Factors Influencing the Continued Usage Intention of AI-Powered Tools Among University Students

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Approval

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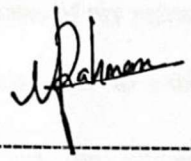
II. Declaration

It hereby declares that **I** have done this thesis under the supervision of **Ms. Nusrat Jahan**, Head, Department of Information Technology and Management, Daffodil International University. It also declares that neither this thesis nor any part of this has been submitted elsewhere for the award of any degree.



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Abstract

This study investigates the factors influencing the continued usage intention of AI-powered tools among university students in Bangladesh, utilizing an extended Theory of Planned Behavior (TPB) framework. The research integrates constructs such as trust in AI, perceived usefulness, interpersonal influence, social media influence, self-efficacy, and technological infrastructure to provide a comprehensive understanding of students' adoption behaviors. A quantitative, cross-sectional survey was conducted with 250 university students, employing stratified random sampling to ensure diverse representation. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) to test the hypothesized relationships.

The findings reveal that perceived usefulness, interpersonal influence, self-efficacy, and positive attitude significantly enhance students' continuous intention to use AI-powered tools. In contrast, trust in AI and technological infrastructure did not demonstrate a statistically significant effect in this context. The results underscore the importance of social and individual factors over technical aspects in driving sustained engagement with AI technologies in higher education. These insights offer valuable guidance for educators, policymakers, and technology developers aiming to maximize the benefits of AI integration in academic settings. The study also highlights limitations and suggests avenues for future research, including the need for longitudinal and cross-cultural studies to further explore evolving patterns of AI adoption among university students.

Chapter 1

Introduction

Artificial Intelligence (AI) is a system designed for computers to act, think, and learn like humans. AI can extract meaning from vast data sets, detect patterns, and respond to inputs. It can be applied in any industry, including education (Yu et al., 2024). The integration of AI-based learning tools into education has revolutionized the old school model, providing the new generation of learners with new means to learn, analyze, and use knowledge (Soundararajan, 2025). With these benefits, these applications take advantage of NLP, machine learning, and automation to facilitate a wide range of academic activities (Almufarreh, 2024).

AI-based tools are increasingly incorporated into higher education institutions globally, with 86% of students worldwide using artificial intelligence (AI) in their studies (Digital Education Council, 2024). Such platforms offer a very responsive learning experience, where AI modifies educational material depending on the progress of students, making studying more interactive and interesting (Tewari, 2024). AI tutors and chatbots help resolve queries instantaneously, minimizing reliance on teachers as well as promoting self-learning (Mittal, 2024).

AI/ML has recently become a disruptive force in the education space, enabling personalized learning experiences for students. AI-based tools such as ChatGPT, Grammarly, Turnitin, and AI-supported tutoring systems offer support to students in writing, research work, plagiarism detection, and even coding (Rahman et al., 2023). These apps help students write better-structured essays, paraphrase information, and

provide them with real-time feedback. For instance, Grammarly improves academic writing by providing recommendations for grammar, syntax, and style, while Turnitin helps identify any form of plagiarism and promotes ethics in academia (Wang et al., 2024). Furthermore, AI-backed language learning apps, including but not limited to Duolingo, alongside AI-powered coding platforms such as GitHub Copilot, all enhance the quality of students' academic experiences (Maheshwari, 2024).

AI learning tools have been attracting much attention in Bangladesh due to good internet connections, growing government digital education projects, and the demand for more effective ways of studying (Rahman et al., 2023). The government introduced a number of digital education initiatives in an effort to introduce AI-based solutions at public universities (Bhuiyan, 2024). Schools and colleges have increasingly been incorporating technology-based pedagogies, providing students with opportunities to use AI-assisted tools for research, personalized training, and follow-up self-study (Maheshwari, 2024). AI's spread into education signifies a transition from the traditional way of learning to a technology-intensive, interactive, and adaptive learning environment, which redefines how users gain and use knowledge (Wang et al., 2024).

Despite the recent uptake of AI tools in university education, long-term acceptance and use are still underexplored. Although some students adopt AI as part of their academic routine, whether these behaviors persist is influenced by multilateral factors (i.e., trust, perceived usefulness, social influence, and perceived behavioral control) (Wang et al., 2024). However, trust is paramount for AI systems: students’ trust in the robustness and ethical concerns of AI products when they trust them drives their inclination to use these tools further (Rodway & Schepman, 2023). Misinformation, threats to privacy, and data

security cause students to be wary of fully trusting AI-enabled solutions (Hamilton, 2024). A report discovered that more than 46% of parents with children use data privacy as the main concern when dealing with AI-powered educational tools, indicating a key barrier to adoption (Norton, 2024).

Furthermore, the perceived credibility of content generated by AI is also an important factor in determining its acceptability among students. A number of students are concerned that AI tools will restrict their creativity and critical thinking abilities, while others worry about issues like plagiarism and the legitimacy of projects that have been assisted by AI (Pokryshen, 2024). The digital literacy gap also hampers AI adoption, especially for students in rural areas with less access to technological resources (Tzeng et al., 2022). According to the literature, differences in students' AI awareness and proficiency also affect their capacity to critically assess outputs created by AI (Saqr et al., 2024). As reported by AP News (2024), AI-powered learning tools have the potential to either close or widen the digital divide depending on access and training.

In Bangladesh, though AI integration in education is still in its early stages, the prospects of contributing to better educational outcomes are being acknowledged (Maheshwari, 2024). Nevertheless, the lack of infrastructure and ethical issues, along with the absence of AI education policies, prevents widespread implementation (Rahman et al., 2023). AI-based learning tools are accessible to only 32% of Bangladesh's students, compared to over 70% in developed countries. There is a gap that must be addressed (Kong et al., 2024). These challenges must be overcome in order for students to benefit from AI-powered tools without compromising academic integrity (Alsulami et al., 2024).

The aim of this research is to examine the variables that affect the continued use intention of AI-based tools among university students in Bangladesh. In particular, the study intends to advance our existing knowledge of how AI may influence students' learning behaviors and future educational practices by examining factors such as trust, perceived usefulness, social influences, and perceptions of behavioral control (Wang et al., 2024). These factors are proving to be critical landmarks that educators, policymakers, and technology developers need to navigate when looking to improve AI-based educational tools so that learners may achieve their potential while mitigating concerns about trust, accessibility, and ethics (Rahman et al., 2023).

1.1 Problem Statement

To help teaching and learning, a number of schools worldwide are pushing for the application of AI in the classroom. At San Diego State University, students and faculty are also leveraging AI-powered solutions from Google, including NotebookLM and Gemini, which facilitate active learning experiences, writing support, and 24/7 study help (Sinha, 2025). Anticipating a world in which artificial intelligence tools are ubiquitous, NotebookLM enables students at the University of California Riverside to argue and probe their knowledge of content (Sinha, 2025). There are also two ways that Gemini aids Wake Forest University in facilitating administrative efficiency as it automates note-taking and data processing continuously (Sinha, 2025). By integrating Gemini into BSU's marketing pipeline, we gain creativity and drive to start our brains churning out content (Sinha, 2025). In addition, AI-focused curricula and pedagogies have been designed within the larger framework of embedding AI in education. Such efforts include the AACP's 2025 AI Institute and AAC&U's 2025-26 Institute on AI, Pedagogy, and the Curriculum (American Association of Colleges of Pharmacy, 2025; American Association of Colleges & Universities, 2025).

Some institutions are embracing AI in the classroom, while others have limited it (or outright banned it) due to ethical, privacy, and academic integrity concerns. It is now illegal to utilize artificial intelligence (AI) in the creation of research questions, algorithms, and language for undergraduate thesis projects, as laws were passed by Fudan University in China (Wenting, 2025). AI can be used for things like literature retrieval, as long as the supervisor approves. Fears about academic integrity and child safety have led to ChatGPT being banned in Los Angeles Unified and Public Schools in New York City

(Villasenor, 2023). Due to concerns about its appropriateness for children, the Virginia Fairfax County Public Schools' Children's Internet Protection Act (CIPA) has also limited ChatGPT access (Villasenor, 2023). Due to concerns about the safety of students and academic integrity, the Austin Independent School District in Texas curtailed the use of AI (Villasenor, 2023). Multiple artificial intelligence (AI) writing tools, including ChatGPT, were banned by Seattle Public Schools (Villasenor, 2023). Work is underway at Maine School Administrative District 75 to develop guidelines for artificial intelligence use, specifically highlighting safe and ethical use that does not cross basic academic integrity boundaries (Anderson, 2025).

While AI is becoming more widely used in higher education, the reasons why university students will or will not use them are multi-dimensional. Although platforms like ChatGPT, Grammarly, and other AI-supported educational systems could be game-changers in academic essay writing, learning, and problem-solving, their wider use appears dubious. In terms of the frequency of these tools' use, it depends on students' prior experience with technology, whether they are satisfied with them, their trust in AI information, and so forth (Wang et al., 2024). But students are skeptical about using AI to its full potential due to concerns for the accuracy of predictions and recommendations, as well as data privacy and misinformation (Rodway & Schepman, 2023). AI data will be useful; however, the general validity of such data has also been questioned by others who are not convinced that it is always accurate (Rahman et al., 2023). Second, some students have an ethical opposition to AI-supported help, mainly based on plagiarism and academic dishonesty (Ivanov et al., 2024). The lack of understanding of how AI systems

actually work is an obstacle to the successful application of such technologies (Pokryshen, 2024).

Some students may have doubts regarding how AI works in creating content, resulting in either over-dependence on or complete refusal of these innovations (Almufarreh, 2024). Students' inconsistent digital literacy (Wang et al., 2024) poses another barrier to the effective adoption of AI tools. Most students may not have the critical thinking skills to assess AI outputs (Wang et al., 2024), which raises concerns that they are at risk of believing false information or completely ignoring AI help. Disparities in access to computers and the internet, particularly between urban and rural students, may also restrict the regular and widespread use of AI-enabled learning tools, exacerbating these issues (Rahman et al., 2023). The digital ecosystem and education policies of Western and Middle-Eastern countries are not similar to those in Bangladesh (Wang et al., 2024), although a stream of writing about the use of AI in education has been emerging. As Maheshwari (2024) explains, there is little understanding of what factors are influencing the current usage of AI tools by university students in Bangladesh.

Due to this knowledge gap, there is limited understanding of the incentives and barriers that affect student use of AI-enhanced learning applications across Canada. If we seek to understand why AI technologies are being adopted so effectively in Bangladeshi colleges, then these gaps must be filled. Discovering what compels students to stick with AI-driven tools over time, and the trade-offs in using them, is the main goal of this study. This study strives to articulate those considerations so that technology developers, lawmakers, and teachers can work on AI-enabled educational tools to help students achieve their full potential, in terms of trust (Rodway & Schepman, 2023), accessibility, and ethical use.

1.2 Research Objectives

RO1: To examine how trust in AI and perceived usefulness influence students' attitudes toward using AI-powered tools in higher education.

RO2: To analyze the impact of interpersonal influence and social media influence on the formation of subjective norms regarding the adoption of AI-powered tools among university students.

RO3: To evaluate the roles of self-efficacy and technological infrastructure in shaping students' perceived behavioural control over the continuous use of AI-powered tools in academic settings.

1.3 Thesis Organization

There are five major chapters in this thesis.

Chapter 1 is the introduction, which begins with an outline of the study's context, problem statement, research questions, and goals.

Chapter 2 is the theoretical background and literature review. This chapter presents the literature study, introducing the theoretical constructs and explaining the Theory of Planned Behavior model used in this research. We also develop our hypotheses and design our model.

In Chapter 3, the methodology section describes the population, sampling methods, data collection procedure, research design, and analytical statistical tools employed, such as SPSS and PLS-SEM.

Chapter 4 focuses on data analysis, which includes the study model's structural models, measurement evaluation, and respondent profiles.

Chapter 5 presents the conclusion and discussion. This chapter interprets the results regarding the relationships between variables, presents constraints, discusses theoretical and practical implications, and provides future recommendations.

Chapter 2

Literature Review

2.1 Introduction

To extend the understanding of factors related to the continuance use intention of AI-enabled tools in universities, it is crucial to closely examine a valid and rigorous literature in this domain. The current study contributes to the body of existing knowledge by offering a comprehensive review of the theoretical background and empirical evidence on the use of AI-powered tools, with specific attention given to the Theory of Planned Behavior (TPB). The review is structured into three sections: the historical origins of the Theory of Planned Behavior, a systematic literature review, and model development.

2.2 Theory of Planned Behaviour

The Theory of Planned Behavior (TPB) is a prominent psychological model that explains how human behavior is guided by intentions, which are, in turn, shaped by three core components: attitude toward the behavior, subjective norms, and perceived behavioral control (Theory of Planned Behavior, 2025; Steele, 2024; Chen & Slade, 2025).

Attitude refers to a person's assessment of engaging in a particular conduct, whether favorable or unfavorable.

Subjective norms encapsulate the perceived societal pressure from important others to perform or not perform the behavior.

Perceived behavioral control represents the perception of the capacity to act while considering both internal and external factors of control. These three beliefs, taken together, influence the degree to which an individual intends to act and are considered immediate predictors of actual behavior according to TPB. TPB has been used in various fields, such as health, marketing, education, and technology adoption, to conceptualize and predict different types of human behaviors (Theory of Planned Behavior, 2025; Boslaugh, 2022; Steele, 2024; Chen & Slade, 2025).

2.2.1 Origin of TPB

Icek Ajzen, a social psychologist, established the Theory of Planned Behavior in the 1980s, based on the general framework of an earlier model called the Theory of Reasoned Action (TRA), which he co-developed with Martin Fishbein (Theory of Planned Behavior, n.d.; Development of Theory of Planned Behavior, n.d.; Zhang, 2018). Despite the fact that TRA suggested that intentions are a direct function of attitudes and subjective norms, it stated that these intentions are assumed to be under complete volitional control by individuals. Acknowledging that behavior can depend on external conditions and is not always under voluntary control, Ajzen included the element of perceived behavioral control to increase the predictive ability of the model (Development of Theory of Planned Behavior, n.d.; Theory of Planned Behavior, n.d.). This addition made TPB more inclusive of cases in which an individual might be motivated to carry out a behavior but is prevented from doing so by, for example, a lack of resources, skills, or opportunities. Since its development, the TPB has emerged as one of the most influential

models used to understand decision-making and behavior change in various research areas (Boslaugh, 2022; Theory of Planned Behavior, n.d.).

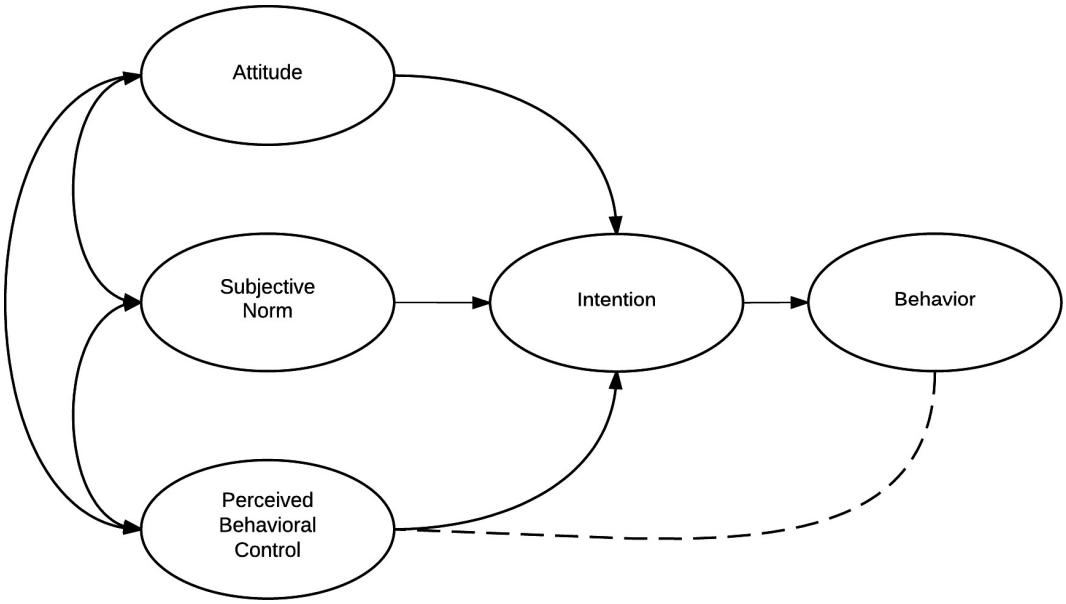

Figure 2.1 TPB Model (*Theory of Planned Behavior*, 2025)

2.2.2 Systematic Literature Review

A synthesis of recent empirical studies indicated that the acceptance and usage of AI-enabled systems in higher education are influenced by perceived usefulness, ease of use, system quality, and social influences (Yu et al., 2024; Alsulami et al., 2024; Sivaperumal et al., 2024). Findings from studies conducted in varied settings – such as Bangladesh, Saudi Arabia, India, Vietnam, China, as well as the UK and USA – all suggest that favorable attitudes (Maheshwari et al., 2024; Wang et al., 2024), strong subjective norms (Ivanov et al., 2024), and high technological infrastructure conviction influence student AI tool use intention (Rahman et al., 2023). Challenges remain, but some of these barriers include access, training, and fears about AI's role in grading or its impact on young people's mental health (Pokryshen, 2024; Rodway & Schepman, 2023). The use of theoretical frameworks such as TAM, TPB, and ISSM is widespread in these existing studies. However, more longitudinal research is needed.

Recent studies have investigated various issues that affect the acceptance and ongoing application of AI technologies in higher education. A summary of selected studies and the main findings of some of the reviewed studies are presented below:

Table 2.1 Table of Systematic Literature Review

SL	Author	Year	Journal Name	Title	Data Source	Method	Outcome	Gap	Feature
1	Yu C, Yan J, Cai N	2024	Frontiers in Education	ChatGPT in higher education: factors influencing ChatGPT user satisfaction and continued use intention	328 college students; Survey-through Prolific	Structural Equation Modeling	Compatibility and efficiency influence perceived ease of use and usefulness, leading to user satisfaction and continued use.	Limited exploration of ChatGPT's impact in diverse educational settings.	Technology Acceptance Model, Satisfaction
2	Sami Ghazzai Alsulami et al.	2024	Pakistan Journal of Life and Social Sciences	Evaluating AI Educational Interventions: Impact on Student Satisfaction and Performance in Higher Education Islamic Studies	246 students at the Islamic University of Medina; Structured questionnaires	Information Systems Success Model (ISSM)	System and information quality positively affect student evaluation, satisfaction, and performance.	Need for broader application beyond Islamic studies.	AI-Powered Quran Reader, NLP, Virtual Assistants
3	Dr. K. Sivaperumal et al.	2024	Educational Administration: Theory and Practice	Satisfaction Of Users Towards AI Tools In Education Institutions With Reference To Tamil Nadu	666 AI tool users in education institutions in Tamil Nadu; Survey-based	Pearson correlation and regression analysis	Quality AI tools improve student satisfaction.	Lack of diverse case studies.	Human-Computer Interaction
4	Raneem Rashad Saqr et al.	2024	Sustainability	Exploring the Acceptance and User Satisfaction of AI-Driven e-Learning	500 Saudi university students; Cross-sectional survey-social media platform	Cross-sectional study, stratified random sampling	AI-based social learning networks and personal learning portfolios significantly impact	Limited regional application and lack of cross-cultural comparison.	Technology Acceptance Model, Expectation-Confirmation Model

				Platforms (Blackboard, Moodle, Edmodo, Coursera, and edX): An Integrated Technology Model			perceived usefulness and ease of use.		
5	Dmytro A. Pokryshen	2024	CEUR Workshop Proceedings	Evaluation of satisfaction with the use of artificial intelligence in the educational process by teachers in Ukraine	Survey of 807 Ukrainian teachers	Survey-based statistical analysis	AI increases accessibility and improves education quality, but dependency and technical limitations exist.	Need for better AI infrastructure and teacher training.	Distance Learning, Virtual Assistants
6	Greeni Maheshwari	2024	Education and Information Technologies	Factors influencing students' intention to adopt and use ChatGPT in higher education: A study in the Vietnamese context	108 Vietnamese university students	Structural Equation Modeling	Perceived ease of use directly influences adoption intention, but perceived usefulness has an indirect effect.	Limited dataset and regional focus.	Technology Acceptance Model
7	Ahmad Almufarreh	2024	Sustainability	Determinants of Students' Satisfaction with AI Tools in Education: A PLS-SEM-ANN Approach	Survey at a Saudi Arabian university	PLS-SEM and ANN	Emotional well-being, content quality, and perceived utility are key factors in AI satisfaction.	Lack of global comparative studies.	Artificial Neural Networks, Emotional Well-being

8	Chengliang Wang et al.	2024	International Journal of Human-Computer Interaction	Factors Influencing University Students' Behavioral Intention to Use Generative Artificial Intelligence: Integrating the Theory of Planned Behavior and AI Literacy	327 Chinese university students; Chinese survey platform	Structural Equation Modeling & Interviews	Attitude, AI literacy, and subjective norms significantly influence students' intention to use GAI technology.	Limited cross-cultural studies on AI literacy and behavioral intention.	Theory of Planned Behavior, AI Literacy
9	Isaac Odai, Elliot Wiley	2024	Department of Communication Studies, Portland State University	Behavioral Intention for AI Usage in Higher Education	51 undergraduate communication students; Qualtrics	Survey-based study	Attitude and subjective norms are positively correlated with behavioral intention to use GenAI.	Small sample size and focus on communication students.	Theory of Planned Behavior, AI in Education
10	Stanislav Ivanov et al.	2024	Technology in Society	Drivers of generative AI adoption in higher education through the lens of the Theory of Planned Behaviour	130 lecturers and 168 students across multiple countries; Google form	PLS-SEM analysis	Attitude, subjective norms, and perceived behavioral control significantly predict intention and actual use of GenAI tools.	Need for longitudinal studies on AI adoption trends.	Theory of Planned Behavior, AI Adoption
11	Md. Shahinur Rahman et al.	2023	Australasian Journal of Educational Technology	Examining students' intention to use ChatGPT: Does trust matter?	344 university students from Bangladesh; Questionnaire Google form	Structural Equation Modeling	Perceived usefulness, informativeness, and trust impact ChatGPT adoption.	Lack of long-term impact analysis.	Technology Acceptance Model

12	Paul Rodway, Astrid Schepman	2023	Computers and Education: Artificial Intelligence	The impact of adopting AI educational technologies on projected course satisfaction in university students	302 UK university students; Prolific	General Attitudes towards AI Scale (GAAIS)	Students are moderately comfortable with AI, but satisfaction drops for AI-based grading and well-being support.	Concerns over AI-based grading and mental health support.	AI in Education, Course Satisfaction
13	Sy-Yi Tzeng, Kuen-Yi Lin, Chih-Yu Lee	2022	Frontiers in Psychology	Predicting College Students' Adoption of Technology for Self-Directed Learning: A Model Based on the Theory of Planned Behavior With Self-Evaluation as an Intermediate Variable	285 college students in Taiwan; Paper questionnaire	Modified Social Cognitive Theory	Self-evaluation enhances intention-behavior link in tech adoption for self-directed learning.	Lack of long-term tracking of behavior change.	Self-Evaluation, Theory of Planned Behavior

2.2.3 Theoretical Framework and Hypothesis Development

In order to illuminate the determinants of continued use of AI-powered applications in a university setting, an extended Theory of Planned Behavior (TPB) model is used in this research. The classic model of TPB suggests that the factors determining behavioral intentions are attitude, perceived behavioral control, subjective norm, and consequent behavior (Jiao & Cao, 2024; Wang et al., 2024). However, to be more specific in this setting, due to the high complexity of AI implementation in the higher education context, additional variables such as trust in AI, perceived usefulness, interpersonal influence, and social media influence on behavior change are included, reflecting a holistic model that considers multiple influences on the actual use through technological infrastructure (Tommasetti et al., 2018; Kanont et al., 2024; Zhou & Zhang, 2024).

Current studies show that trust in AI and perceived usefulness are both influential factors that affect the attitudes and intentions of students to use AI tools (Mustofa et al., 2025; Yu et al., 2024; Kanont et al., 2024). Interpersonal and social media influences have expanded the conventional subjective norm to include peers, teachers, and online community effects (Yang, 2024). Self-efficacy and technology support increase perceived behavioral control, suggesting students' confidence (or capability) in performing a behavior with support from environmental resources that are not normally accessed by them (Zhou & Zhang, 2024; Yang, 2024). By integrating these features, the augmented TPB model provides a systemic view of the cognitive, social, and technological antecedents behind the continued use of AI-based tools by university students (Ivanov et al., 2024; Zhou & Zhang, 2024).

a) Trust in AI

This broad view of trust fits into the construct of trust in AI, as it reflects human preferences and implicit attitudes toward trusting or distrusting certain systems (Afroogh et al., 2024; Schulz et al., 2023; Pitts & Motamedi, 2025). In educational fields, trust toward AI-based tools is one of the most important factors that affect student perceptions and their decisions to continue using these technologies (Pitts & Motamedi, 2025; Ramirez et al., 2024; Nazaretsky et al., 2025). Trust is composed of both human-like characteristics (e.g., perceived competence and integrity) and system-like qualities (such as operability, functionality, and reliability), the existence of which may decrease uncertainty and increase user confidence in AI applications (Afroogh et al., 2024; Pitts & Motamedi, 2025; Mustofa et al., 2025). Recent empirical research suggests that trust in AI is positively related to attitudes toward AI tools among university students, based on previous empirical work (Ramirez et al., 2024; Nazaretsky et al., 2025; Mustofa et al., 2025).

H1: Trust in AI has a positive and significant effect on students' attitudes toward using AI-powered tools.

b) Perceived Usefulness

Perceived usefulness (PU) reflects how much students believe that by using AI-based tools, their academic performance or productivity would improve. While PU is derived from TAM, recent literature confirms it has been proposed as a powerful external variable in the extended form of TPB models, particularly pertaining to technology adoption (Jiao

& Cao, 2024; Linh & Huyen, 2025). Research suggests that the positive perceived utility of AI tools increases the likelihood that learners will develop a favorable attitude toward using the tool, thereby enhancing their intention to continue using it (Jiao & Cao, 2024; Linh & Huyen, 2025).

It is empirically evidenced that the addition of PU into TPB has resulted in a significant positive influence on users' attitude toward using (ATU) AI technologies in educational environments (Jiao & Cao, 2024; Linh & Huyen, 2025).

H2: Perceived usefulness positively influences students' attitudes toward using AI-powered tools.

c) Interpersonal Influence

Interpersonal influence is the psychological process by which important others (e.g., peers, family members, and teachers) affect decision-making and actions. In the TPB, such influence is represented by subjective norm, which refers to individuals' belief about the pressure exerted on them to perform or not perform the behavior, and is influenced by these significant others (Theory of Planned Behavior, 2025).

The extant literature demonstrates abundantly that interpersonal influence is a key antecedent of subjective norms in technology adoption contexts, such as AI-based tool usage. The higher the degree to which students have influential others who expect or motivate them to use AI tools, the stronger their perceived norm of AI adoption (Chen & Lin, 2021; Huang et al., 2025). This relationship may be especially true in academic

settings, where encouragement from peers and lecturers during university years might significantly influence students' beliefs about social norms.

H3: Interpersonal influence positively affects the formation of subjective norms regarding AI adoption among university students.

d) Social Media Influence

Social media influence refers to the contribution of social media, online communities, and influencers to individuals' attitudes and behavior with respect to technology adoption. Within the TPB framework, the perceived social pressure to engage in or refrain from engaging in conduct is known as the subjective norm, and this is increasingly influenced by interacting with others and learning information through SNS sites.

Empirical evidence suggests that such subjective norms can be substantially reinforced by social media, which may magnify peer opinions, enhance group consensus, and expose influential users' adoption behaviors (Vannoy & Palvia, 2010; Santoso, 2021; Consumer Technology Adoption: The Impact of Social Media on Consumer Technology Adoption, 2025). Research shows that individuals who are exposed to positive conversations about and endorsements of AI-powered tools on social media are more likely to perceive a higher social expectation to use the technology (Ashraf et al., 2021; Bashir et al., 2022). This dynamic is particularly strong in education, where learners routinely turn to online communities for validation and instruction.

H4: Social media influence positively affects the formation of subjective norms regarding AI adoption.

e) Self-efficacy

Self-efficacy is defined as an individual's perception of their own abilities to use AI-based technology for an academic activity (Rosen & Martin, 1972). Self-efficacy is a central component of perceived behavioral control within the Theory of Planned Behavior (TPB), and represents one's belief in their ability to perform an action, even when faced with barriers to engaging in that behavior (Theory of Planned Behavior, 2025; Ajzen, 2006). In technology adoption situations, greater self-efficacy leads to the idea that students who feel more competent with AI tools are likely to have enhanced perceived behavioral control and, hence, a greater likelihood of continued usage (Polyportis, 2024; Pan, 2020).

Indeed, empirical evidence consistently indicates that technological self-efficacy is a significant determinant of perceived behavioral control, which, in turn, affects students' intention to use and actual use of technology (Pan, 2020). Therefore, the development of self-efficacy is important for students to build up their perceived control in adopting AI tools in higher education.

H5: Self-efficacy positively influences students' perceived behavioural control over the use of AI-powered tools

f) Technological Infrastructure

Technological infrastructure refers to the availability of working phones, a stable internet connection (if the tool depends on one), good computers and software, as well as human

support for using AI-powered interventions in education. According to the TPB, facilitating conditions, such as technological infrastructure, are an important external factor that impacts students' perceived behavioral control (degree of confidence) in using technology.

Research consistently indicates that an adequate technological structure strengthens perceived behavioral control by reducing obstacles to using technology and enhancing students' feelings of efficacy and autonomy when interacting with AI tools (Feng et al., 2025; Mijan et al., 2025; Naseri & Abdullah, 2024). Students empowered with extensive digital resources and institutional support can have considerable confidence to embrace and sustain their use of AI-supported educational technologies. Poor-quality infrastructure, on the other hand, may erode perceived control and undermine continued engagement.

H6: Technological infrastructure positively affects students' perceived behavioural control over the use of AI-powered tools.

g) Attitude

In the context of the TPB, attitude is conceptualized as a general positive or negative evaluation an individual holds about performing any given behavior, such as using AI-based tools. Attitude is an important antecedent of behavioral intention, and many studies have indicated that having a favorable outlook on technology significantly increases the chances of continued use intention (Jiao & Cao, 2024). When referring to

AI adoptability, students are more likely to plan on using such a tool in the future when they find it useful, enjoyable, or relevant for their academic needs (Jiao & Cao, 2024).

Our results related to attitude are supported by empirical findings in the technology and AI literature, which suggest that attitude is highly significantly associated with continuous usage intention and has a significant impact on both initial adoption and sustained use of AI-powered educational tools (Pertami & Sukaatmadja, 2021).

H7: Attitude toward AI-powered tools positively affects students' continuous intention to use these tools.

h) Subjective Norm

According to the Theory of Planned Behavior (TPB), subjective norm is perceived social pressure from significant others, i.e, peers, instructors, or family, whether or not to engage in a conduct (Wang & Wang, 2024; Nurtanto et al., 2025). In the AI-based tool setting, subjective norm indicates that students' continuance intention of using AI-based tools is influenced by their peers and significant others (Wang et al., 2024). Empirical studies have supported that students are more willing to continuously use AI technology when they feel a higher level of social support or AI tool usage normative expectations (Wang & Wang, 2024; Wang et al., 2024). It's a reminder that peer and institutional validation play an important role in sticking with AI-powered educational resources.

H8: Subjective norm positively influences students' continuous intention to use AI-powered tools.

i) Perceived Behavioural Control

Perceived behavioral control (PBC) refers to the amount of ease or difficulty that one believes exists in performing a behavior, taking into account both internal resources and proximate influences. In the framework of the TPB, PBC is an important predictor of behavioral intention and behavior. For AI-enabled tools, those students who are confident about the use of technology and feel they can get resources that help with the use will be more likely to report an intention to continue using them.

Empirical studies have found that stronger perceived behavioral control is positively related to stronger intention of continuous usage toward technology, such as AI in education (Jiao & Cao, 2024; Wang & Wang, 2024; Huang et al., 2025; Li et al., 2022). It has been found that students are nearly three times more likely to remain engaged when they believe there is a low barrier to use and high self-efficacy in utilizing the AI tools. This relationship has been supported within diverse educational technology settings, indicating that PBC is a strong predictor of continued technology use (Wang & Wang, 2024; Huang et al., 2025; Li et al., 2022).

H9: Perceived behavioural control positively influences students' continuous intention to use AI-powered tools.

j) Continuous Intention to Use

Continuous intention to use denotes a person's continued will or considerations for future continuation in using some technology/ service (Song et al., 2023). This construct, in the TPB, is formed by attitude, subjective norm, and perceived behavior control, where it predicts that users will continue to use a technology (Sansom & Young, 2021; Li et al., 2022). In the field of educational technology as well, including AI-based solutions, studies demonstrate that perceived usefulness, social influences, and students' satisfaction and control have positive effects on students' intention to continue using tools in learning (Li et al., 2022; Mehrabioun, 2024). In other words, continued intention to use

is the core variable of long-term technology adoption and sustained usage in a higher education environment (Dhiman et al., 2021; Song et al., 2023; Mehrabioun, 2024.

2.3 Research Model

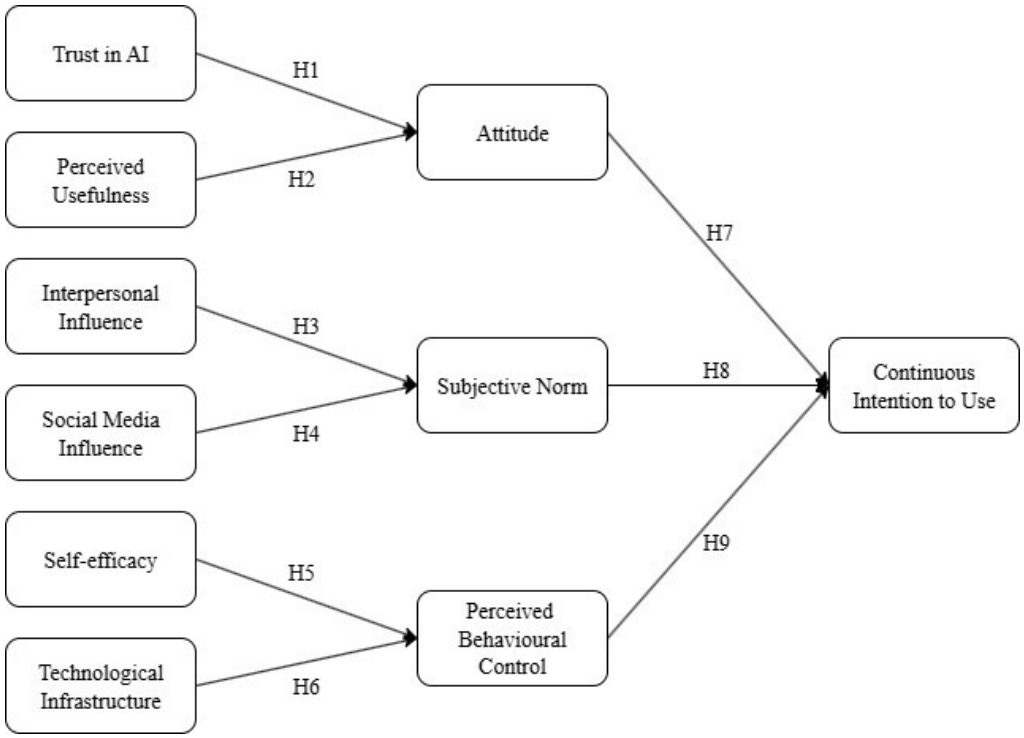

Figure 2.2 Research Model

Chapter 3

Methodology

3.1 Introduction

The academic approach for the work presented in this thesis is described in depth in this chapter. The organization of this chapter encompasses multiple large sections. First, the chapter discusses the choice of paradigm and design of research before describing both studies' population, sample approach, and sample size. The next section discusses the construction of the survey instrument, including information about its visual form and organization, individual measures employed, and demographic measures. In addition, this chapter discusses how to collect data in terms of ethics, survey administration, participants, and the duration for which data has been collected, as well as discussing how researchers can control common method variance – both procedurally and statistically. Section III explains the statistical methods and data analysis techniques used, with a precise explanation of how Statistical Package for Social Sciences (SPSS) was used as well as Partial Least Squares Structural Equation Modeling (PLS-SEM), its justification for use, and the measurement model analysis.

3.2 Research Paradigm

This study is guided by a quantitative research paradigm that follows the positivist tradition, which seeks to prioritize objectivity and the measurement of hypotheses using empirical measures (Creswell, 2014). Using structured surveys and statistical tools like Structural Equation Modeling (SEM), the investigation systematically investigates links among trust in AI, perceived usefulness, social influences, self-efficacy, and technology infrastructure with students' AISBI in higher education. Such a model is suitable to test theoretical concepts such as the Theory of Planned Behavior and the Technology Acceptance Model, because it allows detecting significant predictors and for us to

generalize results for a larger population, which makes research rigorous, reliable, and replicable (Bhattacherjee 2012).

3.3 Research Design

This study employs a quantitative, cross-sectional survey design to examine the factors influencing the continued usage intention of AI-powered tools among university students. The research is grounded in the Theory of Planned Behavior (TPB) and extends the traditional TPB framework by incorporating additional constructs relevant to the context of the continued usage intention of AI-powered tools.

3.4 Population

Students, some from public universities and others from private. These students will have had at least one full semester of exposure to academia and be 18 years or older, so they can bring some academic experience and maturity to their views on AI-powered educational tools. The reason for choosing this population is based on the research purpose that aims to decipher those determinants that influence the continuance intention of AI-powered tools among university students in Bangladesh who are using AI-based tools as a key demographic involved in academic interactions with technologies. Participants must be students currently enrolled in school with some exposure or knowledge of AI-infused educational tools and are ineligible if not currently enrolled, younger than 18 years old, or lack awareness of AI tools. This population is of interest as university students are often early adopters of technology in education, and findings from this group can help to shape more general strategies surrounding digital transformation and equitable access to AI in higher education, with potential for transferability across similar contexts within the developing world (Thomas, 2023; Bhandari, 2020)

3.5 Sampling Technique

Participants: The study participants are university-level students who have completed one semester in an academic session and are over 18 years old from higher education institutions in the whole of Bangladesh. These students are the respondents of this study, cut across different public and private-owned universities, and different disciplines in higher learning. The broader population under study is all university students in Bangladesh who had the opportunity and knowledge regarding exposure to AI-based education tools, which is in line with the aim of examining determinants that drive their continued intention toward adopting this technology (Talukder & Ahsan, 2025; Tamanna & Sinha, 2024).

There are two dominant categories of sampling methods: probability (random) and non-probability sampling (Webster, n.d.). Probability sampling methods, like simple random sampling, stratified sampling, and cluster sampling, select by chance to ensure that every member of the population has a specified (non-zero) probability of being selected. This increases the representativeness of the sample and provides a basis for extrapolating findings to other contexts (Webster, n.d.). On the other hand, non-probability sampling— such as convenience, purposive, and quota sampling is not based on random selection, thus introducing bias in the sample, but can be operational when it is impossible or expensive to employ probability samples; or in situations where we want to target already known subsets of a population (Mulisa, 2022).

For the sake of this research, stratified random sampling was used. The population was stratified according to type of university (state, private), year (in what year(s) the study programme is taken up), and specialty. In each stratum, students were chosen at random to respond to the questionnaire. This ensured representative samples in terms of the number of different subgroups, which will reflect a diverse range of university student population in Bangladesh (Lammers & Badia, 2004).

It was preferred to use stratified random sampling in order to get a sample that is representative and unbiased and closely resembles the diversity of the reference population. Through the random and systematic initiation of individuals from multiple universities, academic years, and faculties, sampling bias was reduced to a minimum, making the findings more generalizable. This is especially beneficial for research targeting the exploration and comparison of behavioral predictors across different subpopulations, such as this examination of AI tools used by university students.

3.6 Sample Size

A sample, as explained by Bougie & Sekaran (2019), is a portion of the population fundamental to investment in a study. It is important to investigate sample size issues since sample sizes will greatly affect the model fitting, statistical power, and parameter estimates when used with SEM models (Shah & Goldstein, 2006). Some criteria have been suggested to determine an adequate sample size for research.

According to Roscoe (1975), the recommended sample sizes for most investigations are in excess of thirty and less than five hundred. The sample should exceed ten times the number of variables, irrespective of whether these are independent, mediating, moderating, or dependent (Sekaran, 2019).

Besides these heuristic rules, statistical software such as GPower has developed into a widely used approach to determine appropriate sample sizes by conducting power analyses (Faul et al., 2009). GPower enables scientists to calculate the sample size necessary to detect an effect with a given level of statistical power and effect size.

The minimum sufficient sample size was calculated using the G*Power program (Version 3.1.9.4), considering a priori power analysis for this study. This is important to help ensure that the study has adequate statistical power to show a hypothesized effect, reducing risk of type II errors (failing to detect a true effect). The following values were entered into GPower used for the calculation:

Effect Size (f^2): An effect size of 0.15 was chosen, representing a medium effect size according to Cohen's (1992) guidelines for linear multiple regression. This value is commonly adopted in social science research when no prior studies provide a more precise estimate, indicating a moderate relationship or difference that is considered practically significant.

Alpha (α) Error Probability: Set at 0.05. This is the conventional threshold for statistical significance, indicating a 5% risk of committing a Type I error (incorrectly rejecting a true null hypothesis).

Power (1-β Error Probability): Set at 0.95. This indicates a 95% probability of correctly detecting a true effect if it exists, meaning a 5% risk of committing a Type II error. A power of 0.95 is considered a robust level for research aiming for high confidence in its findings.

Number of Predictors: Based on the proposed research model, the number of independent variables (predictors) was set to 3.

Based on these parameters, the G*Power analysis indicated that a total required sample size of 119 participants would be sufficient to detect large effect sizes with a power of 0.95.

However, to ensure robust analysis, accommodate the complexity of the model, and account for potential non-responses or incomplete data, a larger sample size of 250 university students was chosen. This size aligns with established recommendations for SEM studies involving multiple constructs and enhances the reliability and generalizability of the research findings.

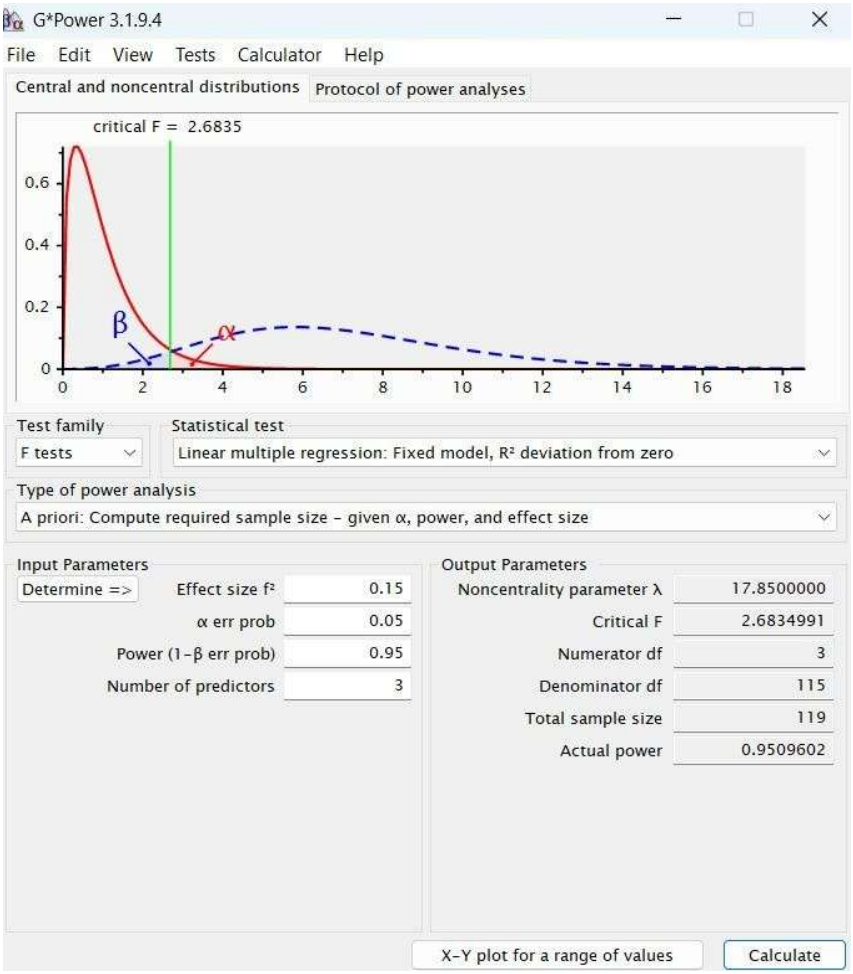

Figure 3.1 Sample size using G*Power

3.7 Survey Questionnaire Development

The development of a robust and valid survey questionnaire is paramount for collecting reliable data that accurately addresses the research objectives. This section details the systematic process undertaken for the design, content validation, and structure of the questionnaire used in this study.

3.7.1 Questionnaire Design and Structure

The questionnaire served as the major data gathering tool, and it was targeted to obtain quantitative data regarding determinants of university students' intention to continue using AI-based tools. The self-administered online survey approach was selected as a means of achieving widespread student participation and to aid data capture.

The questionnaire was divided into clearly defined sections, the first of which was an introductory text explaining the purpose of the research and reassuring respondents of their anonymity and confidentiality, along with instructions for answering. This is consistent with recommendations for survey design, which underline the importance of ethical conduct as well as clarity for participants (Dillman et al., 2014).

The middle section of the QC was composed with this purpose in mind, that is, to assess the different constructs of our research model. These are Trust in AI, Perceived Usefulness, Interpersonal Influence, Social Media Influence, Self-efficacy, Technological Infrastructure Attitude, Subjective Norm, Perceived Behavioural Control, and Intention to use AI-enabled Tools. The items were presented in the form of statements, and responses ranged from 1 (Strongly Disagree) to 7 (Strongly Agree). This ordinal scale is commonly used in surveys and social science research to measure different shades of opinion or perception (Likert, 1932).

An example of the Likert scale and question format used is:

- "I have confidence in the use of AI technology for my academic work."
- 1 (Strongly Disagree) to 7 (Strongly Agree)

The items were carefully worded to be clear, concise, and unambiguous, avoiding leading questions or double-barreled statements, which could introduce bias or confusion (DeVellis, 2017).

3.7.2 Measurement Items

The constructs in this study were operationalized using multiple-item scales, adapted from existing validated instruments to ensure content and construct validity. The specific items for each construct, along with their sources, are presented in the tables below. All items were measured on a 7-point Likert scale, ranging from "1 = Strongly Disagree" to "7 = Strongly Agree."

Table 3.1 Items of Trust in AI

Item	Questionnaire	Source
TRAI1	I have confidence in the use of AI technology for my academic work	(Chowdhury et al., 2022)
TRAI2	I believe AI technology can facilitate routine and trivial academic tasks through automation	
TRAI3	I believe AI-powered tools will operate reliably and consistently without failing	
TRAI4	I believe that AI technology will consistently provide adequate and efficient results for a wide range of academic tasks	

Table 3.2 Items of Perceived Usefulness

Item	Questionnaire	Source
PU1	Using AI-powered tools improves my academic performance	(Legesse et al., 2024)
PU2	AI-powered tools enhance my learning effectiveness in university courses	
PU3	I find AI-powered tools useful for completing my academic tasks	

Table 3.3 Items of Interpersonal Influence

Item	Questionnaire	Source
INTI1	Almost all of my classmates use AI-powered tools for their academic tasks	(Yang et al., 2021)
INTI2	Almost all of my peers think using AI-powered tools is a good idea	
INTI3	My classmates and friends think that we should all use AI-powered tools	
INTI4	Some of my peers have recommended that I try using AI-powered tools	

Table 3.4 Items of Social Media Influence

Item	Questionnaire	Source
SMI1	I often rely on social media platforms to make decisions about products, services, or trends	(Djafarova & Rushworth, 2017)
SMI2	The opinions of influencers or popular figures on social media affect my personal choices	
SMI3	I feel motivated to try something new after seeing it recommended on social media	
SMI4	Social media plays a significant role in shaping my views and preferences	

Table 3.5 Items of Self-efficacy

Item	Questionnaire	Source
SE1	I can complete a research task using AI-powered tools if someone shows me how to do it first	(Acosta-Enriqueza, et al., 2025)
SE2	I can complete a research task using AI-powered tools if I have reference manuals	
SE3	I can complete a research task using AI-powered tools even if I have never used such tools before, provided I have access to necessary resources	

Table 3.6 Items of Technological Infrastructure

Item	Questionnaire	Source
TI1	The technical aspects of AI-powered tools fit well with how my university currently operates	(Legesse et al., 2024)
TI2	My university's present hardware and software infrastructure can work effectively with AI-powered tools	
TI3	The improvements made by AI-powered tools are in line with what is already done in my academic environment	

Table 3.7 Items of Attitude

Item	Questionnaire	Source
ATT1	For me, using AI-powered tools in my academic work is: Extremely Bad	(Ivanov et al., 2024)
ATT2	For me, using AI-powered tools in my academic work is: Extremely Undesirable	
ATT3	For me, using AI-powered tools in my academic work is: Extremely Unpleasant	
ATT4	For me, using AI-powered tools in my academic work is: Extremely Foolish	

Table 3.8 Items of Subjective Norm

Item	Questionnaire	Source
SN1	Most people who are important to me think I should use AI-powered tools while doing my academic work	(Ivanov et al., 2024)
SN2	Most people who are important to me would want me to use AI-powered tools while doing my research/study	
SN3	People whose opinions I value would prefer that I use AI-powered tools while doing my academic work	

Table 3.9 Items of Perceived Behavioural Control

Item	Questionnaire	Source
PBC1	Whether or not I use AI-powered tools while doing my academic work is completely up to me	(Ivanov et al., 2024)
PBC2	I am confident that I can use AI-powered tools effectively for my academic work if I want to	
PBC3	I have the resources, time, and opportunities to use AI-powered tools while doing my academic work	

Table 3.10 Items of Continued Intention to Use

Item	Questionnaire	Source
CINT1	I intend to keep using AI-powered tools for my university studies	(Ivanov et al., 2024)
CINT2	I will continue to rely on AI-powered tools for completing academic tasks	
CINT3	I intend to recommend AI-powered tools to my fellow students	

3.7.3 Demographic Questionnaire

Table 3.11 Demographic Questionnaire

Gender	Male/Female
Age	18-21/22-25/25+
Educational Level	1st year/2nd year/3rd year/4th year

3.8 Data collection procedure

The data collection process of this study was extremely well-designed to obtain high-quality and reliable data, with all due respect to the ethical considerations.

3.8.1 Ethical Considerations and Approval

The participants were told what the study was about and that they may opt out and that participation was entirely voluntary at any time without being penalized. All participants provided informed consent when they took part in the survey. Anonymity and confidentiality of the answers were guaranteed, whether or not the information received through the study would be disclosed, and no personally identifiable information was gathered.

3.8.2 Survey Administration

The online questionnaire was conducted using Google Forms. The implementation of Prospekt-2 made use of the Mobenzi Researcher, which was preferred due to its availability, user-friendly aspects, and strong capability to manage data for easy collection and storage. Further, online presentations were more widely accessible to university students in different geographical areas.

3.8.3 Participant Recruitment and Distribution

Participants were obtained via university Facebook and LinkedIn groups and through the direct recruitment of university departments and faculty. All potential participants initially received an invitation message that provided a short description of the study and a private URL to the online survey. Anonymized reminders to participate were sent

periodically in attempts to increase participation. The recruitment approach was intended to access a diverse sample of university students representative of the target population.

3.8.4 Data Monitoring and Collection Period

The survey was available online for 1 week. I used to check it every day, for data quality and to spot any issues. Incomplete responding and clear patterns of random responding were discarded from the dataset after data cleaning.

The fourth iteration of the questionnaire, modified to reflect all comments and adjustments, was adapted into an online survey. The questionnaire is included in Appendix A.

3.9 Common Method Variance

Common Method Variance (CMV) is characterized as measurement method-related variance in measures rather than construct-based variance in measures (Podsakoff et al., 2003). In research contexts in which independent and dependent variable data are sampled from the same source at a single time point and from the same measurement approach (e.g., self-report paper-and-pencil surveys), CMV has the potential to either overestimate or underestimate observed relationships, producing potentially misleading data.

To minimize the risk of CMV inherent in this study, we discussed several procedural and methodological remedies during the design and data collection period:

3.9.1 Procedural Remedies

Anonymity and Confidentiality: Participants were guaranteed confidentiality and anonymity of their responses. This reduces evaluation apprehension and encourages more honest and accurate responses, thereby minimizing social desirability bias (Podsakoff et al., 2003).

Clear and Concise Instructions: The questionnaire provided clear, unambiguous instructions to minimize ambiguity and ensure that participants understood the questions as intended.

Randomization of Item Order: The order of each participant's answers to the questionnaire was chosen at random where possible. This helps to break up any potential response patterns and reduces the likelihood of participants inferring relationships between constructs based on item proximity (Podsakoff et al., 2003).

Psychological Separation of Constructs: While all data were collected via a single survey, efforts were made to psychologically separate the measurement of different constructs. This was achieved by grouping items related to specific constructs together and introducing brief introductory statements or section breaks between different construct groups (e.g., "Now, please answer questions about your attitude...").

3.9.2 Statistical Remedies

After data collection, statistical methods will be employed to assess and, if necessary, control for CMV. The primary method to be utilized is Harman's Single Factor Test.

Harman's Single Factor Test: This test is an unrotated principal components factor analysis of all items in the questionnaire. If there appears to be one factor or if a general factor explains most of the covariance among measures (usually over 50%), it indicates the presence of substantial CMV (Podsakoff et al., 2003). Again, this test is used as a diagnostic and not necessarily a cure, but it shows that CMV might be something to worry about.

Applying these procedural and statistical strategies, the study attempted to reduce common method variance effects and strengthen the validity of observation.

3.10 Statistical Techniques and Data Analysis

The investigators used to access a wide selection of software and tools for analyzing data and testing hypotheses, depending on their intention, the study design, the complexity of interest, and ease. As the base of our research is qualitative analysis, a number of tools are able to produce the expected results. Two major data analysis software were used in the present research, Partial Least Squares (PLS) with the use of Smart PLS 3.2.7 and SPSS.

3.10.1 Statistical Package for Social Sciences (SPSS)

Among academicians, SPSS (Statistical Package for Social Sciences) is one of the most widely used and popular programs for data analysis (Zikmund, 2013). Thus, in the present analyses, we provided coded numbers and entered the data into SPSS prior to any analysis of the data. The missing values, outliers, and normality of the data for the study were all checked to ascertain the accuracy of the data. Furthermore, descriptive analysis was done to present a summary of the data profile (mean, standard deviation, and percentage) using descriptive statistics analysis.

3.10.2 Partial Least Squares Structural Equation Modeling (PLS-SEM)

After preliminary data analysis and descriptive statistics in SPSS, the researcher used Partial Least Squares Structural Equation Modeling (PLS-SEM) to test hypotheses and run regression in this study. The software employed for this study was Smart PLS-SEM 3.2.7. PLS-SEM is a second-generation statistical method that can be used to evaluate complex multivariate interactions between manifest variables and latent components (Esposito-Vinzi et al., 2010).

The PLS-SEM method, a member-smart link analysis regression tool, has been developed to analyze the links between, on one hand, measurement (indicators) and structural models or constructs on the other (Chin, Marcolin & Newsted, 2003). Due to the many advantages that distinguish this technique from other analysis approaches, PLS has gained increasing attention in academia and is widely studied by scholars all over the world (Hair et al., 2013).

First, in very complex models, PLS can be used with various sample sizes, both small and large (Hair et al., 2011). It is also more defensible when the number of samples is small. PLS can process structures with a small number of indicator elements (Hair et al., 2011). Third, it is less constrained and makes fewer assumptions regarding the distribution that may be used to generate the data (Hair et al., 2011). Fourth, this program supports both formative and reflective measurement models. Finally, due to the biasing effect of measurement error on estimates of association and evidence for theory validity, PLS also provides more accurate estimates of mediating and moderating effects (Hair et al., 2011).

3.10.3 Justifications for Using PLS-SEM in the Current Study

Exploratory analysis, the type of analysis that this program is designed to perform (Hair et al., 2011), can be a valuable approach for examining different constructs and their relationship to the dependent variables. Hair, Hult, Ringle, and Sarstedt (2014) noted that PLS-SEM has also been acknowledged as an appropriate analysis technique to develop theory because it aims to provide an explanation for the dependent variables' variance while examining models. Moreover, PLS-SEM is acceptable and superior to SPSS regression analysis for mediation analyses (Hair, 2014). Moreover, because of the advantages of PLS-SEM and previous reasons mentioned in this study, it is increasingly being used by researchers in the hotel industry (Ali et al., 2018; Islam et al., 2021).

As our conceptual model in this study involves multiple relationships, it seems particularly promising for the reasons and scope of the current study described above. It concentrates on the prediction of dependent variables, such as AI adoption intention and theories, such as TAM. Hence, the application of PLS-SEM in this research is justifiable. Thus, in data analysis, two-stage tests were conducted, namely the structural model and the measurement model.

3.10.4 Measurement Model Analysis

Detecting whether the theoretical constructs are reasonably loaded by the proposed variance in PLS to a certain content is the first step in assessing if the PLS-referenced measures should be correlated (Wold et al. This is in contrast to both the construct validity and internal consistency reliability, which are evaluated during the testing of the measurement model. According to Henseler, Ringle, and Sinkovics (2009), measurement models also need to comply with validity and reliability prerequisites. If the instrument measures what it is supposed to measure, it is valid and reliable if it is stable and

consistent (Sekaran, 2006). In other words, reliability is the ability to consistently measure items in an instrument without error and lower bias by being consistent throughout your study (Bougie & Sekaran, 2019). Contrarily, validity demonstrates how well one measures a concept, and it highlights the accuracy of measurement (Creswell & Clark, 2017). Reliability Measurement of reliability. For testing the reliability, composite reliability is used in this study. Convergent and discriminant validity are also employed to elaborate on construct validity, which is used to test the measurement model.

(a) Reliability- Composite Reliability (CR)

As we mentioned earlier, if an instrument is stable enough so that we can predict its dependability (based on the assumption that test-retest would produce similar results in different administrations of the same instrument), then it should also be stable enough to produce similar findings when used repeatedly, or over repeated attempts. Composite reliability and Cronbach's alpha are illustrations of this, a variable that should be analyzed before performing the next step, i.e., the structural model.

Due to the weaknesses of Cronbach's alpha as an internal consistency metric, composite reliability is recommended for the dependability measurement (Hair et al., 2013). This occurs because CR increases the accuracy of an estimate of true reliability by placing unique loadings on each indicator and weighting them according to their reliability; nevertheless, as Hair et al. (2013). One disadvantage of Cronbach's alpha is that it underestimates by being sensitive to the number of items on the scale, underestimating internal consistency and reliability.

Researchers have defined various threshold values of composite dependability. Hair et al. Xenikou and Simosi (2013) mention that values of 0.70-0.90 are acceptable as sufficient in more advanced stages of the research process, while only in exploratory model building, a value of 0.60-0.70 may be admitted for the coefficient CR.

(b) Construct Validity

Construct validity, the extent to which a collection of measurable variables reliably reflects the hypothetical underlying constructs that are intended to be explored, is known as construct validity(Hair et al., 2013). This claim is also examined in connection with discriminant and convergent validity.

(i) Convergent Validity

Convergent validity is a frequently used measure in various fields of research, such as psychology, behavioral science, and sociology. It is a subset of construct validity. This refers to the degree to which one scale and another scale measuring the same construct are reciprocally related (Hair et al., 2013). In other words, it represents how the metrics of two theoretically related concepts are linked. Convergent validity is measured by AVE for the indicators and their outer loadings (Hair et al., 2013). Loading and AVE values exceeding 0.5 are recommended (Hair et al., 2014). Whenever excluding the outside loading values and composite reliability exceeds the cutoff point, those values between 0.40 and 0.70 should be dropped from the scale (Hair Jr et al., 2020). Indicators with values of outer loading as low as 0.40 should always be eliminated from a scale. It is natural to use reasonable thresholds on loadings and AVEs, so our research follows the same rules.

(ii) Discriminant Validity

Discriminant validity is another aspect of concept validity to which convergent validity belongs. The second point is the most critical: they work together. Thus, establishing both discriminant and convergent validity is just as important as establishing construct validity. Inadequate construct validity is evidenced by a failure of any one of the subparts.

According to Hair et al. (2014), discriminant validity is the degree to which a concept is different from other concepts based on empirical indicators. Fornell and Larcker (1981) recommended the following scale for assessing discriminant validity: for each latent variable, the square root of its AVE should be greater than any correlations with other latent variables.

3.11 Summary of the Chapter

The aim of the present research was to determine and analyze the specific factors driving the intention to continue using AI-based tools by students in their universities. Using a quantitative research design to accomplish this objective was warranted. The study was based on the existing literature in order to obtain a complete historical background for the constructs investigated. Data analysis procedures, such as data reduction and the method of treating common method variance, were rigorously executed. Data were analysed with Partial Least Squares Structural Equation Modeling (PLS-SEM) as the main statistical method, and this is described in detail in relation to its application and rationalisation for use. Lastly, there was a lucid explanation of the analytical framework and tools used so that researchers and examiners can understand methodological rigour.

Chapter 4

Data Analysis

4.1 Introduction

This chapter presents the broad analysis of data collected and empirical results obtained from testing the research hypotheses. The target in this section is to acquire an outline of the respondents' demographic attributes. In other sections, we evaluate common method variance by detailing the submissiveness and the outcomes from Harman's Single Factor Test. We follow the outer models with evaluations on Average Variance Extracted and Composite Reliability, and the investigation on Discriminant Validity by applying Fornell and Larcker Criteria. We finalize with an analysis of the inner model that includes results on the Coefficient of Determination and the Path Coefficients. The focus of this section is to gain an understanding of the outside models by addressing common method variance and the inner model by testing the research hypotheses. We conclude by presenting the final research model previewed below in a figure.

4.2 Respondents' Profile

This section presents an outline of the demographic characteristics of the participants. This information is important to establish the generalizability of the study results. Analysis is based on the data collected through questionnaire direct questions concerning the age, gender, academic level, faculty, and experience using AI-powered tools in education. The study respondents are university students in Bangladesh, selected based on purposive sampling. Data was collected through questionnaires and returned by the targeted 250 respondents after complete filling. Below is the demographic information of the respondents.

Table 4.1 Gender Distribution of Respondents

Gender	Frequency (n)	Percentage (%)
Male	102	40.8%
Female	148	59.3%

Table 4.2 Age Group Distribution

Age Group	Frequency (n)	Percentage (%)
18-21	59	23.6%
22-25	173	69.1%
25+	18	7.3%

Table 4.3 Academic Level Distribution of Respondents

Academic Level	Frequency (n)	Percentage (%)
1st year	39	15.6%
2nd year	65	26%
3rd year	43	17.2%
4th year	103	41.2%

4.3 Common Method Variance

Harmon's single factor test was one of the techniques used in the current study to determine whether CMV was present.

4.3.1 Harmon's Single Factor Test

Common method bias in the current study was checked by performing Harman's Single Factor Test. The first factor in the EFA accounted for 34.95% of the total variance (far less than the desirable level of 50%) with all measurement items on the unrotated axis. This implies that common method bias is likely not an issue in the data, providing support for the robustness and validity of the study's results (Podsakoff et al., 2003).

Total Variance Explained

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	12.452	36.623	36.623	11.884	34.951	34.951
2	4.490	13.205	49.828			
3	2.086	6.135	55.962			
4	1.578	4.641	60.604			
5	1.242	3.654	64.258			
6	1.138	3.347	67.605			
7	1.046	3.076	70.681			
8	.948	2.788	73.468			
9	.862	2.535	76.004			
10	.812	2.388	78.392			
11	.685	2.015	80.406			
12	.611	1.798	82.204			
13	.564	1.658	83.862			
14	.526	1.546	85.408			
15	.492	1.448	86.857			
16	.446	1.313	88.170			
17	.399	1.173	89.343			
18	.376	1.106	90.449			
19	.336	.989	91.438			
20	.327	.960	92.398			
21	.296	.870	93.268			
22	.276	.813	94.081			
23	.265	.781	94.862			
24	.234	.687	95.549			
25	.229	.675	96.224			
26	.206	.607	96.830			
27	.196	.576	97.406			
28	.179	.527	97.933			
29	.172	.505	98.439			
30	.138	.407	98.846			
31	.119	.350	99.196			
32	.100	.293	99.489			
33	.094	.277	99.766			
34	.079	.234	100.000			

Extraction Method: Principal Axis Factoring.

Figure 4.1 Total Variance using SPSS

4.4 Outer Model Evaluation

4.4.1 Average Variance Extracted and Composite Reliability

Once the research model has been created, Hair et al. suggested that researchers should test the outer model. (2014). The outer model was evaluated using AVE, CR, and discriminant validity in this study.

AVE, also known as the construct's communality, is obtained by squaring the loadings and summing them over all indicators. It is the average of the general mean of the squared factor loadings for a set of items associated with the construct. A construct is considered to account for more than 50% of the variance in its indicators if its AVE is greater than 0.50 (Bhattacherjee & Premkumar, 2004; Alzahrani et al., 2017).

Table 4.4 Construct Reliability and Validity

Variable	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
ATT	0.936	0.947	0.954	0.839
CINT	0.900	0.904	0.938	0.834
INTI	0.843	0.866	0.894	0.679
PBC	0.803	0.826	0.883	0.715
PU	0.833	0.874	0.897	0.744
SE	0.840	0.874	0.903	0.757
SMI	0.858	0.872	0.903	0.699
SN	0.879	0.894	0.925	0.804
TI	0.831	0.860	0.898	0.746
TRAI	0.792	0.925	0.739	0.675

4.4.2 Discriminant Validity- Fornell and Larcker Criteria

Table 4.5 demonstrates that all diagonal values were bigger than corresponding row and column values, suggesting discriminant measures.

Table 4.5 Fornell-Larcker Criterion

	ATT	CINT	INTI	PBC	PU	SE	SMI	SN	TI	TRAI
ATT	0.916									
CINT	-0.270	0.913								
INTI	-0.036	0.618	0.824							
PBC	-0.184	0.745	0.625	0.846						
PU	-0.192	0.631	0.688	0.637	0.863					
SE	-0.002	0.536	0.602	0.604	0.610	0.870				
SMI	0.236	0.247	0.473	0.267	0.356	0.500	0.836			
SN	0.137	0.550	0.567	0.533	0.565	0.519	0.359	0.897		
TI	0.063	0.506	0.628	0.474	0.557	0.648	0.628	0.512	0.864	
TRAI	0.195	0.186	0.195	0.242	0.232	0.321	0.232	0.227	0.327	0.524

4.5 Inner Model Evaluation

The squared multiple correlations (R^2) and the path coefficients' significance levels can be used to gauge the structural model's explanatory capacity (Chin, 1998). Using 500 and 5,000 samples, the bootstrap technique was used to evaluate the t-values for the examination of the path coefficients in the research model (Henseler et al. 2009).

4.5.1 Coefficient of Determination (R^2)

Although many academic fields welcome R2, researchers must use a rough guideline to determine what constitutes an acceptable R2, with corresponding values of 0.75, 0.50, and 0.25 denoting significant, moderate, or poor predictive accuracy. (Hair et al., 2011; Henseler et al., 2009). This study found the value of R2 is 38.3% in Table 4.6.

Table 4.6 Coefficient of Determination

	R^2	R^2 Adjusted
ATT	0.097	0.081
CINT	0.626	0.616
PBC	0.377	0.366
SN	0.332	0.320

4.5.2 Path Coefficient

After a PLS model is run, the route coefficients predict the relationships between the constructs. Strong positive correlations are indicated by coefficients closer to +1; in contrast, coefficients show strong negative relationships. closer to -1. Path coefficient values are normalized in a range from -1 to +1. Bootstrapping is required to generate a standard error to test for significance, even though values near -1 or +1 are nearly always statistically significant (Henseler et al., 2010). Out of the 9 hypotheses put out for this investigation, 3 were discovered to lack support from the structural model's final conclusion, specifically SMI -> SN, TI -> PBC, and TRAI -> ATT (see Table 4.7).

Table 4.7 Path Coefficient and Hypothesis Test Result

	Original Sample (O)	**Sample Mean (M)**	**Standard Deviation (STDEV)**	**T Statistics**	**P Values**
ATT -> CINT	0.206	0.214	0.056	3.708	**0.000**
INTI -> SN	0.512	0.512	0.068	7.491	**0.000**
PBC -> CINT	0.556	0.553	0.071	7.787	**0.000**
PU -> ATT	0.250	0.273	0.123	2.029	**0.043**
SE -> PBC	0.512	0.525	0.111	4.593	**0.000**
SMI -> SN	0.117	0.127	0.080	1.456	**0.146**
SN -> CINT	0.283	0.286	0.069	4.083	**0.000**
TI -> PBC	0.142	0.136	0.113	1.259	**0.209**
TRAI -> ATT	0.252	0.158	0.245	1.030	**0.303**

4.6 Final Research Model

The final research model is presented in Figure 4.2 with the path coefficient, R^2, and the level of significance.

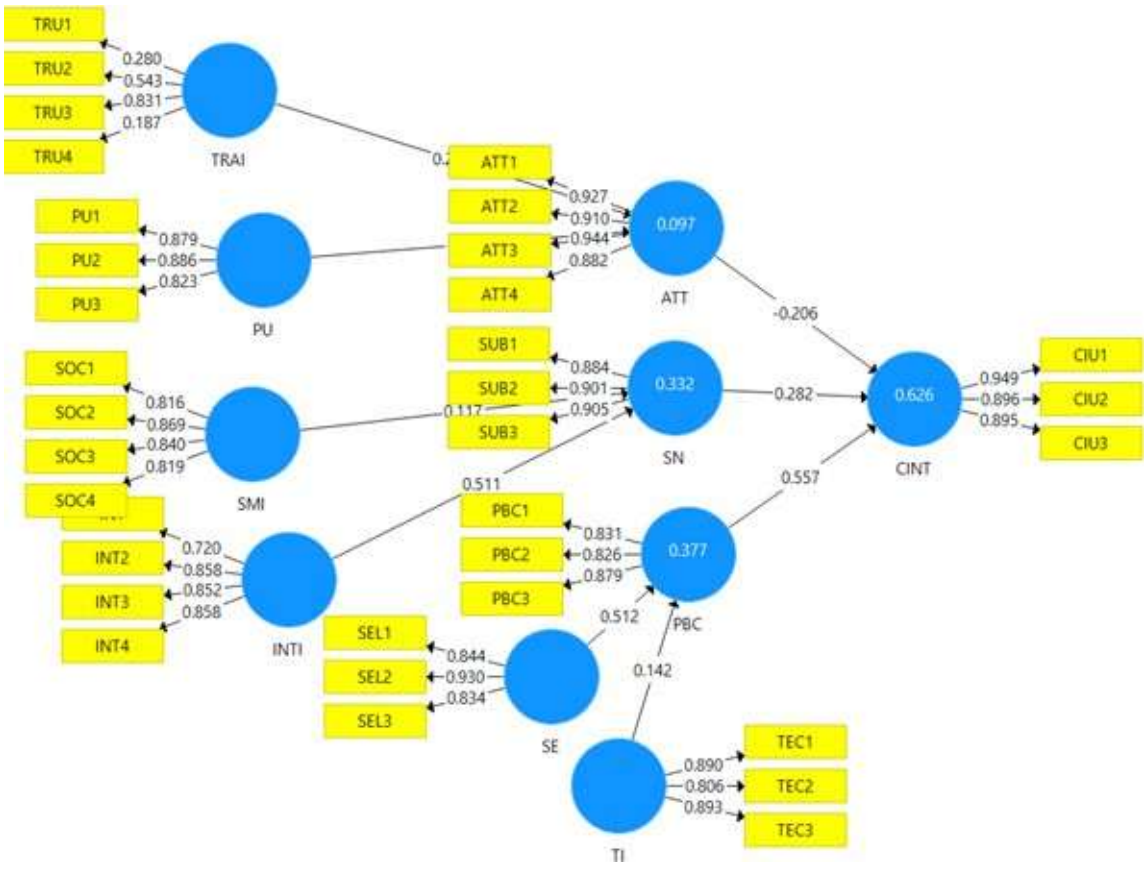

Figure 4.2 Final Research Model

Chapter 5: Discussion and Conclusion

5.1 Introduction

This chapter provides a discussion of the implications and results from the analysis of factors affecting the continued use intention of AI-powered tools among university students in Bangladesh. It provides insight into the relationships among central constructs of an expanded TPB model, with implications for theory and practice. The chapter ends with a review of the limitations of the work and recommendations for future research, before recapping on the major findings of the study.

5.2 Discussions of Findings on Relationships

5.2.1 Relationship between Trust in AI and Attitude

The examination on trust (whether students are confident in the reliability and transparency of AI-powered tools) showed no statistically significant effect on students' attitude toward using these applications. Although previous literature implies trust may be essential to the adoption of technology, the report suggests that when it comes to AI-powered educational technologies among Bangladeshi university students, trust cannot stand on its own feet for developing favorable attitudes. This implies that other elements, including perceived usefulness or social influence, might be more influential in this environment.

5.2.2 Relationship between Perceived Usefulness and Attitude

Attitude was strongly predicted by usefulness. toward AI-supported tools, and this relationship was significantly positive. The students, who perceive the AI tools to improve their educational effectiveness and efficiency, will have favorable attitudes toward using them. This, in turn, consolidates perceived benefits as among the antecedent factors that determine positive attitudes and influence the intention to keep utilizing AI technology in higher education, according to the research's enhanced TPB model.

5.2.3 Relationship between User Interpersonal Influence and Subjective Norm

Interpersonal influence, including the influence of peers, colleagues, and professors, was found to positively and significantly impact the development of subjective norms on AI adoption. The more students have the impression that the key persons of their academic context approve or recommend them to use FMCT, the higher such social pressure will be perceived. This highlights how important social contacts are. and peer networks in influencing technology adoption among college students.

5.2.4 Relationship between Social Media Influence and Subjective Norm

As opposed to the hypotheses, social media influence did not significantly affect subjective norms. While the information transmission and trend-setting role of social media is pervasive, their influence on students' perceived social expectations towards AI tool adoption is seemingly less significant in this course. This could be because

real-person relationships of professors in the academic medium are more than the virtual relationships in social networks.

5.2.5 Relationship between Self-efficacy and Perceived Behavioural Control

Self-efficacy showed a strong, favorable connection with perceived behavioural control. Pupils who have faith in their capacity to use AI-powered tools, even when facing challenges, feel a greater sense of control over their usage. This result emphasizes the importance of building students' technical skills and self-confidence to encourage the long-term use of AI technology.

5.2.6 Relationship between Technological Infrastructure and Perceived Behavioural Control

There was no meaningful connection found with perceived behavioral control for technological infrastructure, which consists of access to adequate hardware, software, and high-speed connections. This implies that infrastructure overall may be necessary, but not the primary driver of students' perceived ability to use AI tools, as individual skills and support systems may be more important.

5.2.7 Relationship between Attitude and Continuous Intention to Use

A hands-on attitude in terms of AI/technology-related tools explains students' continuous intention to use such methods. Students who consider AI tools to be useful, enjoyable, and closely related to their academic requirements are more willing to adopt them in the

long term. This result supports the powerful influence of attitude in the TPB model and suggests that it is a strong predictor for long-term technology usage.

5.2.8 Relationship between Subjective Norm and Continuous Intention to Use

Subjective norm, reflecting the perceived social pressure from peers and important others, was shown to have a significant positive effect on students' continuous intention to use AI-powered tools. When pupils believe that their social surroundings encourage or expect the use of such technologies, their likelihood of ongoing usage increases. This emphasizes how crucial it is to create a welcoming academic environment for technology integration.

5.2.9 Relationship between Perceived Behavioural Control and Continuous Intention to Use

Perceived behavioural control was also found to be a reliable indicator of continuous intention to use AI-powered tools. Students who think they have the necessary opportunities to leverage AI technologies, resources, and talents are more likely to intend to use them regularly. This emphasizes the need for universities to provide adequate training and support to empower students.

5.3 Implications of the Study

5.3.1 Theoretical Implications

This study integrates trust in AI and self-efficacy, which extends the theory of planned behavior, offering a thorough comprehension of the adoption of AI in higher education. The findings indicate the crucial functions of perceived usefulness, interpersonal influence, and self-efficacy in the development of PBC, attitudes, and subjective norms. Notably, the research shows little influence of trust in AI or technological infrastructure, hinting that personal and social factors are more important in this case than systemic and technical ones. These findings, on a broader basis, may serve to enrich technology acceptance theories with respect to both developing countries and emerging technologies.

5.3.2 Practical Implications

Into academic settings by emphasizing their perceived utility and clear academic pay-offs. It is recommended that universities and policymakers incorporate these tools into curricula and promote an environment in which peer-led workshops and mentorship can help encourage positive attitudes towards, as well as the employment of, data sharing. Highlighting training interventions that elevate students' self-efficacy will be important in improving their perceived behavioral control and continued use of AI technologies. While infrastructure enhancements are important, guided interventions designed to impact students' skills and attitudes could result in more impactful and enduring engagement with AI tools. Lastly, fostering a positive academic environment towards adopting AI- by openly communicating its advantages and ethical considerations- will

also contribute to promoting continuous and meaningful student involvement in the long run.

5.4 Limitations and Future Recommendations

The restrictions of this analysis also have implications for the analysis of its findings as well as for future work. As the design of cross-sectional studies precludes measurement of long-term changes in behaviour, longitudinal research is required to provide a clearer picture of changing patterns. Despite the fact that the sample size was adequate, the use of stratified random sampling may not have fully represented the Bangladeshi university student population, including rural and less technologically advanced institutions. Self-report is subject to response biases [63] and, thus, future studies may consider supplementing self-reported data using behavioral tracking or qualitative methods for richer insight. The national context specificity of the study does not allow for wide generalization of results, and we suggest conducting comparative work across countries or regions. Future research should also consider incorporating cultural context, policy interventions, and the influence of specific AI tools into its investigations to advance our understanding of technology adoption dynamics.

5.5 Conclusion

This research thus aimed to explore the critical determinants of university students in Bangladesh regarding their intention for continuous usage of AI-driven tools with an extended use of the Theory of Planned Behavior. The findings underscore the significant role of perceived usefulness, interpersonal influence, and self-efficacy, as well as positive attitudes, for continued use of AI devices. Trust in AI and technological platforms was not such a reliable predictor in this case, but creating conducive social contexts of support and increasing students' technical literacy are found to be important strategies for long-term adoption. The results give educators insightful information, policy makers, and technologists who wish to harness the potential of AI in higher education, as well as establishing the necessity for continued research to take on new tasks and opportunities in this field, developing at breakneck speed.

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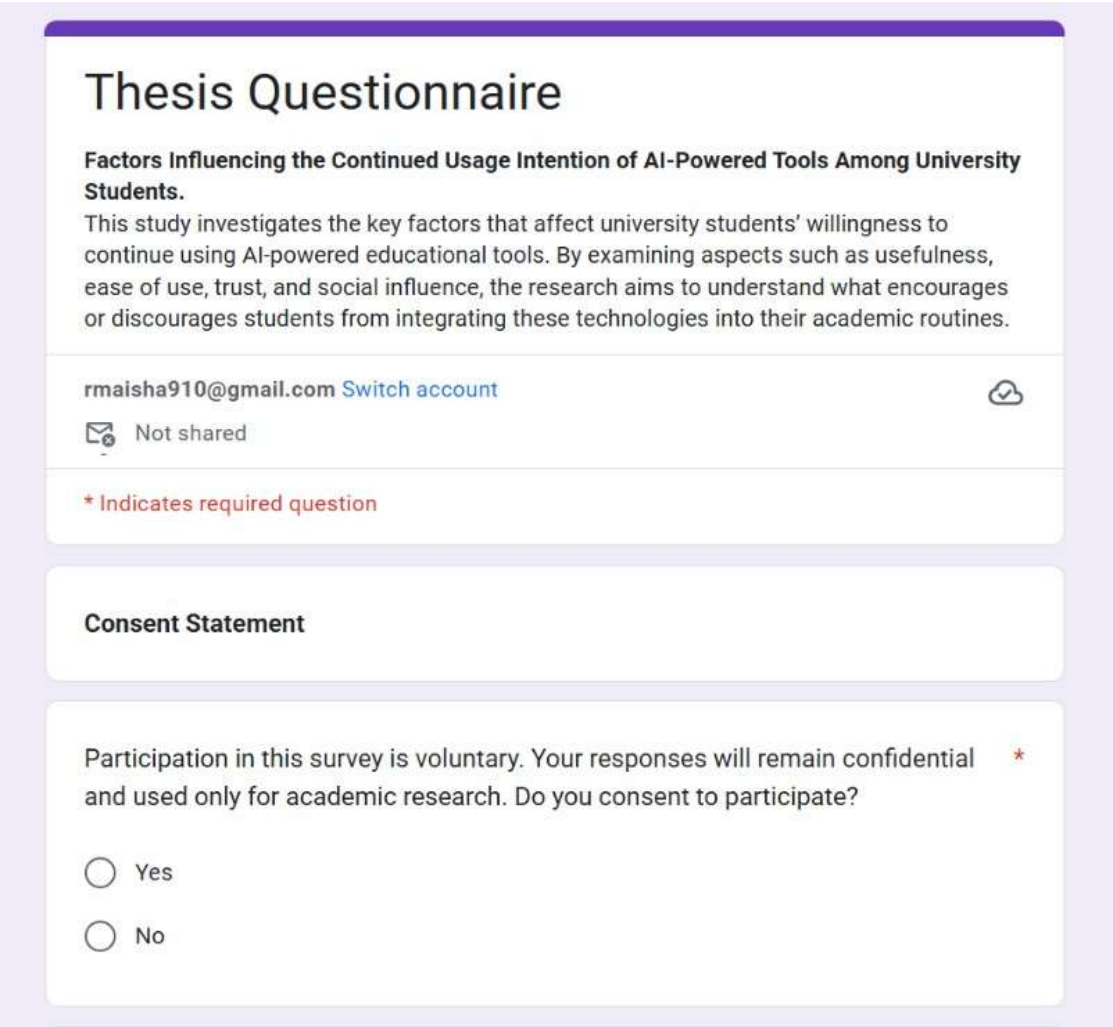
APPENDICES

Appendix A: Survey Questionnaire



Thesis Questionnaire

Factors Influencing the Continued Usage Intention of AI-Powered Tools Among University Students.

This study investigates the key factors that affect university students' willingness to continue using AI-powered educational tools. By examining aspects such as usefulness, ease of use, trust, and social influence, the research aims to understand what encourages or discourages students from integrating these technologies into their academic routines.

rmaisha910@gmail.com Switch account

Not shared

* Indicates required question

Consent Statement

Participation in this survey is voluntary. Your responses will remain confidential and used only for academic research. Do you consent to participate? *

- Yes
- No

Demographic Questions

Age: *

Your answer

Gender: *

- ◯ Male
- ◯ Female

University *

Your answer

Year of Study *

Choose

Have you used AI-powered educational tools (e.g., ChatGPT, Grammarly, Turnitin, Duolingo, GitHub Copilot)? *

- ◯ Yes
- ◯ No

Next Clear form

Never submit passwords through Google Forms.

This form was created inside of Daffodil International University. - Contact form owner

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Main Questionnaire

Instructions for Respondents:
Please indicate your level of agreement with the following statements regarding your experience with AI-powered educational tools, where 1 = Strongly Disagree and 7 = Strongly Agree.

I have confidence in the use of AI technology for my academic work. *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

I believe AI technology can facilitate routine and trivial academic tasks through automation. *

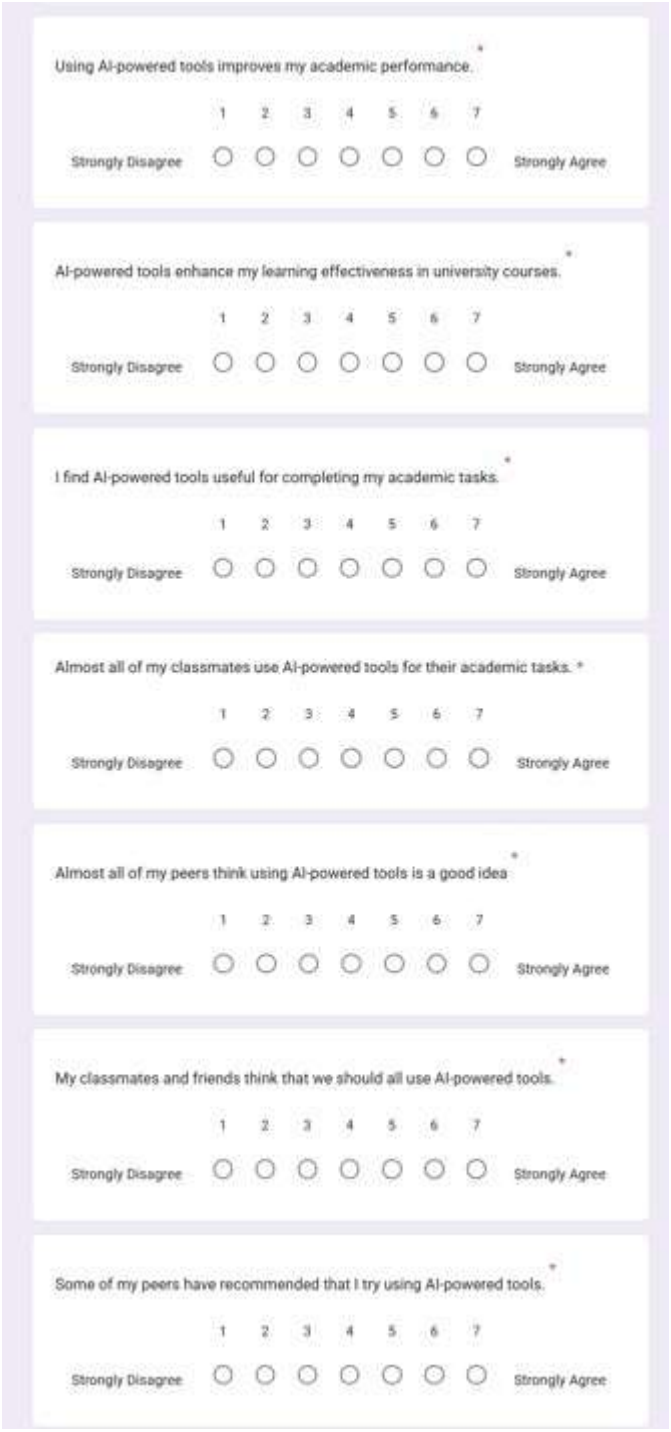
	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

I believe AI-powered tools will operate reliably and consistently without failing. *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

I believe that AI technology will consistently provide adequate and efficient results for a wide range of academic tasks. *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree



I often rely on social media platforms to make decisions about products, services, or trends.

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

The opinions of influencers or popular figures on social media affect my personal choices. *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

I feel motivated to try something new after seeing it recommended on social media. *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

Social media plays a significant role in shaping my views and preferences. *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

I can complete a research task using AI-powered tools if someone shows me how to do it first. *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

I can complete a research task using AI-powered tools if I have reference manuals. *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

I can complete a research task using AI-powered tools even if I have never used such tools before, provided I have access to necessary resources. *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

The technical aspects of AI-powered tools fit well with how my university currently operates. *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

My university's present hardware and software infrastructure can work effectively with AI-powered tools. *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

The improvements made by AI-powered tools are in line with what is already done in my academic environment. *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

For me, using AI-powered tools in my academic work is: Extremely Bad *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

For me, using AI-powered tools in my academic work is: Extremely Undesirable *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

For me, using AI-powered tools in my academic work is: Extremely Unpleasant *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

For me, using AI-powered tools in my academic work is: Extremely Foolish *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

Most people who are important to me think I should use AI-powered tools while doing my academic work. *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

Most people who are important to me would want me to use AI-powered tools while doing my research/study. *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

People whose opinions I value would prefer that I use AI-powered tools while doing my academic work. *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

Whether or not I use AI-powered tools while doing my academic work is completely up to me. *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

I am confident that I can use AI-powered tools effectively for my academic work if I want to. *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

I have the resources, time, and opportunities to use AI-powered tools while doing my academic work. *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

I intend to keep using AI-powered tools for my university studies *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

I will continue to rely on AI-powered tools for completing academic tasks *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

I intend to recommend AI-powered tools to my fellow students. *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

Thank You for your time!

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