). *Educational Technology Research and Development*, *65*, 743-763. https://doi.org/10.1007/s11423-016-9508-8

Emon, M. M. H., Hassan, F., Nahid, M. H., & Rattanawiboonsom, V. (2023). Predicting adoption intention of artificial intelligence. *AIUB Journal of Science and Engineering (AJSE)*, *22*(2), 189-199. https://doi.org/10.53799/ajse.v22i2.797

Essel, H. B., Vlachopoulos, D., Tachie-Menson, A., Johnson, E. E., & Baah, P. K. (2022). The impact of a virtual teaching assistant (chatbot) on students' learning in Ghanaian higher education. *International Journal of Educational Technology in Higher Education*, *19*(1), 1-19. https://doi.org/10.1186/s41239-022-00362-6

Fadzil, F. H. (2018). A study on factors affecting the behavioral intention to use mobile apps in malaysia. *Social Science Research Network (SSRN).* http://dx.doi.org/10.2139/ssrn.3090753

Fishbein, M., & Ajzen, I. (2005). Theory-based behavior change interventions: Comments on Hobbis and Sutton. *Journal of health psychology, 10*(1), 27 31. https://doi.org/10.1177/1359105305048552

Fu, J. R., Lu, I. W., Chen, J. H., & Farn, C. K. (2020). Investigating consumers' online social shopping intention: An information processing perspective. *International Journal of Information Management, 54*, 102-189. http://dx.doi.org/10.1016/j.ijinfomgt.2020.102189

García de Blanes Sebastián, M., Sarmiento Guede, J. R., & Antonovica, A. (2022). Application and extension of the UTAUT2 model for determining behavioral intention factors in use of the artificial intelligence virtual assistants. *Frontiers in Psychology, 13*, 993935. https://doi.org/10.3389/fpsyg.2022.993935

Gatzioufa, P., & Saprikis, V. (2022). A literature review on users' behavioral intention toward chatbots' adoption. *Applied Computing and*

Informatics. https://doi.org/10.1108/ACI-01-2022-0021

George, T. (2023). Mixed Methods Research | Definition, Guide & Examples. *Scribbr*. https://www.scribbr.com/methodology/mixed-methods-research/

Ghalandari, K. (2012). The effect of performance expectancy, effort expectancy, social influence and facilitating conditions on acceptance of e-banking services in Iran: The moderating role of age and gender. *Middle-East Journal of Scientific Research*, *12*(6), 801-807. 10.5829/idosi.mejsr.2012.12.6.2536

Gümüş, N., & Çark, Ö. (2021). The effect of customers' attitudes towards Chatbots on their experience and behavioral intention in Turkey. *Interdisciplinary Description of Complex Systems 19*(3), 420-436. http://dx.doi.org/10.7906/indecs19.3.6

Gupta, M. S. (2023). *All the ChatGPT updates to know about.* Augustman. https://www.augustman.com/in/gear/tech/chatgpt-updates-to-know-about/#:~:text=Improved%20factuality%20and%20maths%20capabilities,improved%20factuality%20and%20mathematical%20capabilities

Hair, Jr., Money, A. H., Samouel, P., & Page, M. (2007). Research methods for business. Chichester. West Sussex: John Wiley & Sons, Inc.

Hameed, F., Qayyum, A., & Khan, F. A. (2022). A new trend of learning and teaching: Behavioral intention towards mobile learning. *Journal of Computers in Education*, 1-32. https://doi.org/10.1007%2Fs40692-022-00252-w

Heaven, W. D. (2023). *ChatGPT is going to change education, not destroy it.* MIT Technology Review. Retrieved July 10, 2023, from https://www.technologyreview.com/2023/04/06/1071059/chatgpt-change-not-destroy-education-openai/

Hern, A. (2022). *AI-assisted plagiarism? ChatGPT bot says it has an answer for that.* The Guardian. Retrieved July 10, 2023, from https://www.theguardian.com/technology/2022/dec/31/ai-assisted-plagiarism-chatgpt-bot-says-it-has-an-answer-for-that

Hien, H. T., Cuong, P. N., Nam, L. N. H., Nhuang, H. L. T. K., & Thang, L. D. (2018). Intelligent assistants in higher-education environments: The FIT-EBot, a chatbot for administrative and learning support. *In Proceedings of the 9th International Symposium on Information and Communication Technology*, 69-76. https://doi.org/10.1145/3287921.3287937

Hsieh, S. H., Lee, C. T., & Tseng, T. H. (2021). Branded app atmospherics: Examining the effect of pleasure–arousal–dominance in brand relationship building. *Journal of Retailing and Consumer Services, 60*(1), 1-11.https://doi.org/10.1016/j.jretconser.2021.102482

Huang, C. Y., & Kao, Y. S. (2015). UTAUT2 based predictions of factors influencing the technology acceptance of phablets by DNP. *Mathematical Problems in Engineering*, *2015*, 1-23. https://doi.org/10.1155/2015/603747

Hwang, G. J., & Chang, C. Y. (2021). A review of opportunities and challenges of chatbots in education. *Interactive Learning Environments*, *31*(7), 4099-4112.

https://doi.org/10.1080/10494820.2021.1952615

Ina. (2022). *The history of chatbots – from ELIZA to ChatGPT*. Onlim. https://onlim.com/en/the-historyofchatbots/#:~:text=History%20of%20chatbots%20%E2%80%93%20chatbot%20development,20th%20century%20later%20on

Introduction - Universiti Tunku Abdul Rahman. (n.d.). Retrieved August 12, 2023, from https://utar.edu.my/Introduction.php

Jan. I. U., Ji, S., & Kim, C. (2023). What (de) motivates customers to use AI-powered conversational agents for shopping? The extended behavioral reasoning perspective. *Journal of Retailing and Consumer Services, 75,* 1-16. https://doi.org/10.1016/j.jretconser.2023.103440

Kamita, T., Ito, T., Matsumoto, A., Munakata, T., & Inoue, T. (2019). A chatbot system for mental healthcare based on SAT counseling method. *Mobile Information Systems*, *2019*. https://doi.org/10.1155/2019/9517321

Kasilingam D. L. (2020). Understanding the attitude and intention to use smartphone chatbots for shopping. *Technology in Society, 62, 101280.* https://doi.org/10.1016/j.techsoc.2020.101280

Kementerian Kewangan. (2023). Belanjawan 2023 Malaysia Madani. https://belanjawan.mof.gov.my//pdf/belanjawan2023/ucapan/ub23-BI.pdf

Keong, W. E. Y. (2022). *Factors influencing adoption intention towards chatbot as a learning tool.* The International Conference on Social Sciences and Humanities. https://humanities.utm.my/ticssh2022/wpcontent/uploads/sites/108/2022/12/e-Proceeding-ICE2022.pdf#page=104

Kijsanayotin B., Pannarunothai S., Speedie S. M. (2009). Factors influencing health information technology adoption in Thailand's community health centers: Applying the UTAUT model. *International Journal of Medical Informatics, 78(6), 404–416.* https://doi.org/10.1016/j.ijmedinf.2008.12.005

Kim J. W., Jo H. I., Lee B. G. (2019). The study on the factors influencing on the behavioral intention of chatbot service for the financial sector: Focusing on the UTAUT model. *Journal of Digital Contents Society, 20(1), 41–50.*

Kim, H. W., Chan, H. C., & Gupta, S. (2007). Value-based adoption of mobile internet: An empirical investigation. *Decision Support Systems, 43*(1), 111–126. https://doi.org/10.1016/j.dss.2005.05.009

Kim, S. S., & Malhotra, N. (2005). A longitudinal model of continued is use: An integrative view of four mechanisms underlying post-adoption phenomena. *Management Science, 51*(5), 741-755. https://doi.org/10.1287/mnsc.1040.0326

Kooli, C. (2023). Chatbots in education and research: A critical examination of ethical implications and solutions. *Sustainability, 15*(7), 1-15. https://doi.org/10.3390/su15075614

Krejcie, R.V., & Morgan, D. W. (1970). Determining sample size for research activities. *Educational and Psychological Measurement, 30*, 607-610.

Kuberkar, S., & Singhal, T. K. (2020). Factors influencing adoption intention of AI powered chatbot for public transport services within a smart city.

International Journal of Emerging Technologies in Learning, *11*(3), 948-958.

Kułak, J. P., Trojanowski, M., & Barmentloo, E. (2019). A literature review of the partial unifiedtheory of acceptance and use of technology 2 (UTAUT2) model. *Annales Universitatis Mariae Curie-Skłodowska, sectio H–Oeconomia*, *53*(4), 101-113. https://doi.org/10.17951/h.2019.53.4.101-113

Kumar, J. A., & Silva, P. A. (2020). Work-in-progress: A preliminary study on students' acceptance of chatbots for studio-based learning. *2020 IEEE Global Engineering Education Conference (EDUCON), 1627-1631*. https://doi.org/10.1109/EDUCON45650.2020.9125183

Labadze, L., Grigolia, M., & Machaidze, L. (2023). Role of AI chatbots in education: systematic literature review. Int*ernational Journal of Educational Technology in Higher Education, 20*(56), 1-17. https://doi.org/10.1186/s41239-023-00426-1

Laumer, S., Maier, C., & Gubler, F. T. (2019). Chatbot acceptance in healthcare: Explaining user adoption of conversational agents for disease diagnosis. https://aisel.aisnet.org/ecis2019_rp/88

Lee, J., & Hong, I. B. (2016). Predicting positive user responses to social media advertising: The roles of emotional appeal, informativeness, and creativity. *International Journal of Information Management, 36*(3), 360-373. https://doi.org/10.1016/j.ijinfomgt.2016.01.001

Li, M., and J. Mao. (2015). "Hedonic or utilitarian? Exploring the impact of communication style alignment on user's perception of virtual health advisory services." *International Journal of Information Management, 35 (2), 229–243.* https://doi.org/10.1016/j.ijinfomgt.2014.12.004

Lian, J. W. (2015). Critical factors for cloud based e-invoice service adoption in Taiwan: An empirical study. *International Journal of Information Management*, *35*(1), 98-109. https://doi.org/10.1016/j.ijinfomgt.2014.10.005

Limayem, M., Hirt, S. G., & Cheung, C. M. (2007). How habit limits the predictive power of intention: The case of information systems continuance. *MIS Quarterly, 31*(4), 705- 737. https://doi.org/10.2307/25148817

Loeb, S., Dynarski, S., McFarland, D., Morris, P., Reardon, S., & Reber, S. (2017). Descriptive analysis in education: A guide for tesearchers. NCEE 2017-4023. *National Center for Education Evaluation and Regional Assistance*. http://ies.ed.gov/ncee/pubs/20174023/

Lowhorn, G. L. (2007, May). Qualitative and quantitative research: How to choose the best design. In *Academic Business World International Conference. Nashville, Tennessee*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2235986

Mallow, J. (2023). *ChatGPT for students: How AI Chatbots are revolutionizing education.* ELearning Industry. Retrieved July 10, 2023, from https://elearningindustry.com/chatgpt-for-students-how-ai-chatbots-are-revolutionizing-education#:~:text=The%20chatbot%20can%20interpret%20student,their%

20academic%20performance%20over%20time.

Martins, A. S. R., Quintana, A. C., & Quintana, C. G. (2021). Factors that influence the intention of using an app in higher education. *Revista Catarinense da Ciência Contábil*, *20*, e3193-e3193. https://doi.org/10.16930/2237-766220213193

Melián-González, S., Gutiérrez-Taño, D., & Bulchand-Gidumal, J. (2019). Predicting the intentions to use chatbots for travel and tourism. *Current Issues in Tourism*, 1-19. https://doi.org/10.1080/13683500.2019.1706457

Mendoza, S., Hernández-León, M., Sánchez-Adame, L. M., Rodríguez, J., Decouchant, D., & Meneses-Viveros, A. (2020). Supporting student-teacher interaction through a chatbot. Learning and Collaboration Technologies. *Human and Technology Ecosystems*, 93–107. https://doi.org/10.1007/978-3-030-50506-6_8

Merhi, M., Hone, K., & Tarhini, A. (2019). A cross-cultural study of the intention to use mobile banking between Lebanese and British consumers: Extending UTAUT2 with security, privacy and trust. *Technology in Society*, *59*, 101151. https://doi.org/10.1016/j.techsoc.2019.101151

Ministry of Economy Department of Statistics Malaysia Official Portal. (2021, February 9). *Services: Revenue for services sector fourth quarter 2020.* https://www.dosm.gov.my/portal-main/release-content/revenue-for-services-sector-fourth-quarter-2020

Ministry of Economy Department of Statistics Malaysia Official Portal. (2022, February 9). *Services: Revenue for services sector fourth quarter 2021.* Retrieved July 15, 2023, from https://www.dosm.gov.my/portal-main/release-content/revenue-for-services-sector-fourth-quarter-2021#:~:text=Total%20revenue%20of%20Services%20sector,9%20billion%3B%205.1%25

Moore G. C., Benbasat I. (2001). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information Systems Research, 2(3), 192–222.* https://doi.org/10.1287/isre.2.3.192

Moore, D. S., Notz, W. I, & Flinger, M. A. (2013). The basic practice of statistics (6th ed.). New York, NY: W. H. Freeman and Company. Page (138).

Morosan, C., & DeFranco, A. (2016). It's about time: Revisiting UTAUT2 to examine consumers' intentions to use NFC mobile payments in hotels. International Journal of Hospitality Management, 53, 17-29. https://doi.org/10.1016/j.ijhm.2015.11.003

Mogaji, E., Balakrishnan, J., Nwoba, A. C., & Nguyen, N. P. (2021). Emerging-market consumers' interactions with banking chatbots. *Telematics and Informatics*, *65*(2), 101-111. http://dx.doi.org/10.1016/j.tele.2021.101711

Molnár, G., & Szüts, Z. (2018, September). The role of chatbots in formal education. In *2018 IEEE 16th International Symposium on Intelligent Systems and Informatics (SISY)* (pp. 000197-000202). IEEE. https://doi.org/10.1109/SISY.2018.8524609

Muchran, M., & Ahmar, A. (2018). Application of TAM model to the use of information technology. *International Journal of Engineering & Technology*, 7(2), 37–40. https://arxiv.org/ftp/arxiv/papers/1901/1901.11358.pdf

Murphy, R. R. (2019). *Introduction to AI robotics*. MIT press.

Njeri-Otieno, G. (2022, November 14). SPSS Tutorial #4: Data cleaning in SPSS. *Resourceful Scholars' Hub*. Retrieved August 15, 2023, from https://resourcefulscholarshub.com/data-cleaning-in-spss/

Oliveira, T., Thomas, M. A., & Baptista, G. (2016). Mobile payment: Understanding the determinants of customer adoption and intention to recommend the technology. *Computers in Human Behavior, 61*(2), 404-414. https://doi.org/10.1016/j.chb.2016.03.030

Onaolapo, S., & Oyewole, O. (2018). Performance expectancy, effort expectancy, and facilitating conditions as factors influencing smart phones use for mobile learning by postgraduate students of the University of Ibadan, Nigeria. *Interdisciplinary Journal of e-Skills and Lifelong Learning, 14*(1), 95-115. https://doi.org/10.28945/4085

Ortiz, S. (2023). *The best AI chatbots: ChatGPT and other noteworthy alternatives.* ZDNET. Retrieved August 10, 2023, from https://www.zdnet.com/article/best-ai-chatbot/

Papacharissi, Z., & Mendelson, A. (2010). 12 Toward a new (er) sociability: uses, gratifications and social capital on Facebook. *Media perspectives for the 21st century, 212*. https://doi.org/10.4324/9780203834077

Pasadeos, Y. (1990). Perceived informativeness of and irritation with local advertising. *Journalism Quarterly, 67(1), 35–39.* https://doi.org/10.1177/107769909006700107

Pavlou, P., Liang, H., & Xue, Y. (2007). Understanding and mitigating uncertainty in online exchange relationships: A principal-agent perspective. *MIS Quarterly, 31*(1), 105-136. https://doi.org/10.2307/25148783

Ragheb, M. A., Tantawi, P., Farouk, N., & Hatata, A. (2022). Investigating the acceptance of applying chat-bot (Artificial intelligence) technology among higher education students in Egypt. *International Journal of Higher Education Management, 8*(2), 1-13. http://dx.doi.org/10.24052/IJHEM/V08N02/ART-1

Rahim, N. I. M., Iahad, N. A., Yusof, A. F., & Al-Sharafi, M. A. (2022). AI-Based chatbots adoption model for higher-education institutions: A hybrid PLS-SEM-Neural network modelling approach. *Sustainability*, *14*(19), 12726. https://doi.org/10.3390/su141912726

Rahm, E., & Do, H. H. (2000). Data cleaning: Problems and current approaches. *IEEE Data Eng. Bull.*, *23*(4), 3-13. https://www.researchgate.net/publication/220282831_Data_Cleaning_Problems_and_Current_Approaches

Rajaobelina, L., Tep, S. P., Arcand, M., & Ricard, L. (2021). Creepiness: Its antecedents and impact on loyalty when interacting with a chatbot. *Psychology and Marketing, 38*(2), 2339–

2356. http://dx.doi.org/10.1002/mar.21548

Ramu, M. M., Shaik, N., Arulprakash, P., Jha, S. K., & Nagesh, P. (2022). Study on potential AI applications in childhood education. *International Journal of Early Childhood Special Education, 14* (2), 10375-10382. 10.9756/INT-JECSE/V14I3.1215

Raman, A., & Don, Y. (2013). Preservice teachers' acceptance of learning management software: An application of the UTAUT2 model. *International Education Studies*, *6*(7), 157-164. https://doi.org/10.5539/ies.v6n7p157

Regan, P. M., & Jesse, J. (2019). Ethical challenges of edtech, big data and personalized learning: Twenty-first century student sorting and tracking. *Ethics and Information Technology, 21*, 167-179. https://doi.org/10.1007/s10676-018-9492-2

Reja, U., Manfreda, K. L., Hlebec, V., & Vehovar, V. (2003). Open-ended vs. close-ended questions in web questionnaires. *Developments in applied statistics*, *19*(1), 159-177. https://www.researchgate.net/publication/242672718_Open-ended_vs_Close-ended_Questions_in_Web_Questionnaires

Remian, D. (2019). Augmenting education: ethical considerations for incorporating artificial intelligence in education. https://scholarworks.umb.edu/instruction_capstone/52/

Rotzoll, K. B., & Haefner, J. E. (1990). Advertising in contemporary society (2nd ed.). Cincinnati, OH, South-Western Publishing.

Saini, N. (2023). ChatGPT becomes fastest growing app in the world, records 100mn users in 2 month. *Mint*. https://www.livemint.com/news/chatgpt-becomes-fastest-growing-app-in-the-world-records-100mn-users-in-2-month-11675484444142.html

Sandu, N., & Gide, E. (2019, September). Adoption of AI-Chatbots to enhance student learning experience in higher education in India. In *2019 18th International Conference on Information Technology Based Higher Education and Training (ITHET)* (pp. 1-5). IEEE. http://dx.doi.org/10.1109/ITHET46829.2019.8937382

Schober, P., Boer, C., & Schwarte, L. A. (2018). Correlation coefficients: appropriate use and interpretation. *Anesthesia & analgesia, 126*(5), 1763-1768. https://doi.org/10.1213/ANE.0000000000002864

Schmidt, A., Giannotti, F., Mackay, W., Shneiderman, B., & Vaananen, K. (2021). Artificial intelligence for humankind: A panel on how to create truly interactive and human-centered AI for the benefit of individuals and society. *IFIP Conference on Human- Computer Interaction*. 335-339

Self-Accreditation Malaysia Qualifications Agency. (n.d.). *Frequently asked questions (FAQs)*. Retrieved August 9, 2023, from, https://www2.mqa.gov.my/portal_swa/FAQ.cfm

Sekaran, U., & Bougie, R. (2016). *Research methods for business: A skill building approach*. john wiley & sons.

Shan C., Lu Y. (2009). Trust transference in mobile banking: An investigation of the initial trust [Conference session]. 2009 IITA International Conference on Services Science, Management and Engineering, Zhangjiajie, China. https://doi.org/10.1109/SSME.2009.123

SharifStudy. (2022). *Malaysia university ranking 2024.* Retrieved July 10, 2023, from https://sharifstudy.com/en/malaysia-university-ranking

Shwetarani. (2023). *The implications of CHAT GPT on the education sector.* Linkedin. Retrieved August 5, 2023, from https://www.linkedin.com/pulse/implications-chat-gpt-education-sector-shwetarani—1c#:~:text=Ethical%20Concerns%3A%20There%20are%20ethical,with%20relevant%20laws%20and%20regulations

Sitthipon, T., Kaewpuang, P., Jaipong, P., Sriboonruang, P., Siripipattanakul, S., & Auttawechasakoon, P. (2022). Artificial Intelligence (AI) adoption in the medical education during the digital era: A review article. *Review of Advanced Multidispliniary Science, Engineering & Innovation, 1*(2), 1-7. https://www.researchgate.net/publication/362146675_A_Review_of_Intentions_to_Use_Artificial_Intelligence_in_Big_Data_Analytics_for_Thailand_Agriculture

Sohn, K., Kwon, O., 2020. Technology acceptance theories and factors influencing artificial intelligence-based intelligent products. *Telematics and Informatics, 47*, 1-14. https://doi.org/10.1016/j.tele.2019.101324.

Stahl, B. C. (2021). Artificial intelligence for a better future: An ecosystem perspective on the ethics of AI and emerging digital technologies. *Springer*

Nature, 124 https://library.oapen.org/handle/20.500.12657/48228

Stahl, B. C., & Wright, D. (2018). Ethics and privacy in AI and big data: Implementing responsible research and innovation. *IEEE Security & Privacy*, *16*(3), 26-33. https://doi.org/10.1109/MSP.2018.2701164

Taddeo, M., Floridi, L., 2018. How AI can be a force for good. *Science, 361*(6404), 751–752. https://doi.org/10.1126/science.aat5991.

Tak, P., & Panwar, S. (2017). Using UTAUT 2 model to predict mobile app based shopping: evidences from India. *Journal of Indian Business Research*, 9(3), 248-264. https://doi.org/10.1108/JIBR-11-2016-0132

Tamilmani, K., Rana, N. P., Wamba, S. F., & Dwivedi, R. (2021). The extended Unified Theory of Acceptance and Use of Technology (UTAUT2): A systematic literature review and theory evaluation. *International Journal of Information Management*, *57*, 102269. http://hdl.handle.net/10454/18159

Tano, D. G., & Gidumal, J. B. (2019). Predicting the intentions to use chatbots for travel and tourism. *Taylor & Francis*, *24*(2), 192-210 https://doi.org/10.1080/13683500.2019.1706457

Tavakol, M., & Dennick, R. (2011). Making sense of cronbach's alpha. *International Journal of Medical Education*, *2*, 53. https://doi.org/10.5116/ijme.4dfb.8dfd

Tep, S. P., Arcand, M., Rajaobelina, L., & Ricard, L. (2021). From what is promised to what is experienced with intelligent bots. *Advances in Information and Communication, 1,* 560–565. http://dx.doi.org/10.1007/978-3-030-73100-

7_40

Terblanche, N., & Kidd, M. (2022). Adoption factors and moderating effects of age and gender that influence the intention to use a non-directive reflective coaching Chatbot. *SAGE Open*, 1-16. https://doi.org/10.1177/21582440221096136

Thompson, R. L., Higgins, C. A., & Howell, J. M. (1991). Personal computing: Toward a conceptual model of utilization. *MIS quarterly*, 125-143. Personal computing; https://doi.org/10.2307/249443

Tian, X., Risha, Z., Ahmed, I., Lekshmi Narayanan, A. B., & Biehl, J. (2021). Let's Talk It Out. *Proceedings of the ACM on Human-Computer Interaction*, 5(CSCW1), 1–32. https://doi.org/10.1145/3449171

Trivedi, J. P. (2019). Examining the customer experience of using banking chatbots and its impact on brand love: The moderating role of perceived risk. *Journal of Internet Commerce*, *18*(6), 1-21. https://doi.org/10.1080/15332861.2019.1567188

Turner, D. P. (2020). Sampling methods in research design. *Headache: The Journal of Head and Face Pain*, *60*(1), 8-12. https://doi.org/10.1111/head.13707

Turner, M., Kitchenham, B., Brereton, P., Charters, S. & Budgen, D. (2010). Does the technology acceptance model predict actual use? A systematic literature review. *Information and Software. Technology*, *52*(5), 463–479.

Uyanık, G. K., & Güler, N. (2013). A study on multiple linear regression analysis. *Procedia-Social and Behavioral Sciences*, *106*, 234-240.

https://doi.org/10.1016/j.sbspro.2013.12.027

Van Pinxteren, M. M., Pluymaekers, M., & Lemmink, J. G. (2020). Human-like communication in conversational agents: A literature review research agenda. *Journal of Service Management*, *31*(2), 203-225. http://dx.doi.org/10.1108/JOSM-06-2019-0175

Vassilakopoulou, P., Haug, A., Salvesen, L. M., & Pappas, I. O. (2023). Developing human/AI interactions for chat-based customer services: Lessons learned from the Norwegian government. *European Journal of Information Systems*, *32*(1), 10–22. https://doi.org/10.1080/0960085X.2022.2096490

Venkatesh, V. (2000). Determinants of perceived ease of use: integrating control, intrinsic motivation, and emotion into the technology acceptance model. *Information Systems Research*, *11*(4), 342-365.

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, *36*(1), 157-178. https://doi.org/10.2307/41410412

Wang, Y.-S., Wu, M.-C., & Wang, H.-Y. (2009). Investigating the determinants and age and gender differences in the acceptance of mobile learning. British Journal of Educational Technology, 40(1), 92–118. https://doi.org/10.1111/j.1467-8535.2007.00809.x

Wang, J., Hwang, G.-W., & Chang, C.-Y. (2021). Directions of the 100 most cited chatbot-related human behavior research: A review of academic publications. *Computers and Education: Artificial Intelligence*, 2, 100023. https://doi.org/10.1016/j.caeai.2021.100023

Wang, S. M., Huang, Y. K., & Wang, C. C. (2020). A model of consumer perception and behavioral intention for AI service. *International Conference on Management Science and Industrial Engineering*, 196-201. http://dx.doi.org/10.1145/3396743.3396791

Wagner, K., Nimmermann, F., & Schramm-Klein, H. (2019). Is it human? The role of anthropomorphism as a driver for the successful acceptance of digital voice assistants. http://hdl.handle.net/10125/59579

Webb, T. L., Sheeran, P., & Luszczynska, A. (2008). Planning to break unwanted habits: Habit strength moderates implementation intention effects on behaviour change. *British Journal of Social Psychology, 48*(3), 507–523. https://doi.org/10.1348/014466608X370591

Williams, A. (2023). Which London universities ban ChatGPT and AI chatbots? Evening Standard. https://www.standard.co.uk/tech/london-universities-ban-chatgpt-ai-chatbots-plagiarisation-b1065331.html

Williams, R. T. (2024). The ethical implications of using generative chatbots in higher education. *Frontiers, 8,* 1-8. https://doi.org/10.3389/feduc.2023.1331607

Xing, X., Song, M., Duan, Y., & Mou, J. (2022). Effects of different service failure types and recovery strategies on the consumer response mechanism of chatbots. *Technology in Society, 70*(5), 102049.

http://dx.doi.org/10.1016/j.techsoc.2022.102049

Xu, A., Liu, Z., Gua, Y., Sinha, V., & Akkiraju, R. (2017). A new chatbot for customer service on social media. *Conference Paper*. https://doi.org/10.1145/3025453.3025496

Xu, X. (2014). Understanding users' continued use of online games: An application of UTAUT2 in social network games. *The Sixth International Conferences on Advances in Multimedia (MMEDIA 2014)*, 58-65. https://www.researchgate.net/publication/285954564_Understanding_users'_continued_use_of_online_games_An_application_of_UTAUT2_in_social_network_games

Yablonsky, S., & Petersburg, S. (2017). *Concentration -Information Technologies and Innovation Management Artem Efremov Research advisor*. https://dspace.spbu.ru/bitstream/11701/9653/1/efremov_thesis_1_0_5.pdf

Yang, S., & Evans, C. (2019). Opportunities and challenges in using AI chatbots in higher education. *2019 3rd International Conference on Education and E-Learning (ICEEL). 79 -83.* https://doi.org/10.1145/3371647.3371659

Yen, C., & Chiang, M.-C. (2020). Trust me, If You can: a Study on the Factors That Influence Consumers' Purchase Intention Triggered by Chatbots Based on Brain Image Evidence and self-reported Assessments. *Behaviour & Information Technology, 40(11), 1–18. https://doi.org/10.1080/0144929X.2020.1743362*

Yin, J., Goh, T. T., Yang, B., & Xiaobin, Y. (2021). Conversation technology with micro-learning: The impact of chatbot-based learning on students' learning motivation and performance. *Journal of Educational Computing Research*, *59*(1), 154-177. https://doi.org/10.1177/0735633120952067

Yu C. S. (2012). Factors affecting individuals to adopt mobile banking: Empirical evidence from the UTAUT model. *Journal of Electronic Commerce Research, 13(2), 104–121.* https://www.researchgate.net/publication/298411901_Factors_affecting_individuals_to_adopt_mobile_banking_Empirical_evidence_from_the_utaut_model

Zarouali, B., Van den Broeck, E., Walrave, M., & Poels, K. (2018). Predicting consumer responses to a chatbot on Facebook. *Cyberpsychology, Behavior, and Social Networking*, *21*(8), 491–497. https://doi.org/10.1089/cyber.2017.0518

Zhou, T., Lu, Y., & Wang, B. (2010). Integrating TTF and UTAUT to explain mobile banking user adoption. *Computers in human behavior*, *26*(4), 760-767. https://doi.org/10.1016/j.chb.2010.01.013

Zikmund, W. G., Babin, B. J., Carr, J. C., & Griffin, M. (2013). Business Research Methods (9th ed.). New York: South-Western/Cengage Learning. https://dokumen.pub/business-research-methods-9thnbsped-8131518515.html

Appendices

Appendix 1: Sample size for given population

Table for Determining Sample Size from a Given Population

N	*S*	*N*	*S*	*N*	*S*
10	10	220	140	1200	291
15	14	230	144	1300	297
20	19	240	148	1400	302
25	24	250	152	1500	306
30	28	260	155	1600	310
35	32	270	159	1700	313
40	36	280	162	1800	317
45	40	290	165	1900	320
50	44	300	169	2000	322
55	48	320	175	2200	327
60	52	340	181	2400	331
65	56	360	186	2600	335
70	59	380	191	2800	338
75	63	400	196	3000	341
80	66	420	201	3500	346
85	70	440	205	4000	351
90	73	460	210	4500	354
95	76	480	214	5000	357
100	80	500	217	6000	361
110	86	550	226	7000	364
120	92	600	234	8000	367
130	97	650	242	9000	368
140	103	700	248	10000	370
150	108	750	254	15000	375
160	113	800	260	20000	377
170	118	850	265	30000	379
180	123	900	269	40000	380
190	127	950	274	50000	381
200	132	1000	278	75000	382
210	136	1100	285	1000000	384

Note.—*N* is population size.
S is sample size.

Appendix 2: Permission Letter

UNIVERSITI TUNKU ABDUL RAHMAN
Wholly Owned by UTAR Education Foundation (Company No. 578227-M)

Re: U/SERC/246/2022

26 September 2023

Dr Siti Fazilah Binti Abdul Shukor
Head, Department of Business and Public Administration
Faculty of Business and Finance
Universiti Tunku Abdul Rahman
Jalan Universiti, Bandar Baru Barat
31900 Kampar, Perak.

Dear Dr Siti Fazilah,

Ethical Approval For Research Project/Protocol

We refer to the application for ethical approval for your students' research projects from Bachelor of Business Administration (Hons) programme enrolled in course UBMZ3016. We are pleased to inform you that the application has been approved under Expedited Review.

The details of the research projects are as follows:

No.	Research Title	Student's Name	Supervisor's Name	Approval Validity
1.	A Study on Factors Affecting the Adoption of AI Chatbots Among Students' Perspectives in Malaysian Universities	1. Tan Zhi Yi 2. Woon Zheng De 3. Soo Yue Er 4. Kho Zong Wei	Dr Peter Tan Sin Howe	26 September 2023 – 25 September 2024
2.	Factors that Impact the Intention of Artificial Intelligence Adoption in Retail Industry Among Gen Z Employees in Malaysia	1. Pong Kai Ping 2. Wu Qiao Jie 3. Low Kai Yang 4. Chin Zhi Kang	Ms Norharyani Binti Adrus	
3.	Factors Affecting Female Employee Turnover in Fast-food Restaurants in Malaysia	1. Tang Pei Shan 2. Loke Jia Xuan 3. Loo Siew Mei 4. Tneh Kar Seng	Pn Che Natheera Banu Binti Syed Abdul Aziz	
4.	Impact of Personality Types on Transformational Leadership Effectiveness in Technology Startup Industry	1. Sean Kam Yu Xuan 2. Tan Dong Ye 3. Tan You Jun 4. Yeoh Jun Xiang	Mr Julian Teh Hong Leong	
5.	A Study on the Factors Affecting Work Engagement Among Employees in Fast Food Industry in Malaysia	1. Chan Ying Xuan 2. Choy Li Hua 3. Foo Wen Kei 4. Lai Hor Lay	Dr Azeyan Binti Awee	
6.	Impacts of Academic Resilience, Procrastination and Self-regulation on Student Engagement Among Undergraduates in a Malaysian Private University	1. Ng Huat Lin 2. Low Xiao Ying 3. Ng Shi Qin 4. Koghulan a/l Agilananath	Dr Ng Lee Peng	
7.	A Study on the Influence of Corporate Social Responsibility Dimensions on Employee Engagement in Banking Industry	1. Hew Kah Mun 2. Chen Yen Teng 3. Siak Wen Jing 4. Prem Kumar a/l Munusamy	Mr Kuek Thiam Yong	
8.	Leadership Styles' Effects on Students Performance in Extracurricular Activities and Academic Work	1. Beh Ze Feng 2. Leong Siu Chung 3. Ng Chan Hong 4. Taryshiniy a/p Sathivell	Ms Khairunnisa Binti Ishak	

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Website: www.utar.edu.my

No.	Research Title	Student's Name	Supervisor's Name	Approval Validity
9.	Factors Affecting Employee Turnover Intention Among Generation Z Workers in Fast-Food Industry	1. Lum Li Heng 2. Yap Chen Mun 3. Khor Wei Man 4. Too Jing Yu	Dr Tee Chee Wee	26 September 2023 – 25 September 2024
10.	The Relationship Study-Life Balance and Academic Performance	1. Ng Siao Wei 2. Yew Fang Yan 3. Cheoh Wen Hui 4. Kasturi Manikam	Pn Farhana Hanim Binti Mohsin	
11.	A Study on the Factors Affecting Students' Motivation in Learning Among UTAR Students	1. Angeline Cheam Ching Ie 2. Chia Khai Xin 3. Lee Ker Xin 4. Lee Min Yee	Ms Lim Yong Hooi	
12.	Factors Affecting Stress Among Private Universities Students	1. Hoo Min Wei 2. Tiong Hor Jie 3. Tay Wei Quan 4. Kogilavany Ravi Shanker	Ms Norhayati Binti Md Isa	

The conduct of this research is subject to the following:

(1) The participants' informed consent be obtained prior to the commencement of the research;

(2) Confidentiality of participants' personal data must be maintained; and

(3) Compliance with procedures set out in related policies of UTAR such as the UTAR Research Ethics and Code of Conduct, Code of Practice for Research Involving Humans and other related policies/guidelines.

(4) Written consent be obtained from the institution(s)/company(ies) in which the physical or/and online survey will be carried out, prior to the commencement of the research.

Should the students collect personal data of participants in their studies, please have the participants sign the attached Personal Data Protection Statement for records.

Thank you.

Yours sincerely,

Professor Ts Dr Faidz bin Abd Rahman
Chairman
UTAR Scientific and Ethical Review Committee

c.c Dean, Faculty of Business and Finance
Director, Institute of Postgraduate Studies and Research

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Appendix 3: Questionnaire

UNIVERSITI TUNKU ABDUL RAHMAN
FACULTY OF BUSINESS AND FINANCE (FBF)
BACHELOR OF BUSINESS ADMINISTRATION (HONS)
A Study on Factors Affecting the Behaviour Intention towards Using AI Chatbots among
Students' Perspectives in Private University

Dear respondents,

We are final year students from Universiti Tunku Abdul Rahman (UTAR). The purpose of this study for our final year project is to study factors affecting the behaviour intention towards using AI Chatbots among students' perspectives in private university. This study can help universities consider the option of adopting Chatbots in the education field.

There are (8) sections in this questionnaire. Section A is filter questions, Section B is on demographics. Section C, D, E, F, G, and H cover all of the variables in this study. Please read the instructions carefully before answering the questions. Please answer ALL questions in ALL sections. Completion of this questionnaire will take you approximately 2 to 4 minutes.

The information collected from you will be kept strictly private and confidential. All responses and findings will be used solely for academic purposes.

Your assistance in completing this questionnaire is very much appreciated. Thank you for your participation. If you have any questions regarding to this questionnaire, you may contact us at Microsoft Team or by E-mail.

Thank you very much for your cooperation and willingness to participate in this study.

If you have any enquiries, please do not hesitate to contact:

Name	Student ID	E-mail Address
Tan Zhi Yi	20ABB01043	gracezytan02@1utar.my
Woon Zheng De	21ABB01782	zhengde0930@1utar.my
Soo Yue Er	20ABB02252	yueersoo@1utar.my
Kho Zong Wei	20ABB01270	zongwei95361474@1utar.my

PERSONAL DATA PROTECTION NOTICE

Please be informed that in accordance with Personal Data Protection Act 2010 ("PDPA") which came into force on 15 November 2013, Universiti Tunku Abdul Rahman ("UTAR") is hereby bound to make notice and require consent in relation to collection, recording, storage, usage and retention of personal information.

Acknowledgement of Notice

☐ I have been notified and that I hereby understood, consented and agreed per UTAR above notice.

☐ I disagree, my personal data will not be processed. (End of the questionnaire, thank you)

Section A: Filter Questions
Please click on the appropriate box.

1. Education Level:

☐ Degree

☐ Others (End of the questionnaire, thank you)

2. Your program is:

☐ Bachelor of Business Administration (Honours)

☐ Bachelor of Business Administration (Honours) Banking and Finance

☐ Bachelor of Business Administration (Honours) Entrepreneurship

☐ Bachelor of Business Administration (Honours) Healthcare Management

☐ Bachelor of Business Administration (Honours) in Logistics and Supply Chain Management

☐ Bachelor of Business Administration (Honours) Retail Management

☐ Bachelor of Business Administration (Honours) Risk Management

☐ Bachelor of Business Administration (Honours) Tourism Destination Marketing

☐ Bachelor of Marketing (Honours)

☐ Bachelor of International Business (Honours)

☐ Bachelor of Computer Science (Honours)

☐ Bachelor of Information System (Honours) Business Information Systems

☐ Bachelor of Information System (Honours) Digital Economy Technology

☐ Bachelor of Information System (Honours) Information Systems Engineering

☐ Bachelor of Information Technology (Honours) Communications and Networking

☐ Bachelor of Information Technology (Honours) Computer Engineering

☐ Bachelor of Information Technology (Honours) Industrial Intelligence Systems

☐ Bachelor Science (Honours) Software Engineering

☐ Others (End of the questionnaire, thank you)

3. Do you have experience in using AI Chatbots?

☐ Yes

☐ No (End of the questionnaire, thank you)

4. Which AI Chatbots that you use? Can choose more than one.

☐ ChatGPT

☐ Google Bard

☐ Microsoft Bing AI

☐ Meta BlenderBot

☐ Others

5. How frequently do you use AI Chatbots? (Per week)

☐ Less than 5 times

☐ 5 to 10 times

☐ 11 to 20 times

☐ More than 20 times

Section B: Demographic Profile
Please click on the appropriate box.

1. Gender

☐ Male

☐ Female

2. Age

☐ 17 and below

☐ 18 - 20

☐ 21 - 23

☐ 24 and older

3. Ethnic Group

☐ Chinese

☐ Malay

☐ Indian

☐ Others

4. Year of Study

☐ Year 1

☐ Year 2

☐ Year 3

☐ Year 4

☐ Year 5

☐ Others

Section C: Behaviour Intention

Based on your experience, please choose the most appropriate option that best indicate your agreement level about the following statement.

Following are the five points Likert scale response framework:

1= Strongly disagree
2= Disagree
3= Neutral
4= Agree
5= Strongly agree

Behaviour Intention refers to the willingness of users to accept, use, purchase, or try on using AI Chatbots.

No.	Questions	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1.	I believe AI Chatbots is very easy to learn by beginner.	**1**	**2**	**3**	**4**	**5**

2.	I am willing to learn the experience of AI education application from others.	**1**	**2**	**3**	**4**	**5**
3.	I am willing to learn the case of AI education application from the internet.	**1**	**2**	**3**	**4**	**5**
4.	I am happy to share my AI experience with others.	**1**	**2**	**3**	**4**	**5**
5.	I will use AI Chatbots to solve problems related to my academic query.	**1**	**2**	**3**	**4**	**5**
6.	I will recommend others to use AI Chatbots for academic matters.	**1**	**2**	**3**	**4**	**5**
7.	I intend to use AI in learning or teaching in the future.	**1**	**2**	**3**	**4**	**5**
8.	I plan to use AI Chatbots frequently.	**1**	**2**	**3**	**4**	**5**

Section D: Performance Expectancy
Based on your experience, please choose the most appropriate option that best indicate your agreement level about the following statement.

Performance Expectancy refers to which you can get the exact answers or adequate information generated by AI Chatbots, thus enhancing your academic performance.

No.	**Questions**	**Strongly Disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
1.	I find AI Chatbots to be useful in my daily life.	**1**	**2**	**3**	**4**	**5**
2.	Using AI Chatbots enables me to accomplish tasks more quickly.	**1**	**2**	**3**	**4**	**5**
3.	Using AI Chatbots increases my productivity.	**1**	**2**	**3**	**4**	**5**
4.	Using AI Chatbots increases my chances of achieving information that is important to me.	**1**	**2**	**3**	**4**	**5**
5.	The use of AI Chatbots will improve my academic performance.	**1**	**2**	**3**	**4**	**5**

Section E: Effort Expectancy
Based on your experience, please choose the most appropriate option that best indicate your agreement level about the following statement.

Effort Expectancy refers to how effortlessly you interact with AI Chatbots and obtain assistance from AI Chatbots.

No.	Questions	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1.	Learning to operate AI Chatbots is easy for me.	1	2	3	4	5
2.	My interaction with AI Chatbots would be clear and understandable.	1	2	3	4	5
3.	It would be easy for me to become skilful at using AI Chatbots.	1	2	3	4	5
4.	I do require much technical expertise to effectively use AI Chatbots.	1	2	3	4	5

Section F: Social Influence
Based on your experience, please choose the most appropriate option that best indicate your agreement level about the following statement.

Social Influence refers to colleagues, instructors, and friends that are likely to influence your decision on whether or not to use AI Chatbots.

No.	Questions	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1.	People who are important to me think that I should use AI Chatbots.	1	2	3	4	5
2.	People who influence my behavior think that I should use AI Chatbots.	1	2	3	4	5
3.	I would use AI Chatbots because a proportion of my friends use AI Chatbots.	1	2	3	4	5
4.	Using AI Chatbots will be a status symbol in my social networks. (e.g., friends, and family)	1	2	3	4	5
5.	In general, university has supported use of AI Chatbots for academic purposes.	1	2	3	4	5

Section G: Habit

Based on your experience, please choose the most appropriate option that best indicate your agreement level about the following statement.

Habit refers to the automatic integration of AI Chatbots into your academic routines due to consistent and repetitive use.

No.	Questions	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1.	The use of AI Chatbots has become a habit for me.	**1**	**2**	**3**	**4**	**5**
2.	Using AI Chatbots has become natural to me.	**1**	**2**	**3**	**4**	**5**
3.	I am addicted to using AI Chatbots.	**1**	**2**	**3**	**4**	**5**
4.	I must use AI Chatbots.	**1**	**2**	**3**	**4**	**5**

Section H: Informativeness

Based on your experience, please choose the most appropriate option that best indicate your agreement level about the following statement.

Informativeness refers to the perception that AI Chatbots provide accurate, relevant, and useful information to you, enhancing your understanding and aiding in your academic pursuits.

No.	Questions	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1.	AI Chatbots provide timely information.	**1**	**2**	**3**	**4**	**5**
2.	AI Chatbots are a convenient source of information.	**1**	**2**	**3**	**4**	**5**
3.	AI Chatbots supply complete information for my question.	**1**	**2**	**3**	**4**	**5**
4.	AI Chatbots supply relevant information for my question.	**1**	**2**	**3**	**4**	**5**

Thank you very much for your participation.

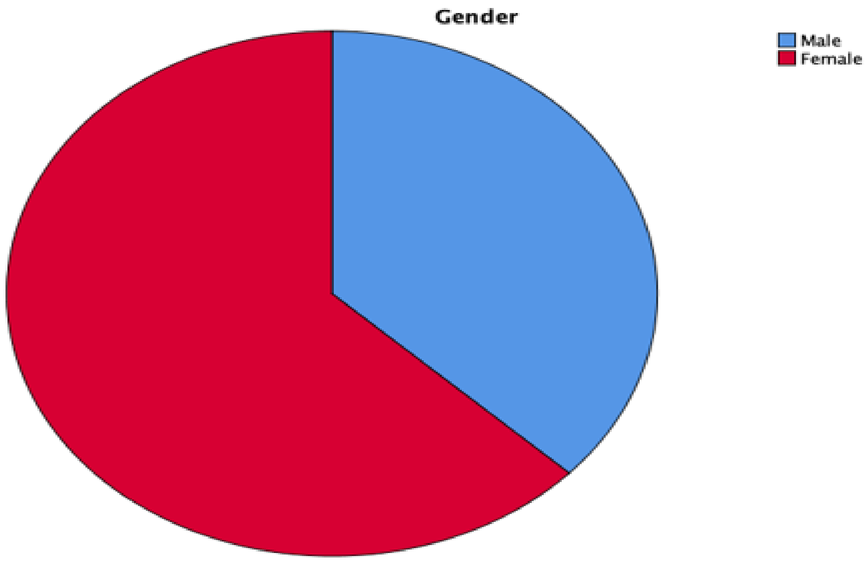
Your time and opinion are greatly appreciated!

Appendix 4: Descriptive Analysis

Demographic Profile: Gender

Gender

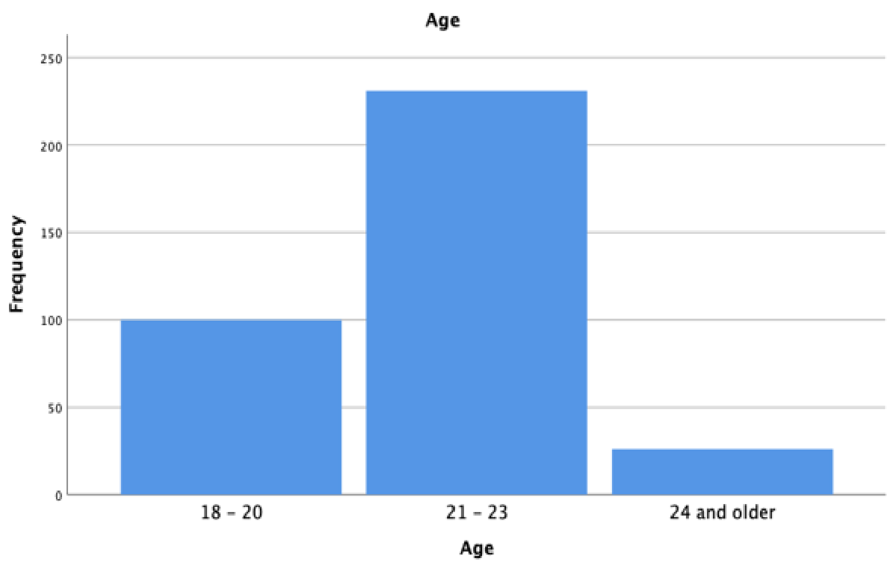
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	132	37.0	37.0	37.0
	Female	225	63.0	63.0	100.0
	Total	357	100.0	100.0	



Demographic Profile: Age

Age

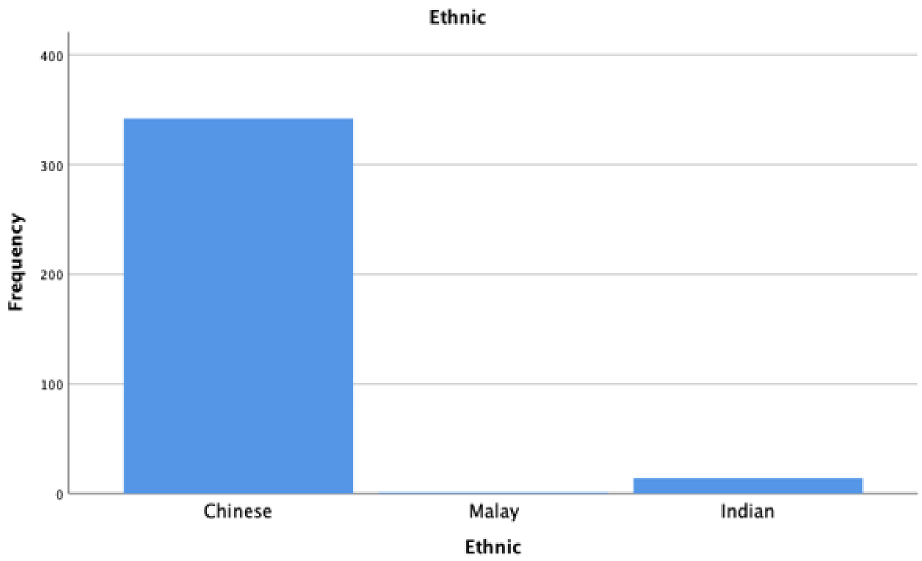
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	18 – 20	100	28.0	28.0	28.0
	21 – 23	231	64.7	64.7	92.7
	24 and older	26	7.3	7.3	100.0
	Total	357	100.0	100.0	



Demographic Profile: Ethnic Group

Ethnic

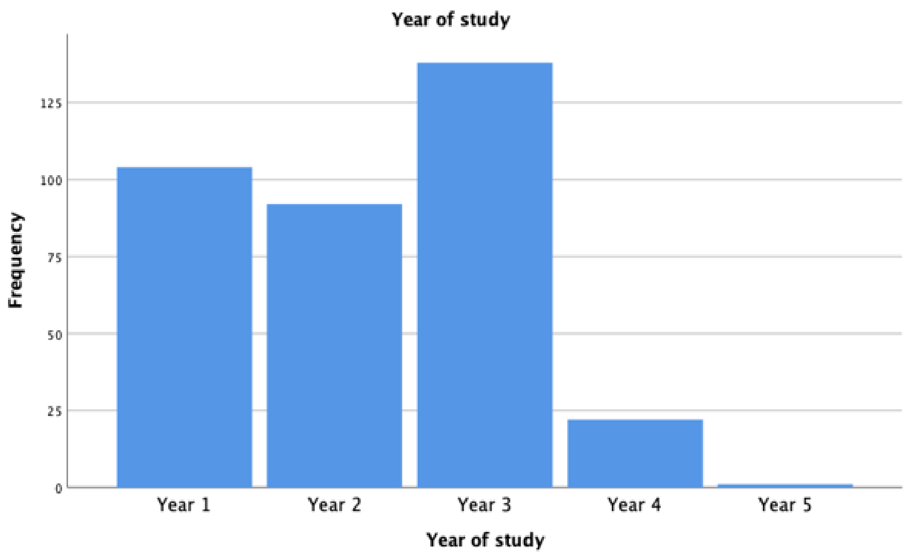
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Chinese	342	95.8	95.8	95.8
	Malay	1	.3	.3	96.1
	Indian	14	3.9	3.9	100.0
	Total	357	100.0	100.0	



Demographic Profile: Year of Study

Year of study

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Year 1	104	29.1	29.1	29.1
	Year 2	92	25.8	25.8	54.9
	Year 3	138	38.7	38.7	93.6
	Year 4	22	6.2	6.2	99.7
	Year 5	1	.3	.3	100.0
	Total	357	100.0	100.0	



Appendix 5: Reliability Test for Pilot Study

Dependent Variable: Behavioural Intention

```
RELIABILITY
  /VARIABLES=BI1 BI2 BI3 BI4 BI5 BI6 BI7 BI8
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /STATISTICS=SCALE CORR
  /SUMMARY=TOTAL.
```

Reliability

[DataSet0]

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	50	100.0
	Excluded[a]	0	.0
	Total	50	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.850	.858	8

Inter-Item Correlation Matrix

	Easy for beginner	Learn from others	Learn from internet	Share with others	Solve problem (academic)	Recommend for academic	Use in future	Plan use frequently
Easy for beginner	1.000	.444	.310	.416	.641	.408	.377	.227
Learn from others	.444	1.000	.537	.441	.276	.365	.506	.306
Learn from internet	.310	.537	1.000	.693	.232	.428	.336	.313
Share with others	.416	.441	.693	1.000	.398	.429	.445	.176
Solve problem (academic)	.641	.276	.232	.398	1.000	.649	.579	.423
Recommend for academic	.408	.365	.428	.429	.649	1.000	.658	.480
Use in future	.377	.506	.336	.445	.579	.658	1.000	.552
Plan use frequently	.227	.306	.313	.176	.423	.480	.552	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Easy for beginner	29.3400	16.351	.539	.518	.838
Learn from others	29.4200	16.493	.574	.482	.835
Learn from internet	29.5800	14.779	.559	.625	.837
Share with others	29.5200	15.479	.595	.599	.831
Solve problem (academic)	29.3400	15.698	.638	.656	.827
Recommend for academic	29.4200	14.698	.699	.591	.818
Use in future	29.3800	14.608	.704	.628	.817
Plan use frequently	29.7600	14.839	.490	.405	.850

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
33.6800	19.651	4.43290	8

Independent Variable: Performance Expectancy

```
RELIABILITY
  /VARIABLES=PE1 PE2 PE3 PE4 PE5
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /STATISTICS=SCALE CORR
  /SUMMARY=TOTAL.
```

Reliability

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	50	100.0
	Excluded[a]	0	.0
	Total	50	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.866	.878	5

Inter-Item Correlation Matrix

	Useful in daily life	Accomplish task quickly	Increase productivity	Increase achieve information	Improve performance
Useful in daily life	1.000	.596	.569	.597	.707
Accomplish task quickly	.596	1.000	.665	.543	.553
Increase productivity	.569	.665	1.000	.415	.628
Increase achieve information	.597	.543	.415	1.000	.633
Improve performance	.707	.553	.628	.633	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Useful in daily life	17.3200	5.202	.750	.580	.828
Accomplish task quickly	16.8600	6.735	.697	.549	.840
Increase productivity	16.9400	6.996	.661	.553	.850
Increase achieve information	17.1400	5.756	.656	.487	.851
Improve performance	17.1800	6.191	.776	.631	.818

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
21.3600	9.337	3.05567	5

Independent Variable: Effort Expectancy

```
RELIABILITY
  /VARIABLES=EE1 EE2 EE3 EE4
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /STATISTICS=SCALE CORR
  /SUMMARY=TOTAL.
```

Reliability

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	50	100.0
	Excluded[a]	0	.0
	Total	50	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.794	.811	4

Inter-Item Correlation Matrix

	Easy operate	Interact clear	Skilful	Technical expertise effective
Easy operate	1.000	.551	.628	.321
Interact clear	.551	1.000	.595	.483
Skilful	.628	.595	1.000	.529
Technical expertise effective	.321	.483	.529	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Easy operate	12.6000	4.408	.586	.448	.765
Interact clear	12.8800	3.332	.658	.447	.715
Skilful	12.8000	3.673	.720	.546	.691
Technical expertise effective	12.8400	3.402	.532	.330	.797

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
17.0400	6.162	2.48226	4

Independent Variable: Social Influence

```
RELIABILITY
  /VARIABLES=SC1 SC2 SC3 SC4 SC5
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /STATISTICS=SCALE CORR
  /SUMMARY=TOTAL.
```

Reliability

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	50	100.0
	Excluded[a]	0	.0
	Total	50	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.833	.843	5

Inter-Item Correlation Matrix

	People important	People behavior	Friends	Symbol in social network	University support
People important	1.000	.753	.769	.505	.365
People behavior	.753	1.000	.792	.438	.363
Friends	.769	.792	1.000	.513	.288
Symbol in social network	.505	.438	.513	1.000	.397
University support	.365	.363	.288	.397	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
People important	15.4000	10.898	.764	.665	.769
People behavior	15.3000	10.582	.736	.687	.772
Friends	15.3000	10.622	.750	.713	.769
Symbol in social network	15.7600	10.104	.567	.346	.830
University support	15.3600	12.358	.423	.219	.854

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
19.2800	16.369	4.04586	5

Independent Variable: Habit

```
RELIABILITY
  /VARIABLES=Habit1 Habit2 Habit3 Habit4
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /STATISTICS=SCALE CORR
  /SUMMARY=TOTAL.
```

Reliability

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	50	100.0
	Excluded[a]	0	.0
	Total	50	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.871	.872	4

Inter-Item Correlation Matrix

	Habit	Natural	Addict	Must use
Habit	1.000	.621	.709	.570
Natural	.621	1.000	.553	.520
Addict	.709	.553	1.000	.807
Must use	.570	.520	.807	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Habit	10.7400	8.727	.724	.580	.835
Natural	10.5400	9.886	.630	.428	.871
Addict	10.9400	7.935	.830	.743	.790
Must use	11.0400	7.753	.737	.661	.834

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
14.4200	14.616	3.82308	4

Independent Variable: Informativeness

```
RELIABILITY
  /VARIABLES=Info1 Info2 Info3 Info4
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /STATISTICS=SCALE CORR
  /SUMMARY=TOTAL.
```

Reliability

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	50	100.0
	Excluded[a]	0	.0
	Total	50	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.763	.780	4

Inter-Item Correlation Matrix

	Timely info	Convenient	Complete	Relevant
Timely info	1.000	.374	.473	.339
Convenient	.374	1.000	.488	.438
Complete	.473	.488	1.000	.708
Relevant	.339	.438	.708	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Timely info	12.3600	4.031	.475	.251	.783
Convenient	11.8800	4.965	.525	.282	.727
Complete	12.1000	4.255	.711	.581	.629
Relevant	12.0800	4.687	.603	.512	.689

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
16.1400	7.388	2.71812	4

Appendix 6: Reliability Test for Actual Study

Dependent Variable: Behavioural Intention

Descriptives

Descriptive Statistics

	N	Mean	Std. Deviation
Easy for beginner	357	4.2241	.82461
Learn from others	357	4.1653	.79190
Learn from internet	357	4.1204	.81043
Share with others	357	4.0756	.89781
Solve problem (academic)	357	4.2073	.78730
Recommend for academic	357	4.1317	.83264
Use in future	357	4.1232	.84895
Plan use frequently	357	3.8739	1.00745
Valid N (listwise)	357		

Independent Variable: Performance Expectancy

Descriptives

Descriptive Statistics

	N	Mean	Std. Deviation
Useful in daily life	357	4.0196	.89138
Accomplish task quickly	357	4.2689	.76471
Increase productivity	357	4.2269	.79786
Increase achieve information	357	4.1289	.83812
Improve performance	357	4.0364	.86200
Valid N (listwise)	357		

Independent Variable: Effort Expectancy

Descriptives

Descriptive Statistics

	N	Mean	Std. Deviation
Easy operate	357	4.1401	.79499
Interact clear	357	4.0700	.80944
Skilful	357	4.0728	.81438
Technical expertise effective	357	3.9692	.96084
Valid N (listwise)	357		

Independent Variable: Social Influence

Descriptives

Descriptive Statistics

	N	Mean	Std. Deviation
People important	357	3.6443	1.05178
People behavior	357	3.7367	1.02394
Friends	357	3.8095	1.02366
Symbol in social network	357	3.5322	1.20728
University support	357	3.8039	1.02260
Valid N (listwise)	357		

Independent Variable: Habit

Descriptives

Descriptive Statistics

	N	Mean	Std. Deviation
Habit	357	3.6050	1.09045
Natural	357	3.7927	1.02587
Addict	357	3.3473	1.23948
Must use	357	3.2521	1.29531
Valid N (listwise)	357		

Independent Variable: Informativeness

Descriptives

Descriptive Statistics

	N	Mean	Std. Deviation
Timely info	357	3.7283	1.03945
Convenient	357	4.0896	.86299
Complete	357	3.8039	.99193
Relevant	357	3.9580	.85521
Valid N (listwise)	357		

Appendix 7: Pearson Correlation Coefficient Analysis

Performance Expectancy with Behavioural Intention

Correlations

Correlations

		Behavioural Intention	Performance Expectancy
Behavioural Intention	Pearson Correlation	1	.783**
	Sig. (2-tailed)		.000
	N	357	357
Performance Expectancy	Pearson Correlation	.783**	1
	Sig. (2-tailed)	.000	
	N	357	357

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

Effort Expectancy with Behavioural Intention

Correlations

Correlations

		Behavioural Intention	Effort Expectancy
Behavioural Intention	Pearson Correlation	1	.723**
	Sig. (2-tailed)		.000
	N	357	357
Effort Expectancy	Pearson Correlation	.723**	1
	Sig. (2-tailed)	.000	
	N	357	357

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

Social Influence with Behavioural Intention

Correlations

Correlations

		Behavioural Intention	Social Influence
Behavioural Intention	Pearson Correlation	1	.602**
	Sig. (2-tailed)		.000
	N	357	357
Social Influence	Pearson Correlation	.602**	1
	Sig. (2-tailed)	.000	
	N	357	357

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

Habit with Behavioural Intention

Correlations

Correlations

		Behavioural Intention	Habit
Behavioural Intention	Pearson Correlation	1	.547**
	Sig. (2-tailed)		.000
	N	357	357
Habit	Pearson Correlation	.547**	1
	Sig. (2-tailed)	.000	
	N	357	357

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

Informativeness with Behavioural Intention

Correlations

Correlations

		Behavioural Intention	Informativen ess
Behavioural Intention	Pearson Correlation	1	.558**
	Sig. (2-tailed)		.000
	N	357	357
Informativeness	Pearson Correlation	.558**	1
	Sig. (2-tailed)	.000	
	N	357	357

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

Appendix 8: Multiple Linear Regression Analysis

Regression

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Informativeness, Habit, Effort Expectancy, Social Influence, Performance Expectancy[b]	.	Enter

a. Dependent Variable: Behavioural Intention

b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.819[a]	.670	.665	.35995

a. Predictors: (Constant), Informativeness, Habit, Effort Expectancy, Social Influence, Performance Expectancy

b. Dependent Variable: Behavioural Intention

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	92.364	5	18.473	142.576	.000[b]
	Residual	45.477	351	.130		
	Total	137.841	356			

a. Dependent Variable: Behavioural Intention

b. Predictors: (Constant), Informativeness, Habit, Effort Expectancy, Social Influence, Performance Expectancy

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.837	.129		6.468	.000
	Performance Expectancy	.451	.045	.493	10.012	.000
	Effort Expectancy	.264	.046	.280	5.689	.000
	Social Influence	.036	.036	.050	1.014	.311
	Habit	.059	.027	.095	2.171	.031
	Informativeness	-9.455E-6	.036	.000	.000	1.000

a. Dependent Variable: Behavioural Intention

Casewise Diagnostics[a]

Case Number	Std. Residual	Behavioural Intention	Predicted Value	Residual
154	-3.529	3.38	4.6453	-1.27028
315	3.285	4.88	3.6926	1.18239
324	4.256	4.50	2.9681	1.53192
326	-3.160	3.75	4.8874	-1.13743
336	3.777	5.00	3.6404	1.35963

a. Dependent Variable: Behavioural Intention

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1.7934	4.8874	4.1152	.50936	357
Residual	-1.27028	1.53192	.00000	.35741	357
Std. Predicted Value	-4.558	1.516	.000	1.000	357
Std. Residual	-3.529	4.256	.000	.993	357

a. Dependent Variable: Behavioural Intention