Islamic University of Technology (IUT)

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Students' Acceptance and Adoption of Generative AI Tools: Evidence from a Bangladeshi Engineering University

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A thesis submitted in partial fulfillment of the requirements for the Degree of Master of Science in Technical Education with a specialization in Computer Science and Engineering

DEPARTMENT OF TECHNICAL AND VOCATIONAL EDUCATION

ISLAMIC UNIVERSITY OF TECHNOLOGY (IUT)

BOARD BAZAR, GAZIPUR, DHAKA, BANGLADESH

Academic Year: 2022-2023

October, 2025

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Dedication

To the soul of my late father, whose wisdom and inspiration continue to guide me each day. To my beloved mother, for her unwavering love, guidance, and constant strength. To my brother and sister, for their enduring care, belief in me, and support.

This thesis is dedicated to their everlasting impact on my life.

Acknowledgment

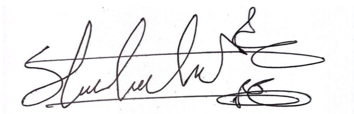
The journey to completing this thesis has been both long and demanding. I am deeply grateful to Allah, the Most Compassionate and Merciful, for granting me the strength, patience, and wisdom to overcome challenges and accomplish this work. Without His guidance, this achievement would not have been possible.

I owe my heartfelt gratitude to my esteemed supervisor, Professor Dr. Md Abdullah Al Mamun. His invaluable guidance, encouragement, and insightful advice have been crucial throughout this journey. He treated me with warmth and kindness, making me feel like a younger brother under his care, while also giving me the freedom and space to explore my ideas independently. He listened attentively to my suggestions, corrected me patiently, and helped simplify complex tasks, making the research process both manageable and rewarding.

I am especially thankful for the exceptional resources, opportunities, and supportive environment he provided, which fostered creativity and scholarly growth. With the help of the Almighty, completing this thesis successfully is a testament to his mentorship, patience, and unwavering support.

Declaration of the Author

This is to certify that the work presented in this thesis is an original work of me, Mazen Abdulwahab Mahyoub Salem Asag, a student of the Department of Technical and Vocational Education (TVE) with a specialization in Computer Science and Engineering, Islamic University of Technology (IUT), The Organization of Islamic Cooperation (OIC), Dhaka, Bangladesh. This work has not been submitted to any other institutions for any other degree.



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Abstract

Generative AI is quickly spreading across higher education, but adoption remains inconsistent in low-resource settings where institutional support and infrastructure lag behind student demand. This study explores how social cues and cognitive evaluations affect engineering students' adoption of generative AI at an international university in Bangladesh. Using an integrated UTAUT–TAM2 framework, we analyze the combined effects of subjective norms and student image with job relevance, output quality, result demonstrability, perceived usefulness, and perceived ease of use on the intention to use. A cross-sectional survey of 378 undergraduate and graduate engineering students employed 31 validated Likert-scale items; data were analyzed in SmartPLS using PLS-SEM with 5,000-sample bootstrapping after establishing reliability and validity. Group comparisons tested for gender and domestic–international differences. The model explained 64% of the variance in usage behavior. Sixteen of twenty hypotheses were supported: subjective norms significantly influenced perceived usefulness and perceived ease of use, and had a small direct effect on intention; student image affected perceived usefulness only; job relevance strongly predicted perceived usefulness, perceived ease of use, and intention; output quality impacted perceived usefulness and perceived ease of use (but not intention); result demonstrability increased intention and perceived ease of use (but not perceived usefulness). Aligned with TAM, perceived usefulness and perceived ease of use influenced intention, which was the strongest predictor of Usage Behavior. Gender effects were minimal, while domestic students reported higher perceived usefulness, perceived ease of use, job relevance, demonstrability, intention, and use than international peers.

Findings underscore the importance of integrating AI into authentic coursework, fostering faculty and peer support, and offering inclusive training to close participation gaps. Limitations include the cross-sectional, single-site design.

Contents

List of Tables

List of Figures

Chapter 1 Introduction

This chapter sets the stage for the study. It explains how rapid progress in generative AI is changing learning and problem-solving, especially for engineering students, and why the Bangladeshi context matters. It then shows the gap: adoption is growing, but we still need a clear picture of how social influence (subjective norms, student image) and cognitive factors (perceived usefulness, perceived ease of use, job relevance, output quality, result demonstrability) work together to shape intention and real usage. The chapter states the problem, research objective, and four research questions, and identifies the audience who can use the results. Finally, it outlines how the rest of the thesis is organized to answer these questions.

1.1 Background and Context of the Study

Over the last five years, the rapid growth of machine learning and generative artificial intelligence has transformed the way technology is utilized (Nay, 2022). Companies such as OpenAI with ChatGPT, Google with Gemini, and DeepSeek, X with Grok, have made significant investments in developing conversation systems that can provide reasoning, explanations, and produce coherent answers while responding to varied user needs (Asag, Al Mamun, & Hasan, 2024). Generative AI now serves as a significant tool influencing multiple domains, particularly education. It provides interactive explanations, customized examples, and personalized feedback that align with individual learning paces (Bernabei, Colabianchi, Falegnami, & Costantino, 2023)

Earlier computer-based systems were largely restricted to fixed templates that limited flexibility and user experience (Debnath & Agarwal, 2019). Today, generative AI tools integrate sophisticated natural language processing with reinforcement learning methods to provide highly customized, adaptable, and context-sensitive learning environments (Baidoo-Anu & Ansah, 2023). With the powerful interaction abilities of these tools students can engage with complex theories by breaking down hard concepts into clear ideas, and explaining them using practical examples that align with specific real-world scenarios (Dahri et al., 2024; Grassini, Aasen, & Møgelvang, 2024).

The interactions with generative AI can also foster creativity by encouraging innovative thinking and lightening the mental workload through features like generating alternative problem-solving approaches and automating routine scholarly activities, such as summarizing notes or drafting outlines (Widyaningrum et al., 2024). These abilities of intelligent chatbot systems make learning more engaging and enable students to focus on essential skills, such as critical thinking and applying their knowledge effectively. As a result, students learn more effectively and enjoy the process.

Despite the exciting global momentum around generative AI, its actual integration into engineering education remains uneven. Pilot studies show that while these tools offer real potential, barriers such as infrastructure limitations, unclear policies, and varying levels of access still hinder meaningful adoption (Rana, Siddiqee, Sakib, & Ahamed, 2024). For instance, a recent conference study specifically investigating engineering students found that social influence, student image, job relevance, and perceived usefulness were significant drivers of students' intentions to use generative AI highlighting the role of social and cognitive factors in low-resource educational contexts (Asag et al., 2024). Likewise, a broader mixed-methods preprint documenting ChatGPT use across several Bangladeshi institutions reported a rapid rise in adoption (from single digits in 2022 to nearly half of sampled students by 2025), while also exposing stark urban–rural divides and concerns about equitable access and academic integrity (Karmaker, 2025). Together with recent country-level SEM work showing that perceived usefulness and ease of use strongly predict ChatGPT uptake among university students, these findings confirm that although students adopt generative AI tools, their motivations and constraints are strongly context-dependent (Howlader, Tohan, Zaman, et al., 2025).

Although this study is situated within the broader landscape of Bangladeshi engineering education, its empirical scope is delimited to the Islamic University of Technology. IUT serves as a unique institutional context where engineering students represent multiple nationalities and cultural backgrounds, making it an internationally diverse learning environment within Bangladesh. Accordingly, while this research offers valuable insights into how engineering students adopt and perceive generative AI tools, its findings should be interpreted within the institutional and multicultural context of IUT rather than generalized to all engineering universities in Bangladesh.

In light of these realities, this study aims to deepen the understanding of the complex mix of social and cognitive factors, such as peer norms, perceived usefulness, ease of use, job relevance, and demonstrability, that influence engineering students' intentions to adopt generative AI in Bangladesh. Understanding this is crucial not only to contextualize the global discussion on AI in education but also to explain why this research is important locally and how it can help develop meaningful institutional strategies. Identifying these factors reveals the limitations of existing studies, which help to highlight the critical gaps in understanding this research aims to address.

1.2 Research Gap

Several factors influence students' intention and use of these tools. Understanding these factors can be complex because social and cognitive influences strongly impact students' intentions. Most research tends to focus only on the technical aspects, overlooking other important factors that can shape intention and adoption. Previous studies that are based on the Unified Theory of Acceptance and Use of Technology (Venkatesh & Davis, 2003) and the Technology Acceptance Model (Davis, 1989) have provided strong evidence that the influence of perceived usefulness (PU) and perceived ease of use (PEOU) are core drivers of technology adoption.

While these studies provide insight into general acceptance tendencies, many of them concentrate on technologically mature environments and overlook the multi-layered challenges confronting students in developing countries (Zhao, Li, Xiao, Chang, & Liu, 2024). In the South Asian region, emerging evidence indicates that peer recommendations and institutional endorsement significantly influence the adoption of advanced educational technologies (Awal & Haque, 2024). However, little research examines how social norms combine with cognitive constructs such as trust, perceived relevance, and critical thinking, result demonstrability, to shape generative AI adoption among engineering students, particularly in environments characterized by collectivist norms, multilingual classrooms, and limited institutional resources (Tiwari, Bhat, Khan, Subramaniam, & Khan, 2024).

In Bangladesh Asag et al. (2024) found that for engineering students , social influence, student image, job relevance, and perceived usefulness significantly drive generative AI adoption highlighting how social and cognitive factors work together in low-resource settings . Structural Equation Modeling (SEM) analysis from Howlader et al. (2025) revealed that alongside PU and PEOU, perceived risk also significantly shapes ChatGPT adoption among Bangladeshi university students (Howlader et al., 2025). Moreover, studies in broader higher education contexts show that while AI brings promise for academic assistance, it also raises critical concerns especially regarding academic integrity, critical thinking, and equitable access (Jamal Eddine, Gide, & Al-Sabbagh, 2025; Talukder & Ahsan, 2025).

Despite these insights, the interactive effects of social norms (like peer influence and institutional endorsement) and cognitive construct (like trust, perceived relevance, risk, and result demonstrability) remain underexplored. This is especially true within collectivist, multilingual, resource-constrained educational environments such as those in Bangladesh. Few studies have examined how these variables jointly influence generative AI adoption among engineering students in such contexts. Therefore, a critical research gap exists: We lack a deep, context-specific understanding of how intertwined social and cognitive factors shape engineering students' adoption of generative AI in low-resource, collectivist, and multilingual settings. Addressing this gap is vital not only to refine theoretical models of technology acceptance, but also to inform institutional strategies that support equitable, responsible, and culturally informed AI integration in education.

1.3 Problem Statement

The educational sector of developing countries including Bangladesh recognizes generative artificial intelligence as a transformative educational force according to (Asag et al., 2024). The assessment of educational tool adoption requires analysis beyond technical capabilities because social and cognitive factors, including usefulness perception, trust in social norms, and behavioral intentions, determine their successful adoption. (Shahzad, Xu, & Javed, 2024). At the same time, the educational implementation of AI systems in Bangladesh encounters multiple barriers because the country lacks sufficient digital infrastructure and unreliable internet access, and insufficient training programs, which prevent effective AI system utilization (Borg & Östergren, 2015).

Students in environments with inadequate institutional backing typically seek help from their informal peer networks to solve technical problems and develop optimal usage approaches. The value assessments of individual users determine the outcomes of generative AI, yet these results also rely on the social dynamics and supportive frameworks that exist in the broader environment. Addressing these barriers through targeted policy interventions could pave the way for more equitable and impactful implementation in education.

In light of these realities, the core problem this study addresses is the absence of a comprehensive understanding of how social and cognitive factors jointly influence the adoption of generative AI among engineering students in Bangladesh. While prior research has highlighted either technical determinants or isolated social influences, very little attention has been given to their combined effect in resource-constrained, collectivist, and multilingual educational contexts. This study therefore seeks to fill that gap by systematically examining the interplay between social norms, perceived usefulness, ease of use, trust, job relevance, and result demonstrability, and how these shape students' behavioral intentions toward generative AI. By doing so, the research aims to generate insights that not only advance theoretical models of technology adoption but also inform practical strategies for the responsible and equitable integration of generative AI in higher education.

1.4 Research Objective

The objective of this research is to analyze how social influence (e.g., peer networks, institutional policies, faculty support) and cognitive factors (e.g., perceived usefulness, perceived ease of use, trust in AI, job relevance) interact to influence the adoption and ongoing use of generative AI tools among engineering students at an international university in Bangladesh. By placing the research within a unified conceptual framework, the study aims to develop practical recommendations that encourage context-aware, culturally sensitive AI adoption strategies, capable of enhancing academic performance and providing equitable access in under-resourced educational settings.

1.5 Research Questions

To address the research purpose, the study is guided by the following research questions:

- RQ1: What is the role of social influence, particularly subjective norms and student image, in shaping engineering students' adoption of generative AI?
- RQ2: How do cognitive appraisals (usefulness, usability, job relevance, quality, demonstrability) drive adoption?
- RQ3: How do social and cognitive factors interact through mediation pathways to shape intention and Usage Behavior?

- RQ4: How do demographic differences (e.g., gender and international vs. domestic student status) affect perceptions, intentions, and Usage Behavior of generative AI?

1.6 Audience

This study primarily addresses educators, curriculum developers, policymakers, and higher education administrators interested in integrating AI tools in engineering education. It is also intended for researchers examining the socio-cognitive dimensions of technology adoption in low-resource contexts. Furthermore, the findings may inform developers of generative AI systems on how to design culturally appropriate tools tailored to the needs of engineering learners in developing regions.

1.7 Outline of the Study

This thesis is structured into seven main chapters, supported by appendices. Begin with this chapter; the rest of the study is structured as follows:

- Chapter 2 Provides a comprehensive literature review, starting with the global and Bangladeshi status of generative AI in higher education. Then, it defines the concept within educational contexts and reviews relevant adoption models, including TAM, UTAUT, TPB, VAM, and TPACK. The chapter also examines social and cognitive determinants, highlights findings from related empirical studies, and concludes with the integrated theoretical and conceptual framework guiding this research.

- Chapter 3.1 This chapter presents the methodology. It describes the overall inquiry strategy, research design, study context, sampling method, and survey instrument. Procedures for expert review, pilot testing, reliability and validity assessments, and data collection are explained. The chapter then details the analytical methods used, including descriptive statistics, measurement model evaluation, and structural model analysis using PLS-SEM.

- Chapter 4 reports the findings. It first summarizes descriptive statistics and demographic information, followed by exploratory trends and pairwise relationships. The measurement model is evaluated for validity and reliability, after which the structural model results, mediation analyses, and group comparisons (t-tests by gender and student status) are presented.

- Chapter 5.1 provides the discussion of results. It interprets the cognitive and social drivers of adoption, explores mediation pathways, and examines demographic differences. The discussion connects these findings with prior studies, highlights contextual insights, and elaborates on theoretical contributions.

- Chapter 6.1 outlines the implications and directions for future research. It discusses the theoretical contributions of the study, practical recommendations for educators, administrators, and developers, and addresses methodological limitations. The chapter concludes by suggesting avenues for further research, including advanced methodologies and broader comparative studies. Ultimately, this chapter offers concluding remarks on the contribution of this research to the understanding of generative AI adoption in higher education.

- Appendix includes: Appendix 6.5.2, which presents the initial survey instrument; Appendix 6.5.2, which provides the complete table of outer loadings and outer weights for all measurement items; and Appendix 6.5.2, which presents the independent samples t-test results by gender and student status.

Chapter 2 Literature Review

2.1 Introduction

This chapter reviews the foundations of the study. It begins by defining AI, generative AI, and generative AI in education and situating its rise in global and Bangladeshi higher education. Next, it outlines key adoption models, including TAM, UTAUT, TPB, VAM, and TPACK, to show how technology use has been studied before. The discussion then moves to social influences in collectivist academic environments and the cognitive factors central to adoption, such as usefulness, ease of use, job relevance, and demonstrability. Contradictions in prior findings are noted, along with ethical and institutional concerns. The chapter concludes by presenting the integrated framework (UTAUT + TAM2) that guides this research.

2.2 Defining Generative AI in Education

Artificial Intelligence (AI) broadly refers to computational systems that can perform tasks typically requiring human intelligence, such as reasoning, problem solving, learning, and decision making (Russell & Norvig, 2021). At its core, AI encompasses a variety of approaches, including symbolic reasoning, machine learning, and neural networks, which enable machines to process information and adapt to new inputs.

Generative Artificial Intelligence refers to a category of advanced machine learning techniques designed to produce content, including text, code, or images, based on input data. In educational contexts, generative AI tools such as ChatGPT (OpenAI), Gemini (Google), or Copilot (Microsoft) perform advanced natural language processing tasks to support students and instructors across a wide range of academic activities (Baidoo-Anu & Ansah, 2023). Unlike traditional rule-based learning systems that depend on manually programmed responses, generative AI tools produce original outputs that mirror both the input context and the underlying training data, allowing highly interactive and adaptable forms of digital communication support.

In educational settings, generative AI is becoming a daily assistant for students, helping them with tasks such as summarizing complex concepts, reorganizing outlines, transforming learning content into clearer formats, or generating executable code in programming courses (Al-Abdullatif, 2024; Dahri et al., 2024). It also enhances students' critical thinking by providing interactive feedback that enables them to ask follow-up questions and receive detailed answers. These features set generative AI apart from earlier intelligent tutoring systems, as it can engage with learners, respond to their queries in real-time, and customize explanations according to their level of understanding (Asag et al., 2024).

Apart from all these benefits, there are still some concerns about the revolution of new technology. Recent research highlights risks such as the spread of misinformation, ethical concerns about academic honesty, and students becoming too reliant on these tools. It is important to introduce AI into education carefully and offer clear guidance and support so students can use the technology effectively without harming their ability to think critically or solve problems independently. (Foroughi, Senali, et al., 2024; Grassini et al., 2024). In education, effective use of generative AI tools should rely on clear regulations and guidelines, coupled with informed teaching strategies, to maximize benefits and reduce potential misuse by students. Understanding the current status and adoption of these tools is therefore crucial, as it provides insight into how institutions are implementing AI, the challenges they face, and the opportunities for enhancing learning outcomes. This context is particularly important when examining the global landscape of generative AI in higher education, as well as its specific development and integration within Bangladesh.

2.3 Status of Generative AI in Higher Education Globally and in Bangladesh

Generative Artificial Intelligence has become one of the most disruptive technologies in modern higher education. Worldwide, numerous universities in North America, Europe, and East Asia have started integrating generative AI tools, such as ChatGPT, Gemini, and Copilot, into teaching, learning, and administrative activities. These tools are increasingly used for creating academic support content, organizing coursework, aiding with coding in engineering classes, and assisting students in developing scientific reports and literature reviews (Bernabei et al., 2023; Widyaningrum et al., 2024). In several universities in the United States and South Korea, institutional policies have already been implemented to regulate the use of generative AI in academic tasks, recognizing both its potential benefits and the ethical risks associated with plagiarism and data privacy.

Recent global reviews and empirical studies confirm rapid growth in awareness and experimental use of these tools among faculty and students. Systematic reviews of ChatGPT studies document a surge of empirical work in 2023–2024, showing strong interest across disciplines but also repeated concerns about academic integrity, output quality, and instructor readiness (Baig et al., 2024; Lee, 2024). Institutional reports from higher-education consortia emphasize that most universities now face a practical choice: ban, regulate, or integrate. The trend in leading institutions is to issue nuanced guidance, provide training, and redesign assessments rather than adopt outright prohibitions (Ithaka, 2025).
However, the pace and scale of adoption vary greatly across regions. While students in technologically advanced countries benefit from well-developed digital infrastructure and targeted AI literacy programs, the educational systems of low- and middle-income countries face significant barriers in access and institutional readiness (Awal & Haque, 2024).

In Bangladesh, for example, the use of generative AI tools is mainly student-led and informal, with limited proactive involvement from universities. Although engineering students increasingly depend on ChatGPT for explaining algorithms, debugging code, or paraphrasing assignments, formal integration into curricula remains absent due to infrastructural and policy constraints (Anik & Rahman, 2025; Asag et al., 2024). Peer influence seems to offset institutional shortcomings by fostering the spread of generative AI through informal learning groups. As a result, the use of generative AI in Bangladesh reflects a wider tension between technological potential and real-world challenges, such as low bandwidth, limited AI knowledge, and inadequate faculty training. These challenges highlight the importance of context-aware approaches that consider the complex between infrastructure and socio-cultural factors in encouraging responsible and fair AI use in higher education.

New empirical studies from Bangladesh (2024–2025) strengthen these observations. Several cross-sectional surveys and mixed-methods reports show fast-growing awareness but large disparities in access. A mixed-method study covering multiple Bangladeshi institutions reports rapid increases in ChatGPT use among students, with urban learners and students at larger universities adopting earlier than rural or resource-constrained peers (Karmaker, 2025). Smaller case studies from public universities and regional campuses document both enthusiasm and practical limits: students appreciate time savings and debugging help, but they also report erratic internet, difficulties verifying AI outputs, and a lack of formal guidance from faculty (Chowdhury, 2025; Islamic University, Kushtia, 2025). Policy-oriented analyses for Bangladesh recommend institution-level AI literacy programs, teacher training, and localized guidelines that reflect cultural expectations about academic honesty (Anik & Rahman, 2025).

At the same time, national and institutional experiments show promising local responses. Some departments have piloted AI-literacy workshops and prompt-design sessions to help students evaluate and use outputs responsibly. Local studies find that short, practical training increases students' ability to spot hallucinations, cite AI outputs appropriately, and use generative tools as a scaffold rather than a shortcut (Ahmed, 2024; Shanto et al., 2024). These interventions suggest pathways for closing the access competence gap even when large-scale infrastructure upgrades are slow.

Having established what generative AI is and how it functions within educational settings, the next step is to examine the theoretical models that explain how and why individuals adopt such technologies. Frameworks such as TAM, UTAUT, VAM, and TPB provide structured ways of understanding the interplay of social and cognitive influences in technology use, which makes them especially relevant for studying the adoption of generative AI in higher education.

2.4 Adoption Models in Technology Use (TAM, UTAUT, VAM, TPB, TPACK)

The study of technology adoption has led to the development of numerous frameworks with varying structures to examine the integration of new technologies into existing environments, providing a clear understanding of how and why individuals use and engage with these technologies. In the educational context, researchers have utilized these frameworks to understand the adoption of generative AI and its usage in higher education. One of these frameworks is the Technology Acceptance Model (TAM) (Davis, 1989), which is especially important and serves as a foundational framework for many studies. It suggests that people are more likely to use technology if they see it as helpful and easy to use.

Recent research based on TAM, such as (Al-Abdullatif, 2024; Foroughi, Senali, et al., 2024; Tiwari et al., 2024), supports this idea, showing that students are more open to using AI tools when these tools help them achieve better academic outcomes and are easy to use. However, TAM has its limits because it does not pay much attention to social and cultural factors, which can be important in some settings, such as collectivist cultures (Mogaji, Viglia, Srivastava, & Dwivedi, 2024).

The Unified Theory of Acceptance and Use of Technology (UTAUT) that developed by (Venkatesh & Davis, 2003) is another important framework emerged from the need to address the shortcomings of earlier models, such as TAM, by incorporating additional constructs such as Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI) and Facilitating Conditions (FC).
UTAUT is widely used to investigate the adoption of generative AI in educational settings, as shown in multiple studies (Asag et al., 2024; Bhat, Tiwari, Bhaskar, & Khan, 2024; Yilmaz, Yilmaz, & Ceylan, 2024). To better capture the dynamics of ongoing use, an extended version of UTAUT2, was introduced. By adding factors such as Hedonic Motivation (HM), Habit, and Price Value (PV), it offers a more comprehensive lens for understanding long-term user engagement (Acosta-Enriquez, 2024; Strzelecki, 2024).

Other frameworks incorporate additional factors that influence the adoption of technology, for example, perceived risk, social influence, and contextual factors. one of these model is the Value-Based Adoption (VAM), that considers benefits and risks, suggesting that people are more likely to adopt technology if they perceived benefits as outweighing the drawbacks (perceived risks), as shown in (Al-Abdullatif, 2024), while the Theory of Planned Behaviour (TPB) (Ajzen, 1991) identifies attitudes, subjective norms, and perceived behavioural control as determinants of intention to use generative AI (Maheshwari, 2024; Tiwari et al., 2024).

Technology Pedagogical Content Knowledge (TPACK) is another framework developed by (Koehler & Mishra, 2009), mainly focus on examining how technology, teaching methods, and subject knowledge interact, emphasizing how teachers can utilize AI tools in ways that align with their teaching goals and support academic integrity (Mishra, Warr, & Islam, 2023). These frameworks fully integrate the technical, pedagogical, social, and ethical aspects, along with the adoption of generative AI in higher education.

2.5 Social Influence and Subjective Norms in a Collectivist Academic Context

It is often observed that in collectivist cultures, people's preferences are usually influenced more by group expectations and peer pressure than by personal desires. In the context of generative AI adoption among university students in Bangladesh, social influence is consistently reported as a key determinant of intention to use (Asag et al., 2024).

Students often depend on their peers' experiences to assess both the perceived trustworthiness of tools like ChatGPT and whether using such tools is suitable for academic purposes. (Anik & Rahman, 2025; Asag et al., 2024). Recent studies conducted in Saudi Arabia and other South Asian contexts (e.g., (Awal & Haque, 2024; Sobaih, Elshaer, & Hasanein, 2024)) highlight the importance of Subjective Norms (SN) in influencing student behavior. When respected peers and teaching staff view AI tools positively, students tend to adopt such technologies more readily. In contrast, vague institutional policies and limited faculty guidance often lead to hesitation, stemming from concerns about misconduct or plagiarism (Mishra et al., 2023; Tiwari et al., 2024). These findings suggest that social influence extends beyond peer interactions to encompass perceived conformity to broader ethical and cultural norms.

2.6 Cognitive Factors: PU, PEOU, Job Relevance, Result Demonstrability

Cognitive factors are internal thought processes and evaluation mechanisms that influence how students decide to use technology, including their perceptions and attitudes toward new tools. In the context of generative AI adoption, Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) consistently stand out as key predictors influencing students' acceptance and continued use(Foroughi, Senali, et al., 2024; Zhao et al., 2024). If students recognise that generative AI tools assist them in understanding complex concepts or completing academic tasks more efficiently, they are more likely to incorporate them into their routine (Al-Abdullatif, 2024).

Additional variables, such as Job Relevance (JR) and Result Demonstrability (RD), also deserve attention. Job Relevance refers to the extent to which learners perceive AI tools as applicable to their specific academic or professional activities, while Result Demonstrability captures how clearly the benefits of using the tool can be observed and communicated (Asag et al., 2024; Shahzad, Xu, & Javed, 2024). Several empirical studies, such as (Almogren, Al-Rahmi, & Dahri, 2024; Du & Lv, 2024), ensured that when outcomes are tangible, such as improved critical thinking or accurate code generation, students develop stronger intentions to use AI tools in the long term. In addition, trust in AI-generated outputs has recently emerged as an important moderating component influencing cognitive evaluations (Acosta-Enriquez, 2024).

2.7 Gender Differences in AI Adoption

Recent empirical studies shows that gender remains a significant factor in how AI (especially Generative AI or LLMs) is adopted, perceived, and used. The findings point to both gaps and contexts where the gap is reduced, depending on exposure, training, and attitudes. A study by Tang, Li, Hu, Zeng, and Du (2025) shows that male researchers saw a 6.4% higher productivity increase than female researchers after the introduction of ChatGPT. It also found men using generative AI more often and reporting greater efficiency gains than women.

Cachero, Tomás, and Pujol (2025) report that female students perceive their AI knowledge, ability to apply AI, and exposure to AI less highly than males. Women also showed lower levels of support and more concern about privacy in data usage. Another systematic review in the Asian higher education context, identifies issues such as technological illiteracy, cultural and personal constraints, lack of training, and concerns around ethics and privacy as being more salient for women than men. The review shows that even when tools are available, gendered differences in access, confidence, and institutional support persist Kalim, Kanwar, Sha, and Huang (2025). In contrast Iddrisu, Iddrisu, and Aminu (2025) found that male and female students did not differ in perceived effectiveness of AI writing tools, despite differences in usage patterns.

2.8 Related Empirical Studies and Contradictions in Findings

Empirical research on the adoption of generative AI has yielded mixed results across various socio-cultural contexts. Studies in high-resource environments generally report positive impacts on learning outcomes, increased engagement, and enhanced productivity (Bernabei et al., 2023; Widyaningrum et al., 2024). In contrast, research conducted in developing countries reveals significant concerns regarding data privacy, overreliance, and the erosion of critical thinking skills (Dube, Ndlovu, & Dube, 2024; Jaiteh, Hasan, Karim, Al Mamun, & Khan, 2024).

Table 2.1: Summary of Studies on Generative AI Adoption Frameworks and Influencing Factors

Authors (Year)	Framework Used	Role of Social Factors	Role of Cognitive Factors
Zhao et al. (2024)	TRI + TAM + TPB	SN	PU, PEOU, Attitude, PBC, Discomfort, Insecurity
Foroughi, Iranmanesh, et al. (2024)	TAM + IS Success Model	SI (not explicitly tested)	PU, PEOU, System Quality, Trust
Cabero-Almenara, Palacios-Rodríguez, Loaiza-Aguirre, and Andrade-Abarca (2024)	UTAUT2	SI, Institutional support, Peer influence	PE, EE, FC, HM, ATT
Ruiz-Rojas, Salvador-Ullauri, and Acosta-Vargas (2024)	UTAUT	Peer-recommendations, Institutional support, Cultural influence	Critical thinking, Collaborative engagement, Problem-solving
Shahzad, Xu, and Javed (2024)	E-TAM (TAM with PI & PT)	SI, Institutional support, Cultural influence	PE, PU, PI, PT, Critical thinking, Creativity

(Authors Year)	Framework Used	Role of Social Factors	Role of Cognitive Factors
Khlaif et al. (2024)	UTAUT	SI, Peer influence	PE, EE, HM, Experience
Dube et al. (2024)	PCFA + TOE	SI, Institutional support, Peer influence	PU, PEOU, SE, Curiosity, Fear
Grassini et al. (2024)	UTAUT2	SI (minimal impact)	PE, Habit, Performance Expectancy
Widyaningrum et al. (2024)	UTAUT	SI, Peer support, Institutional support	PE, EE
Bernabei et al. (2023)	TAM + UTAUT + BOCR	SI (limited impact)	PU, PE, Task efficiency, Critical engagement
Dahri et al. (2024)	E-TAM (Extended TAM)	SI, Peer & Educator influence	PU, PEOU, Enjoyment, AI Intelligence
Almogren et al. (2024)	E-TAM (incorporating UTAUT & TPB)	SN (no significant impact)	PEOU, PU, FQ, PAQ, Trialability, Compatibility, RA
Tiwari et al. (2024)	TAM + TPB	PSP	PU, PEU
Maheshwari (2024)	TAM + TPB	Personal experiences (no explicit SI)	PEU, Personalization, Interactivity
Baidoo-Anu and Ansah (2023)	Generative AI (GPTs)	No explicit social influence	Personalized learning, Content creation, Context awareness
Al-Abdullatif (2024)	TAM + VAM	No explicit social influence	PU, PEOU, Enjoyment, Value, Risk

(Authors Year)	Framework Used	Role of Social Factors	Role of Cognitive Factors
Mishra et al. (2023)	TPACK	Anthropomorphizing, Ethical concerns	Creativity, Higher-order thinking, Critical evaluation
Yilmaz et al. (2024)	UTAUT	SI, Peer & Family influence	PU, EE, Accuracy, Ethics
Du and Lv (2024)	UTAUT + TTF	SI, Peer & Teacher influence, Social media	PE, EE, TTF
Strzelecki (2024)	UTAUT2 + Personal Innovativeness	SI (minimal impact)	PE, EE, Hedonic Motivation
Acosta-Enriquez (2024)	UTAUT2 + Extended with Risk & Ethics	SI, Peer & Instructor influence	PE, EE, HM, Self-efficacy
Foroughi, Senali, et al. (2024)	UTAUT2 + Extended with Learning Value & Innovativeness	SI (minimal effect)	PE, EE, HM, Innovativeness, Accuracy
Sallam et al. (2024)	TAM + Extended with Risks, Anxiety & Social Influence	SI, Social networks, Peer influence	PU, PEOU, Anxiety, Risks, Trust
Sobaih et al. (2024)	UTAUT	SI (Key predictor, Collective culture)	PE, EE, FC, Facilitating Conditions

Note: SN – Subjective Norms; SI – Social Influence; PSP – Personal Social Perception; PE – Performance Expectancy; PU – Perceived Usefulness; PEOU – Perceived Ease of Use; EE – Effort Expectancy; FC – Facilitating Conditions; HM –

Hedonic Motivation; ATT – Attitude toward Technology; SE – Self-Efficacy; RA – Risk Aversion; FQ – Functionality Quality; PAQ – Perceived Accuracy Quality; PT – Perceived Trust; PI – Personal Innovativeness; Curiosity – User Curiosity toward AI; Discomfort – Psychological Discomfort; Insecurity – Perceived Insecurity; Enjoyment – Intrinsic Enjoyment; Critical Thinking – Critical Thinking Skills; Creativity – Creativity Skills; Personalization – Personalization Features; Interactivity – System Interactivity; Anxiety – Anxiety toward AI Use; Risks – Perceived Risks of AI; Task Efficiency – Efficiency in Task Completion; Accuracy – Accuracy of AI Outputs; Ethics – Ethical Considerations.

2.9 Ethical, Privacy, and Academic-Integrity Concerns

Rapid emergence of capable generative models has raised longstanding ethical questions, particularly regarding authorship, attribution, and fairness, and these issues have become urgent policy problems for higher education as generative AI tools gain traction in classrooms. For example, (García-López & Trujillo-Liñán, 2025) emphasize that the ethical and regulatory challenges of generative AI cannot be addressed solely through technical solutions, but instead require coordinated policy and pedagogical strategies. Similarly, (Kovári, 2024) highlights the risks of plagiarism and academic dishonesty associated with students using tools like ChatGPT without proper disclosure, and suggests best practices to mitigate these risks through awareness and assessment reform.

Another concern arises from the models themselves. Hallucinations, factual inaccuracies, and subtle biases in AI-generated content have been observed to mislead students who may not have the skills to critically evaluate these outputs. (Ali et al., 2024) found, in their systematic review, that students often accept AI responses as authoritative, thereby increasing the risk of over-reliance. (Evangelista, 2025) further argues that detection tools alone are insufficient to preserve academic integrity, recommending instead that assessments be redesigned to prioritize higher-order thinking and reflection.

Privacy and data protection also remain pressing issues. (H. Wang, Dang, Wu, & Mac, 2024) show that many universities now face challenges in regulating how student data is handled when interacting with generative AI platforms, particularly when external providers retain prompt and response histories. (García-López & Trujillo-Liñán, 2025) similarly stresses that ethical deployment must address consent and data transparency, as students often lack clarity about how their data is used.

Finally, the academic integrity debate frames AI as both a threat and an opportunity. (Evangelista, 2025) notes that rethinking assessment design can ensure that AI becomes a tool for learning rather than misconduct, while (Kovári, 2024) argues for transparent disclosure practices as a new academic norm. Together, these perspectives suggest that ethical, privacy, and integrity issues should be approached through multi-pronged institutional policies that balance risk management with innovation.

2.10 Institutional Readiness, Policy, and Pedagogical Strategies

Universities worldwide are rapidly adapting to the rise of generative AI by issuing policies, resources, and guidelines for teaching. (H. Wang et al., 2024) find that leading institutions rarely adopt blanket prohibitions; instead, they provide workshops, syllabus statements, and advisory resources to guide both faculty and students. This pragmatic approach reflects an attempt to align AI use with educational goals rather than resist technological change.

Pedagogical strategies are also evolving (Ali et al., 2024) report that integrating generative AI into classroom activities improves engagement and provides students with formative feedback. Zakarneh et al. (Zakarneh, Aljabr, Al Said, & Jlassi, 2025) further demonstrate how ChatGPT can be incorporated into language teaching, with structured rubrics and scaffolded prompts to enhance learning outcomes. These studies emphasize that intentional integration rather than ad-hoc use yields the most educational value.

In developing contexts, institutional readiness must also consider infrastructural and cultural dynamics.(Ravšelj et al., 2025) In their global survey, they observed that students strongly favor clear institutional policies and training opportunities to guide their AI use. (Yusuf, Pervin, & Román-González, 2024) highlights how multicultural perspectives on integrity and fairness influence the adoption of guidelines differently across regions, with students demanding localized approaches. (Howlader et al., 2025) add that in Bangladesh, perceived usefulness, ease of use, and perceived risks significantly affect adoption, underscoring the importance of context-sensitive policies.

Pedagogical readiness thus requires a multi-level strategy. Evangelista (2025) recommends redesigning assessments to emphasize process and originality, while (Ali et al., 2024) argues for embedding AI literacy into curricula so that students can critically evaluate outputs. Zakarneh et al. (Zakarneh et al., 2025) provide evidence that faculty development and rubric construction can make AI integration pedagogically sound. Together, these insights point to an implementation roadmap where institutions co-develop guidelines with faculty and students, invest in AI literacy, and adapt assessments to safeguard integrity while maximizing the benefits of generative AI.

2.11 Conclusion

This chapter reviewed the key concepts, theories, and evidence that form the foundation of this study. It began with defining artificial intelligence and generative AI, highlighting their growing influence in higher education worldwide and in Bangladesh. The discussion showed that while generative AI tools like ChatGPT and Copilot offer new opportunities for learning and teaching, they also introduce challenges related to ethics, privacy, and institutional readiness.

Next, the chapter examined major technology adoption frameworks TAM, UTAUT, TPB, VAM, and TPACK to explain how individuals decide to adopt new technologies. These models helped identify both cognitive factors (such as perceived usefulness, ease of use, job relevance, and result demonstrability) and social influences (such as peer and institutional support) as critical determinants of adoption. The review also noted variations and contradictions in previous findings, particularly across different cultural and resource contexts.

Finally, the discussion emphasized that successful and responsible use of generative AI in education depends on institutional policies, ethical awareness, and pedagogical strategies that align innovation with integrity.

Building on these insights, the next chapter outlines the study's methodological approach. It explains how the integrated UTAUT–TAM2 framework is applied to examine the adoption of generative AI among university students in Bangladesh, detailing the research design, data collection, and analysis procedures used to achieve the study's objectives.

Chapter 3 Methodology

3.1 Introduction

This chapter describes how the study is designed and carried out. It introduces the theoretical foundations and explains why an integrated UTAUT–TAM2 framework is used. The research strategy and context are presented, along with the population and sampling details. The survey instrument, expert review, pilot testing, and the reliability and validity checks are explained to ensure quality. The chapter then lays out the analysis plan: descriptive statistics, measurement model evaluation, and structural model testing using PLS-SEM, including bootstrapping and model fit indicators. It also notes triangulation steps and the ethical procedures followed in the study.

3.2 Theoretical Foundations of the study

The investigation into the acceptance and use of new technology within an educational context requires a robust theoretical framework to guide the research design, inform data collection, and provide a lens for analyzing findings. This study is grounded in established technology acceptance theories, which offer validated constructs for understanding the factors that influence an individual's decision to adopt and utilize a new information system. The core premise of this research is that the adoption of generative AI (GenAI) tools by university students is not a monolithic event, but a complex process influenced by a confluence of social, cognitive, and facilitating factors. To ignore this complexity would be to provide an incomplete picture of the adoption phenomenon. Therefore, this study does not rely on a single theoretical model but draws upon the strengths of two of the most influential theories in the field: the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT).

3.2.1 Rationale for UTAUT + TAM Integration

As we saw above, there are limitations associated with every framework; while one model may be effective for certain variables and not for others, this study employs an integrated theoretical framework combining UTAUT by (Venkatesh & Davis, 2003) and TAM by (Venkatesh & Davis, 2000). The use of the UTAUT model along with its core factors enabled the study to understand the social and contextual dimensions (Social Influence and Facilitating Conditions), while TAM ensures that cognitive constructs (Perceived Usefulness and Perceived Ease of Use) are adequately represented (Bhat et al., 2024; Yilmaz et al., 2024). The combined model is especially appropriate for the Bangladeshi context, where personal benefit and peer approval both influence adoption intentions.

Since one framework alone fails to capture the complexity of AI adoption in educational contexts, the use of integration and a combined model is also justified, as shown in various studies, such as (Tiwari et al., 2024). For example, the unified theory model does not include Job Relevance and Result Demonstrability, which are unique to engineering education, while TAM does not explicitly consider social norms and institutional support. By combining the two, this study captures multi-directional influences on adoption and reflects the realities of resource-limited, collectivist academic environments.

Recent work on generative AI further supports this integrated approach. Studies on ChatGPT and similar tools show that cognitive evaluations (usefulness and ease) remain central, while social endorsement and infrastructural support strongly shape whether those perceptions translate into actual use (Habibi, Mukminin, et al., 2024; Shahzad, Xu, & Javed, 2024). For example, Cabero-Almenara et al. (2024) applied UTAUT2 to teachers' adoption of generative AI and found that pedagogical beliefs and social processes amplify performance expectations. Similarly, Baroni, Calegari, Scandolari, and Celino (2022a) proposed an AI-specific TAM variant (AI-TAM) that embeds constructs such as trust and perceived output quality, reinforcing the idea that TAM alone needs augmentation for AI contexts.

Two implications follow. First, the two models offer complementary constructs. TAM captures task-related judgments through Perceived Usefulness, Ease of Use, Job Relevance, and Output Quality. UTAUT captures the surrounding conditions through Social Influence, Facilitating Conditions, and moderators. Empirical studies confirm that both pathways operate simultaneously in student evaluations of generative AI (Baig et al., 2024; Camilleri, 2024).

Second, integration addresses context sensitivity. In collectivist and resource-constrained settings like Bangladesh, social endorsement by peers and instructors often amplifies perceived usefulness, while weak infrastructure can dampen adoption despite positive beliefs. Recent surveys of ChatGPT use across Asian universities confirm this interactive effect between cognitive and social-contextual dimensions (Habibi et al., 2024; Shahzad, Xu, & Javed, 2024; Xue, Rashid, & Ouyang, 2024).

Thus, an integrated UTAUT–TAM2 model, as applied here, preserves the explanatory power of TAM while embedding those predictors in the social and institutional frame emphasized by UTAUT. This design both matches current empirical evidence in generative-AI adoption and fits the socio-cultural realities of Bangladeshi engineering students. Moreover, mapping TAM2 constructs such as Job Relevance, Output Quality, and Result Demonstrability into the broader UTAUT frame increases explanatory power and grounds the model in observable classroom practices (Baig et al., 2024; Baroni et al., 2022a).

In short, this study employs UTAUT and TAM together because the combination is not only theoretically coherent but also empirically warranted. It provides a more complete view of adoption by capturing cognitive, social, and contextual determinants that influence students' willingness to engage with generative AI in higher education.

3.2.2 The Unified Theory of Acceptance and Use of Technology (UTAUT)

To capture different dimensions and factors influencing student use and adoption of gen AI, we highlight the need for a combination of two base models that allow us to do so. In this study, we integrated the two models: Unified Theory of Acceptance and Use of Technology (UTAUT) and the Technology Acceptance Model 2 (TAM2). By drawing on both UTAUT and TAM2, the study captures not only the social pressures and infrastructural support that influence adoption but also the cognitive evaluations of task relevance, output quality, and demonstrability of results that are crucial in academic contexts.

The Unified Theory of Acceptance and Use of Technology (UTAUT) was developed by Venkatesh and Davis (2003), it is a synthesis of eight prominent models of technology adoption. Its central purpose was to provide a more comprehensive explanation of user intentions and subsequent usage behavior. The model identifies four key constructs as direct determinants of behavioral intention and use.

- Performance Expectancy (PE): The degree to which an individual believes that using the technology will help them achieve improvements in academic or job performance. This construct closely parallels *Perceived Usefulness* in TAM and has consistently been shown to be the strongest predictor of behavioral intention.

- Effort Expectancy (EE): The perceived ease of use of the technology. It reflects how intuitive and manageable the system is, and corresponds to *Perceived Ease of Use* in TAM.
- Social Influence (SI): The extent to which an individual perceives that important others such as peers, instructors, or family believe they should use the new system. This factor is particularly relevant in collectivist cultural contexts, where peer norms can strongly shape decision-making.
- Facilitating Conditions (FC): The belief that adequate technical and organizational support exists to enable effective use of the system. This includes access to infrastructure, resources, and training.

The original UTAUT model further acknowledges that these four constructs are influenced by demographic and contextual factors, specifically gender, age, experience, and voluntariness of use. These moderators influence the strength of the relationships between the constructs and behavioral intention. Figure 3.1 illustrates the original UTAUT framework.

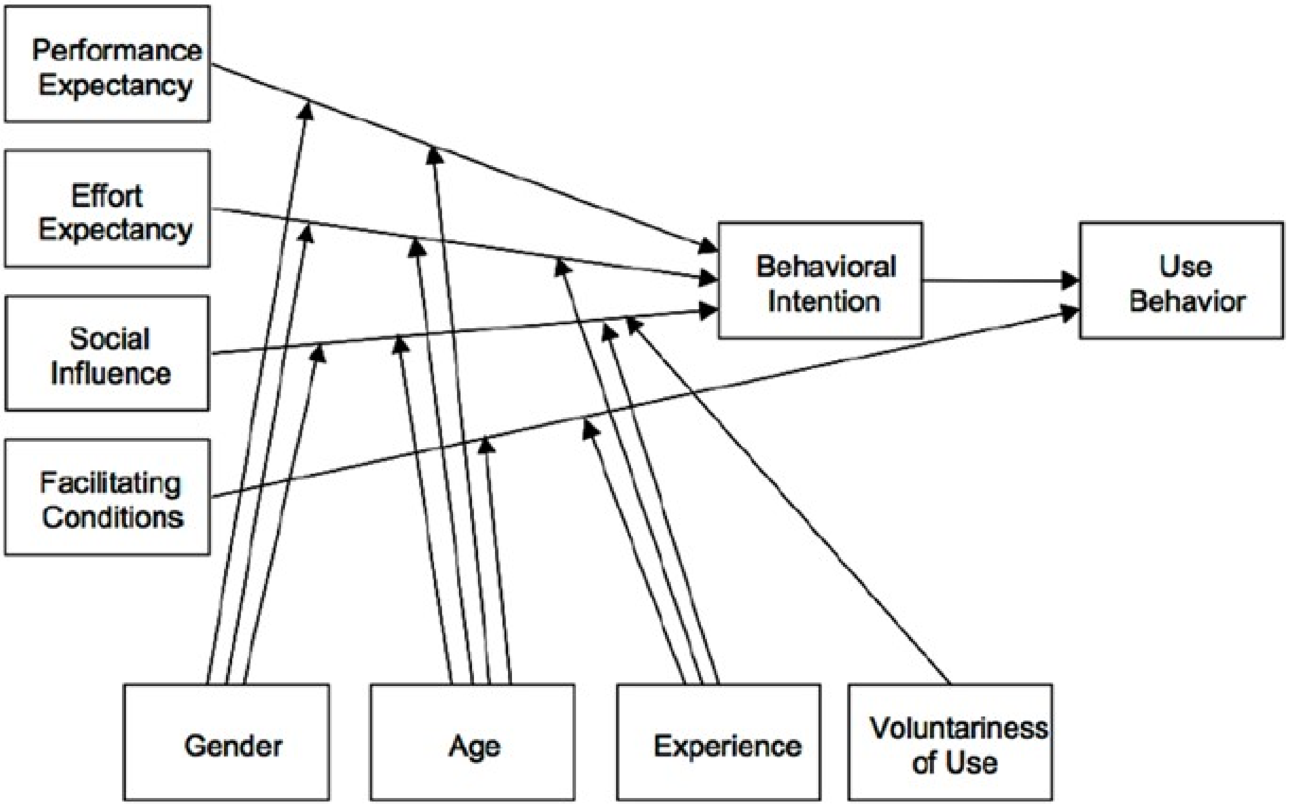

Figure 3.1: Unified Theory of Acceptance and Use of Technology (UTAUT) Framework (Venkatesh & Davis, 2003)

3.2.3 The Technology Acceptance Model 2 (TAM2)

The Technology Acceptance Model 2 (TAM2), developed by Venkatesh and Davis (2000), represents an important extension of the original TAM framework. While TAM emphasized *Perceived Usefulness (PU)* and *Perceived Ease of Use (PEOU)* as primary drivers of adoption, TAM2 sought to explain the antecedents of Perceived Usefulness in greater detail. Specifically, TAM2 incorporates two categories of determinants: social influence processes and cognitive instrumental processes.

Social Influence Processes

- Subjective Norm (SN): The perceived social pressure to use or not use a particular technology, based on the expectations of influential others such as peers or educators.

- Image: The extent to which using a technology enhances one's status or reputation within a social group. Among students, this could involve being perceived as more technologically competent or academically resourceful.

Cognitive Instrumental Processes

- Job Relevance (JR): The degree to which an individual perceives the technology as applicable to their academic or professional tasks. When AI tools are directly linked to coursework or career preparation, their perceived usefulness increases significantly.
- Output Quality (OQ): The perceived accuracy, reliability, and effectiveness of the system's outputs. High-quality outputs strongly reinforce perceptions of usefulness.
- Result Demonstrability (RD): The extent to which the results of using the technology are observable and communicable to others. Clear and tangible benefits enhance both adoption and continued use.

By incorporating these constructs, TAM2 deepens the explanatory power of TAM. Perceived Usefulness (PU) becomes not just a broad belief in utility, but one shaped by concrete cognitive evaluations and social context. In combination with Perceived Ease of Use (PEOU), these constructs predict behavioral intention, which in turn drives actual system use. Figure 3.2 presents the TAM2 framework.

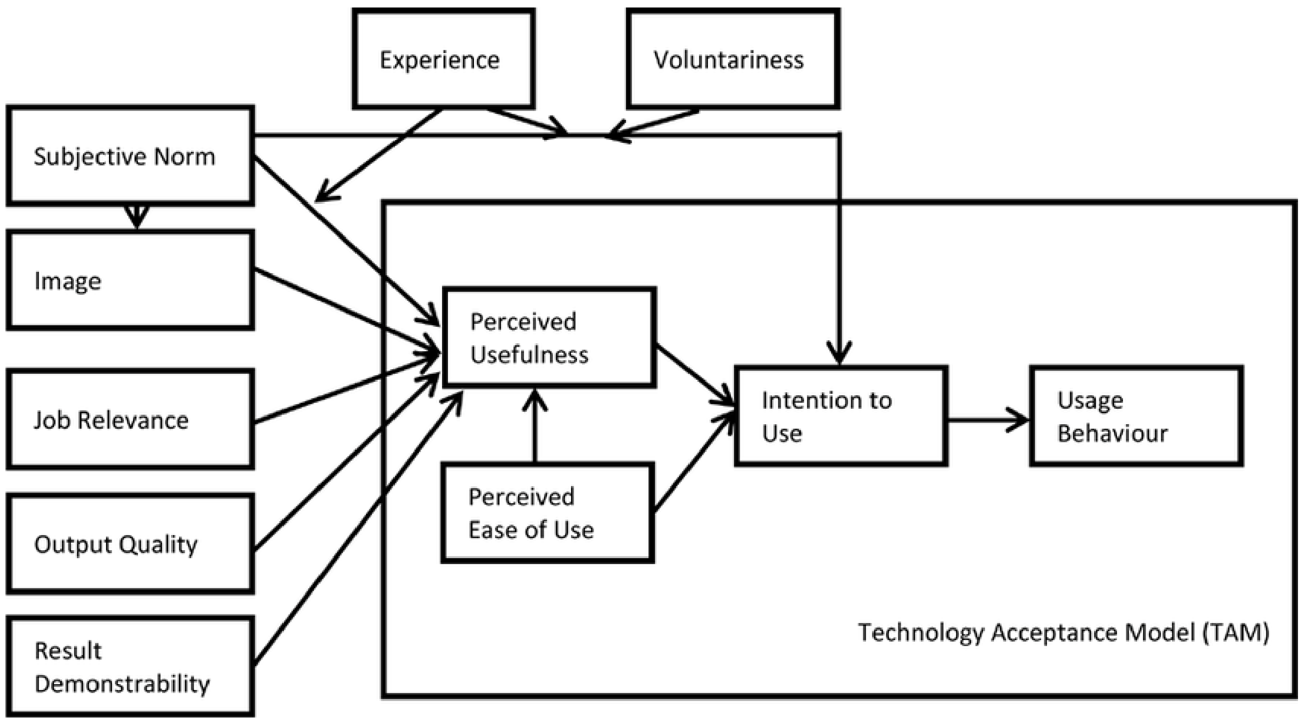

Figure 3.2: Technology Acceptance Model 2 (TAM2) Framework (Venkatesh & Davis, 2000)

3.2.4 The Combining the UTAUT and TAM2

This study combines TAM2 with UTAUT to develop a strong model that explores both the social and cognitive aspects of adopting generative AI. The social aspect highlights the impact of peers, teachers, and perceived image (such as subjective norms and student image), while the cognitive aspect centers on students' task-related evaluations (including job relevance, output quality, result demonstrability, perceived usefulness, and perceived ease of use). These aspects together enable a deeper understanding of how engineering students perceive, assess, and ultimately embrace generative AI in their academic experiences.

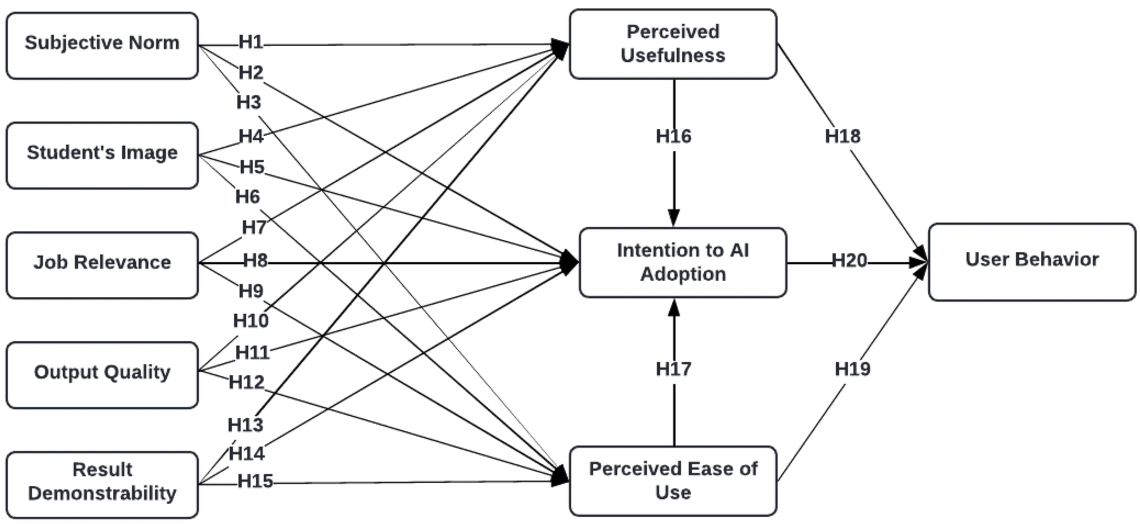

Figure 3.3: Conceptual Framework of the Study

As illustrated in Figure 3.3, the model examines how social effects (subjective norms and student image) and cognitive factors (job relevance, output quality, and result demonstrability) interact to influence students' perceptions of usefulness and ease of use. These perceptions then affect the intention to adopt (IAA), which subsequently drives Usage Behavior (UB). By analyzing these pathways, the framework offers a comprehensive explanation of how engineering students in Bangladesh interact with generative AI chatbots for educational tasks such as problem-solving, coding, and assignment development.

This conceptual framework not only builds on established theories but also adopts them to the unique context of a multicultural and resource-constrained higher education setting. In doing so, it creates the foundation for the twenty hypotheses tested in this study, each of which operationalizes the relationships between social, cognitive, perceptual, and behavioral constructs.

Table 3.1: Study Constructs and Corresponding UTAUT Elements

Focus of the Study	Constructs under Investigation	UTAUT Elements
Social Influences	Subjective Norm	Social Influences and Facilitating Conditions
	Student Image	
Cognitive Processes	Perceived Usefulness	Performance Expectancy and Effort Expectancy
	Output Quality	
	Job Relevance	
	Perceived Ease of Use	
	Result Demonstrability	

Note: Mapping of study constructs to the corresponding UTAUT elements; Social Influences include Subjective Norm and Student Image, while Cognitive Processes include Perceived Usefulness, Output Quality, Job Relevance, Perceived Ease of Use, and Result Demonstrability.

The conceptual framework of the study builds on the integrated UTAUT–TAM2 model, translating the constructs into a set of empirically testable hypotheses; see Table 3.1 for mapping the TAM2 constructs to UTAUT elements.

Figure 3.3 consists of two main pathways: Cognitive pathway: links Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Job Relevance (JR), and Result Demonstrability (RD) to students' Intention to Use (ITU) and Usage Behavior (UB). Social pathway: posits that Social Influence (SI) affects Intention to Use (ITU), particularly when moderated by trust and institutional support. In total 20 hypotheses (H1–H20) are established to explore direct, indirect, and moderating effects between these variables.

H1: Subjective Norms Positively Influence Perceived Usefulness of Gen AI in Learning Subjective norms can shape students' perceptions of usefulness by influencing their attitudes toward AI chatbots (Zhao et al., 2024). In addition, extended TAM studies by Dahri et al. (2024) incorporated social influence (SI) as a predictor for PU, thereby reinforcing the positive impact of social norms on perceived usefulness.

H2: Subjective Norms Positively Influence the Adoption of Gen AI in Learning Subjective norms refer to the perceived social pressure to perform or not perform a behavior, and in educational settings, the opinions and behaviors of peers and educators play a crucial role, as this relationship is supported by prior studies such as Alzoubi (2024); T. Wang et al. (2023), where they identified social influence (SI) as a direct precursor to behavioral intention, a construct closely linked to technology adoption.

H3: Subjective Norms Positively Influence Perceived Ease of Use AI in Learning The influence of peers and educators can also affect how easy students find AI chatbots to use. (Alzoubi, 2024) demonstrated that social norms significantly impacted perceived ease of use (PEOU) in educational settings. In parallel, UTAUT-based evidence from (Widyaningrum et al., 2024) and (Khlaif et al., 2024) supported the idea that social influence enhances PEOU, complementing findings from (Zhao et al., 2024) and (Maheshwari, 2024), who included SN explicitly in their models.

H4: Students' Image Positively Influences Perceived Usefulness When students believed that using AI chatbots enhanced their image or status among peers, they were more likely to perceive these technologies as useful. (Kuhail et al., 2023) provided robust evidence that educational chatbots improved learning outcomes and engagement, thereby enhancing the perceived usefulness of AI. Furthermore, (Al-Kfairy, 2024) incorporated "peer and instructor influence" into a multi-model framework (including DoI and TPB), suggesting that an enhanced student image could directly boost perceptions of usefulness.

H5: Students' Image Positively Influences the Adoption of AI in Learning A student's image, which reflects the extent to which using a system was perceived to enhance one's status, could encourage adoption of AI. (T. Wang et al., 2023) underscored that generative AI and chatbots not only shaped learning outcomes but also influenced the perceived prestige of using these tools. In addition, (Alzoubi, 2024) indicated that the enhancement of a student's image through AI significantly influenced their intention to adopt these technologies, a conclusion supported by frameworks that considered peer recommendations, such as those discussed by (Ruiz-Rojas et al., 2024).

H6: Students' Image Positively Influences Perceived Ease of Use Students who believed that using AI chatbots would enhance their image were also likely to perceive these systems as easier to use. (Sandu & Gide, 2019) provided evidence that positive perceptions of image led to more favorable usability judgments. Similarly, (Al-Kfairy, 2024)'s inclusion of peer/instructor influence suggested that a strong, positive student image could reduce usability concerns, thereby enhancing PEOU.

H7: Job Relevance Positively Influences Perceived Usefulness Job relevance describes the degree to which a system aligned with one's academic or work-related tasks. (Debnath & Agarwal, 2019) discussed a framework for AI-integrated chatbots that clearly demonstrated how task applicability enhanced perceived usefulness. (Maheshwari, 2024) further supported that students' decisions to use ChatGPT were more driven by their personal experiences and perceptions of the tool's utility rather than social pressures or recommendations from peers or educators.

H8: Job Relevance Positively Influences the Adoption of AI in Learning When AI chatbots were perceived as directly relevant to students' educational tasks, the likelihood of their adoption increased. (T. Wang et al., 2023) noted that the relevance of AI to learning and research tasks significantly impacted adoption rates, while (Alzoubi, 2024) also found that perceived task relevance was a major driver for adopting AI in educational environments.

H9: Job Relevance Positively Influences Perceived Ease of Use When AI chatbots aligned closely with students' academic tasks, they were often perceived as easier to use. (Aleedy, Atwell, & Meshoul, 2022) demonstrated that technologies designed to meet user needs tended to improve ease of use. This suggested that job relevance not only influenced perceptions of usefulness but also mitigated usability concerns, thereby making systems more accessible.

H10: Output Quality Positively Influences Perceived Usefulness Students' perceptions of usefulness were strongly shaped by the quality of system outputs. (Alzoubi, 2024) reported that accurate and reliable outputs from AI chatbots increased their perceived usefulness in learning environments. In addition, (Kuhail et al., 2023) noted that well-designed interaction styles and effective system performance enhanced output quality, thereby reinforcing the positive link with usefulness.

H11: Output Quality Positively Influences the Adoption of AI in Learning High-quality outputs were a key factor in students' willingness to adopt AI systems. (Alzoubi, 2024) emphasized that reliable outputs significantly encouraged adoption in educational contexts. Similarly, (Kuhail et al., 2023) showed that students were more likely to integrate chatbots into their studies when the systems consistently produced high-quality responses.

H12: Output Quality Positively Influences Perceived Ease of Use When outputs were accurate and helpful, students generally found AI systems easier to use. (Hiremath et al., 2018) demonstrated that well-performing chatbots improved user satisfaction, which in turn strengthened perceptions of ease of use. Supporting this, (Al-Abdullatif, 2023) and (Sallam et al., 2024) observed that high-quality outputs reduced operational difficulties, allowing students to interact with these systems more smoothly.

H13: Result Demonstrability Positively Influences Perceived Usefulness The visibility of positive outcomes significantly influenced perceptions of usefulness. When students could clearly see the benefits of using AI chatbots, they were more likely to value them. This was confirmed by (Grassini et al., 2024), (Cabero-Almenara et al., 2024), (Acosta-Enriquez, 2024), and (Strzelecki, 2024), who highlighted that demonstrable results strengthened users' perceptions of usefulness.

H14: Result Demonstrability Positively Influences the Adoption of AI in Learning Clear evidence of benefits encouraged the adoption of AI chatbots. (Deng & Yu, 2023) showed that observable improvements in engagement and learning outcomes drove adoption. Further evidence from (Foroughi, Iranmanesh, et al., 2024), (Acosta-Enriquez, 2024), and (Strzelecki, 2024) also indicated that when results were easily demonstrable, students were more likely to adopt these technologies in their learning activities.

H15: Result Demonstrability Positively Influences Perceived Ease of Use The clearer the benefits of AI systems, the easier it was for students to use them. (Kuhail et al., 2023) provided evidence that transparent and observable results improved perceptions of ease, making technology less intimidating. Tangible outcomes helped lower uncertainty and supported smoother user experiences.

H16: Perceived Usefulness Positively Influences the Adoption of AI in Learning Students were more likely to adopt AI chatbots when they perceived them as useful tools for enhancing productivity and improving learning outcomes. (Deng & Yu, 2023) pointed out that increased motivation and engagement through chatbots encouraged adoption, while (Adıgüzel, Kaya, & Cansu, 2023) highlighted the role of personalization and instant feedback in reinforcing the link between usefulness and adoption.

H17: Perceived Ease of Use Positively Influences the Adoption of AI in Learning Ease of use remained a critical determinant of adoption. (Alzoubi, 2024) found that students' positive attitudes were closely tied to their perceptions of usability. Supporting this, (Kuhail et al., 2023) showed that design and interaction quality significantly improved usability, which in turn promoted the adoption of AI in educational settings.

H18: Perceived Usefulness Positively Influences User Behavior in Learning Aligned with TAM, students were more likely to use AI chatbots consistently when they found them useful. Evidence from extended TAM studies, including (Al-Abdullatif, 2024) and (Tiwari et al., 2024), confirmed this link, while (Bernabei et al., 2023) and (Sallam et al., 2024) further demonstrated that perceived usefulness strongly predicted actual user behavior in learning contexts.

H19: Perceived Ease of Use Positively Influences User Behavior in Learning Consistent with the TAM and UTAUT frameworks, a system that students found easy to use was more likely to be embraced and used regularly. Research by (Dahri et al., 2024), (Al-Abdullatif, 2024), and (Tiwari et al., 2024) provided strong evidence that perceived ease of use directly influenced improved user behavior in educational contexts.

H20: Adoption of AI Positively Influences User Behavior in Learning Once students had adapted to AI chatbots, this adaptation naturally led to increased actual usage. (Zhao et al., 2024) and (Maheshwari, 2024) included AI adoption as a construct that predicted user behavior, emphasizing the important role of adoption in increasing engagement. Additional support from extended TAM studies by (Dahri et al., 2024) and (Shahzad, Xu, & Javed, 2024) confirmed that a higher willingness to adopt AI resulted in increased usage, reinforcing the link between adoption and user behavior in learning environments.

3.3 Methods: Strategy of the Inquiry

A strategy of inquiry refers to the overarching plan that guides the selection of research methods and analytical techniques to address specific research questions (Creswell, 2014). It connects the research questions with the design, data collection procedures, and data analysis techniques to ensure that the study is logically coherent and methodologically rigorous.

The overall aim of this study is to examine how social and cognitive factors influence engineering students' adoption and use of *generative AI tools* in higher education. To achieve this aim, the study is guided by the following research questions:

- RQ1: What is the role of social influence, particularly subjective norms and student image, in shaping engineering students' adoption of generative AI?
- RQ2: How do cognitive appraisals (usefulness, usability, job relevance, quality, demonstrability) drive adoption?
- RQ3: How do social and cognitive factors interact through mediation pathways to shape intention and Usage Behavior?
- RQ4: How do demographic differences (e.g., gender and international vs. domestic student status) affect perceptions, intentions, and Usage Behavior of generative AI?

The first research question (RQ1) is designed to explore how external social factors (e.g., peer influence, institutional support) and motivational conditions affect students' acceptance of generative AI, reflecting the importance of collectivist and resource-sensitive settings (Ruiz-Rojas et al., 2024; Sobaih et al., 2024). The second research question (RQ2) focuses on the role of cognitive perceptions, and draws directly on the constructs of the Unified Theory of Acceptance and Use of Technology (UTAUT), with particular emphasis on perceived usefulness, perceived ease of use and other cognitive variables such as job relevance and result demonstrability.

The third research question (RQ3) investigates how social and cognitive factors interact to shape students' actual usage behaviour and therefore connects the full set of constructs in an integrated UTAUT–TAM perspective. The fourth research question (RQ4) examines how demographic differences (e.g., gender and international vs. domestic student status) influence students' perceptions, intentions, and Usage Behavior of generative AI tools in academic contexts.

Table 3.2: Research Questions and Approach

Research Question	Nature of Required Data	Research Approach
RQ1: What is the role of social influence, particularly subjective norms and student image, in shaping engineering students' adoption of generative AI?	Quantitative	Explanatory
RQ2: How do cognitive appraisals (usefulness, usability, job relevance, quality, demonstrability) drive adoption?	Quantitative	Explanatory
RQ3: How do social and cognitive factors interact through mediation pathways to shape intention and Usage Behavior?	Quantitative	Explanatory
RQ4: How do demographic differences (e.g., gender and international vs. domestic student status) affect perceptions, intentions, and Usage Behavior of generative AI?	Quantitative	Explanatory

This combination of research questions clearly aligns with a quantitative explanatory strategy of inquiry, because the intention is not only to describe current behaviours but also to offer an explanation of the causal relationships between latent variables. To that end, a theory-based measurement model is used to test 20 hypotheses derived from the UTAUT framework and its extensions.

3.4 Specific Design of the Study

In line with the above strategy, the study utilises a cross-sectional survey design, which is widely used in technology adoption research in higher education (Al-Abdullatif, 2024; Foroughi, Senali, et al., 2024). This design enabled the efficient collection of data from a large number of students at a single point in time, facilitating the analysis of complex relationships among latent variables using structural equation modelling. In addition, the survey design is appropriate to the fast-evolving nature of generative AI, as it captures student perceptions and behaviours during a period of active experimentation and institutional uncertainty.

3.5 Data Sources of the Study

3.5.1 Engineering Context and Learning Environment

The study was conducted at the *Islamic University of Technology (IUT)*, a Bangladesh-based international university specialising in engineering and technological education. IUT attracts students from South Asia, the Middle East and Africa, and offers a uniquely multicultural and collaborative learning environment. Engineering students at this university routinely engage with complex tasks such as advanced programming, simulation-based experimentation and project-based assignments, which naturally encourage the adoption of tools like ChatGPT and Gemini. These demanding academic practices, coupled with diverse socio-cultural backgrounds, provide a highly appropriate setting for exploring how social and cognitive variables shape AI adoption behaviour.

3.5.2 Undergraduate and Graduate Engineering Students

The primary data were gathered from undergraduate and graduate students enrolled in various engineering programmes (e.g., CSE, EEE, ME) at IUT. Engineering students represent an ideal population for this type of inquiry because they frequently rely on computational tools for coursework and engage in collaborative problem solving. The inclusion of both domestic and international students allowed for the examination of social influence patterns across different cultural backgrounds.

3.6 Sample Size and Sampling Techniques

A mixed sampling approach combining purposive and convenience techniques was adopted to maximize participation and include respondents likely to have experience with generative AI tools. Initially, the survey link was distributed purposively to engineering students through departmental forums, class groups, and student social media channels that were likely to include users familiar with generative AI tools. However, no formal screening instrument was employed to pre-select participants. Instead, the survey was openly accessible, and students voluntarily participated based on their own awareness and experience with such tools. This approach relied on self-selection, assuming that respondents who chose to participate were those with at least some level of familiarity or engagement with generative AI technologies.

A total of 378 responses were received, representing a diverse group of students in terms of gender and student status. As shown in Table 3.3, the sample included 155 female students (41.01%) and 223 male students (58.99%). Regarding student status, 205 participants (54.23%) were domestic students, while 173 (45.77%) were international students, reflecting the multicultural character of IUT.

Table 3.3: Sample Distribution of the Participants

Demographic Info	Category	Count	Percentage (%)
Gender	Male	223	58.99
	Female	155	41.01
Student Status	Domestic	205	54.23
	International	173	45.77

3.7 Data Collection Tools

3.7.1 Structured Survey Questionnaire

A structured questionnaire consisting of 33 items was initially developed based on core constructs from the UTAUT and TAM frameworks. Items were derived and adopted from validated instruments used in prior studies on chatbot and generative AI adoption in higher education (Baharin, Sahadun, Ramli, & Liyana Redzuan, 2024; Khoa, Ha, Nguyen, & Bich, 2020; Patterson, Frydenberg, & Basma, 2024). The questionnaire covered nine constructs: Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Subjective Norms (SN), Student Image (SI), Job Relevance (JR), Result Demonstrability (RD), Output Quality (OQ), Intention to Use (IAA) and Usage Behaviour (UB). All items used a 5-point Likert scale ranging from "strongly disagree" (1) to "strongly agree" (5). The full version of the survey can be found in section 6.5.2, section 6.5.2.

3.7.2 Expert Review and Pilot Testing

To strengthen content validity, the initial questionnaire was reviewed by two experts in educational technology and AI adoption, we then used their feedback to refine the wording and align the items with the study constructs. After this step, we try to assess clarity and identify any items that might be confusing or repetitive, so pilot study involving 20 students was then conducted. Based on both the expert evaluations and pilot results, one item from the Subjective Norm (SN) construct and another from the Usage Behavior (UB) construct were removed, as they showed low factor loadings and conceptual overlap with other items.

3.7.3 Reliability and Validity

After the expert review and pilot testing, we collected the data. And before conducting any further descriptive or structural analysis, we first assessed the reliability and validity of the final 31-item instrument. Metrics like Cronbach's alpha and Composite Reliability (CR) values for all constructs must exceed the minimum acceptable threshold of 0.70, to indicate good internal consistency. Average Variance Extracted (AVE) values also should be above 0.50, to confirm convergent validity (Hair, Hult, Ringle, & Sarstedt, 2017). More details of the reliability and convergent validity analysis are presented in Table 4.3.

Discriminant validity was established using the Fornell–Larcker criterion, cross-loadings and the HTMT ratio (Henseler, Ringle, & Sarstedt, 2015). The detailed results of the reliability and Discriminant validity analysis are presented in Table 4.5 and Table 4.6

3.8 Data Collection Procedure

With departmental approval secured, data collection was carried out over a three-month period. The survey link was distributed via university networks and student groups, together with a brief overview of the study and an informed-consent form. Participation was voluntary and fully anonymous, as no personal data were gathered, students were also assured that they could discontinue their participation at any point without facing any negative consequences.

3.9 Data Analysis Techniques

3.9.1 Descriptive and Inferential Statistics

To gain an initial understanding of the data, descriptive statistics were first calculated for each construct. This process included computing the mean, standard deviation, skewness, and kurtosis, provided an overview of the response distributions and confirmed the data's suitability for subsequent statistical modeling. Following this, independent-samples t-tests were performed using jamovisoftware to investigate potential differences based on gender (male vs. female) and student status (domestic vs. international). These subgroup analyses were crucial for revealing important variations in perception and usage patterns across the different demographic groups.

3.9.2 Measurement Model Assessment

To verify that the latent constructs were measured accurately and consistently, the measurement model was assessed using Partial Least Squares Structural Equation Modelling (PLS-SEM) in SmartPLS 4 (Ringle, Wende, & Becker, 2015).

In line with the established two-step approach by (Anderson & Gerbing, 1988), the evaluation involved four key criteria:

(i) Indicator reliability (outer loadings > 0.60).

(ii) Internal consistency (Cronbach's alpha and CR > 0.70).

(iii) Convergent validity (AVE > 0.50).

(iv) Discriminant validity (Fornell–Larcker criterion, cross-loadings, and HTMT ratio).

These analyses confirmed that the constructs were both empirically distinct and theoretically well defined.(Anderson & Gerbing, 1988).

3.9.3 Structural Model Assessment

After establishing the adequacy of the measurement model, the structural model was evaluated to test the 20 hypothesised relationships between the constructs. Bootstrapping with 5,000 subsamples was performed to calculate *t*-values and *p*-values, thereby determining the statistical significance of each path. Model fit and explanatory power were assessed using the R^2 values of the endogenous constructs. Effect sizes (f^2) were also examined to evaluate the relative contribution of each predictor. This multi-stage analytical strategy is aligned with best practice in recent technology-acceptance research (Almogren et al., 2024; Foroughi, Iranmanesh, et al., 2024; Sova, Tudor, Tartavulea, & Dieaconescu, 2024; Zhao et al., 2024), ensuring the robustness and interpretability of the findings.

3.10 Plan for Data Analysis

The results of the descriptive analysis were first used to identify general patterns and highlight demographic variations. Once the reliability and validity of the constructs were confirmed, the structural model results were interpreted to determine whether the proposed hypotheses were supported. Special attention was given to the practical implications of significant relationships, particularly those involving cognitive and social influence constructs, to ensure the findings could inform evidence-based recommendations for the adoption of generative AI in engineering education.

3.10.1 Alignment of Constructs and Questionnaire Items

A summary of the research constructs and the corresponding questionnaire items is provided in Appendix 6.1. This summary demonstrates how each construct aligns with the research objectives and the analytical methods used in the study.

3.11 Data Triangulation

Although this study primarily used a quantitative survey, data triangulation was achieved by combining statistical findings with theoretical arguments and contextual interpretations derived from the literature review and the characteristics of the IUT learning environment.

3.12 Ethical and Institutional Approval

The research protocol for this study underwent a formal review and received full ethical clearance from the Islamic University of Technology's (IUT) Committee for Advanced Studies and Research

(CASR). The project was also officially funded by IUT. The official approval and funding reference for this research is CASR/57/2025/01/Proc-001. A copy of the official clearance letter is provided in Appendix 6.5.2 for reference.

Ethical standards for research involving human participants were strictly observed throughout the study. Participants were fully informed about the purpose and objectives of the research through the survey introduction, which clearly stated that the study aimed to explore students' adoption of generative AI tools, such as ChatGPT, Google Gemini, and Bing CoPilot, and to understand the factors influencing their adoption and usage. Participation was entirely voluntary, and respondents were explicitly informed that they could withdraw at any time without any consequences. An informed-consent statement was provided at the beginning of the survey, emphasizing that responses would be used solely for research purposes and all collected data would be kept strictly confidential.As part of the study procedures, participants were asked to provide informed consent. A template of this consent form is available in Appendix 6.5.2. No personal identifiers were requested or stored, ensuring the anonymity of all participants. Clear instructions were included in the survey, asking participants to answer honestly and to the best of their ability. This approach ensured that participants were aware of their rights and the intended use of their responses, thereby upholding the highest standards of ethical research practice.

3.13 Conclusion

This chapter has presented a detailed account of the research methodology employed to examine the adoption and use of generative AI tools among engineering students at the Islamic University of Technology (IUT). The study followed a quantitative, explanatory strategy of inquiry, guided by three research questions that explored the influence of social factors, cognitive perceptions, and their interaction on students' AI adoption and usage behaviour.

A cross-sectional survey design was employed, enabling the collection of data from a large and diverse sample of undergraduate and graduate engineering students over a three-month period. The survey was distributed across all university channels and student groups, ensuring broad participation, and included a clear informed-consent statement emphasizing voluntary participation, confidentiality, and anonymity. A total of 378 responses were collected, representing both domestic and international students, as well as a balanced gender distribution.

The primary data collection instrument was a structured questionnaire comprising 31 validated items covering nine core constructs derived from UTAUT and TAM frameworks, including Perceived Usefulness, Perceived Ease of Use, Subjective Norms, Job Relevance, Result Demonstrability, Output Quality, Intention to Use, and Usage Behaviour. The questionnaire underwent expert review and pilot testing to ensure clarity, content validity, and reliability, with Cronbach's alpha and Composite Reliability values exceeding acceptable thresholds and discriminant validity confirmed through multiple measures.

Data analysis followed a rigorous, multi-stage approach. Descriptive statistics were first computed to summarize response patterns and assess data suitability. The measurement model was then assessed using PLS-SEM to confirm reliability, convergent validity, and discriminant validity of the constructs. Finally, the structural model was evaluated to test the 20 hypothesised relationships, with significance determined via bootstrapping, and model fit assessed through R^2 and effect-size metrics. Additionally, independent-samples t-tests were conducted to examine demographic variations across gender and student status.

Although the study was primarily quantitative, data triangulation was achieved by integrating statistical findings with theoretical insights and contextual interpretations derived from the literature and the unique multicultural learning environment at IUT. Ethical standards were strictly observed throughout the research process, ensuring voluntary participation, informed consent, anonymity, and the responsible use of data.

Overall, the methodology described in this chapter provides a comprehensive, systematic, and ethically sound framework for investigating the determinants of generative AI adoption among engineering students. It ensures that the study's findings are robust, valid, and capable of informing both academic understanding and practical recommendations for AI integration in higher education.

Chapter 4 Findings and Data Analysis

4.1 Introduction

This chapter reports the findings. It starts with descriptive statistics on participants and the distributions of key constructs. It then explores trends and pairwise relationships to give an initial picture of behavior across groups. After that, the measurement model is assessed for reliability and validity, followed by the structural model: multicollinearity checks, R^2, hypothesis tests, and the mediation analysis. Finally, group comparisons through independent-samples t-tests show differences by gender and by student status (domestic vs. international). Together these results show how social and cognitive factors interact to shape intention and usage behavior.

4.2 Descriptive Statistics

4.2.1 Distribution of Categorical Variables

This subsection presents the distribution of key demographic variables among participants, including gender, student status, and year of study, as shown in Table 4.1, which provides a clearer understanding of the participants' background, outlining the demographic distribution of the sample across three categorical dimensions: Gender, Student Status, and Year of Study. As the table shows, Male students constitute the majority (58.9%) while Female students represent 41.1% of the surveyed group. In terms of Student Status, the sample is almost evenly split between Domestic (54.23%) and International students (45.77%), indicating broad representation from both groups.

When it comes to Year of Study, the distribution is more varied, with the highest proportion of students in their Third Year (24.40%), followed closely by Second-Year (24.87%) and Fourth-Year students (23.02%). First-Year students account for 18.78% of the responses, while Postgraduate students form the smallest segment (7.94%).

These figures help establish a demographic profile of the respondents and serve as a foundation for interpreting behavioral trends across different groups.

Table 4.1: Demographic Information of the Students

Demographic Info	Category	Counts	% of Total	Cumulative %
Gender	Female	155	41.01%	41.01%
	Male	223	58.99%	100.0%
Student Status	Domestic	205	54.23%	54.23%
	International	173	45.77%	100.0%
Year of Study	First Year	71	18.78%	18.78%
	Second Year	94	24.87%	43.65%
	Third Year	96	25.40%	69.05%
	Fourth Year	87	23.02%	92.07%
	Postgraduate	30	7.94%	100.0%

Note: Counts, percentage of total, and cumulative percentage of students by Gender, Student Status, and Year of Study.

4.2.2 Constructs Summary

To begin interpreting the survey data, we first calculated descriptive statistics for all the major constructs included in this study. These statistics provide a snapshot of how students responded overall, capturing both central tendencies (such as means) and variability (such as standard deviations), while also highlighting the shape and distribution of responses through measures like skewness and kurtosis. Table 4.2 summarizes these results, displaying the mean, standard deviation, minimum and maximum values, skewness, kurtosis, and the Shapiro–Wilk test outcomes for each construct.

Examining the mean scores, the findings suggest generally favorable perceptions of generative AI tools among students. Constructs such as Student Image (SI) and Usage Behavior (UB) recorded higher averages compared to other factors, suggesting that many students associate AI use with a positive reputation and are also actively engaging with these tools in their academic routines. In contrast, constructs such as Output Quality (OQ) and Result Demonstrability (RD) showed more moderate mean values. This pattern suggests that while students are optimistic about AI, they still hold some reservations about the reliability of outputs or the ease with which the benefits of AI use can be clearly demonstrated.

When examining the skewness values, all constructs display negative skewness. This means responses tend to lean toward the higher end of the scale (agreement), but not to an extreme degree. Importantly, these skewness values fall within the commonly accepted threshold (between 2 and +2), meaning that the data are not severely distorted. Similarly, kurtosis values remain within acceptable ranges, pointing to distributions that are neither overly peaked (too concentrated around the mean) nor overly flat (too spread out). Together, these results suggest that the dataset is statistically well-behaved and suitable for structural analysis.

The Shapiro–Wilk test, which checks for normality, yielded significant results for all constructs ($p < 0.001$). In simple terms, this means the data deviate from a perfectly normal distribution a common occurrence in survey-based social science research, especially when responses cluster toward agreement. Due to this irregularity, the study employed Partial Least Squares Structural Equation Modeling (PLS-SEM). This method was particularly appropriate because it is robust to non-normal data, works well with complex models, and is suitable for studies involving multiple latent variables.

Table 4.2: Descriptive Analysis of Key Constructs

Construct	Mean	SD	Min	Max	Skewness	SE	Kurtosis	SE	W	p
SN	14.8	2.72	6	20	-0.495	0.125	0.459	0.250	0.968	$< .001$
PU	16.4	2.77	6	20	-0.826	0.125	0.660	0.250	0.928	$< .001$
PEOU	12.1	2.31	3	15	-0.804	0.125	0.770	0.250	0.920	$< .001$
SI	18.4	3.97	8	25	-0.280	0.125	-0.638	0.250	0.972	$< .001$
RD	11.8	2.11	5	15	-0.686	0.125	0.353	0.250	0.941	$< .001$
OQ	11.0	2.35	4	15	-0.306	0.125	-0.125	0.250	0.964	$< .001$
JR	11.9	2.20	3	15	-0.654	0.125	0.352	0.250	0.944	$< .001$
IAA	16.4	3.01	6	20	-1.013	0.125	0.806	0.250	0.906	$< .001$
UB	16.1	3.05	5	20	-0.759	0.125	0.448	0.250	0.906	$< .001$

Figure 4.1 presents a boxplot of all the numeric constructs and serves to identify potential outliers in the dataset. As can be observed, the median lines are positioned toward the upper half of each box, indicating that the majority of responses fall on the higher end of the scale for most constructs. More importantly, only a few mild outliers are recorded, and these points remain within a reasonable range that does not distort the central tendency of the data. The interquartile ranges are relatively consistent

across constructs, which reinforces the earlier descriptive findings that the data are evenly distributed and statistically appropriate for structural analysis.

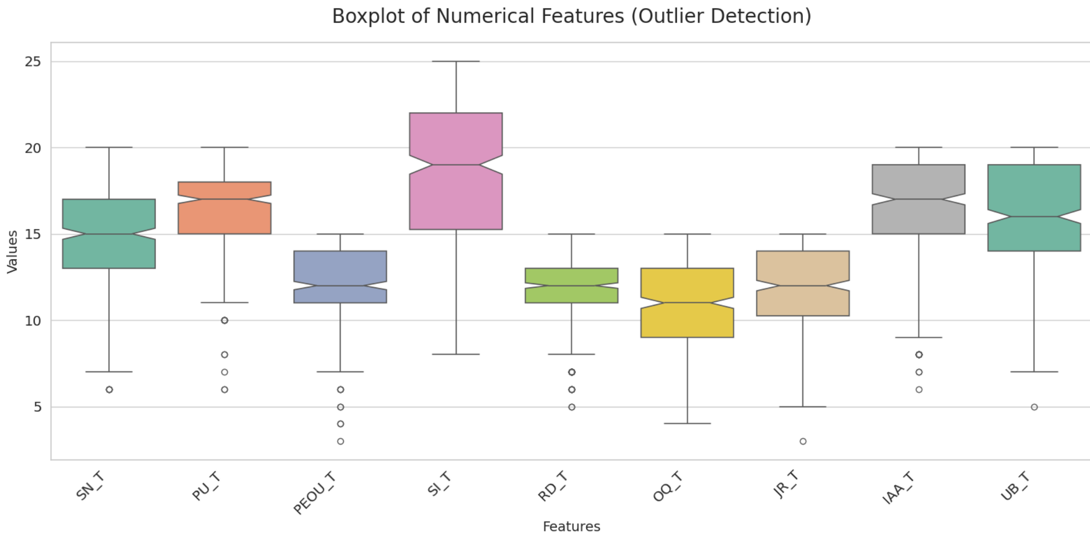

Figure 4.1: Boxplot of Numeric Constructs for Outlier Detection

Figure 4.2 provides a correlation heatmap illustrating the pairwise relationships between the main numeric constructs. The darker shaded areas represent stronger associations, while lighter areas indicate weaker correlations. As expected, a prominent positive correlation is visible between Perceived Usefulness (PU) and Usage Behavior (UB), suggesting that students who perceive AI tools as useful are also more likely to use them actively. A similarly strong association can be seen between Perceived Ease of Use (PEOU) and Job Relevance (JR), indicating that students find AI tools easier to use when they perceive them as relevant to their academic needs. Notably, none of the correlations are excessively high (e.g., above 0.90), which further confirms that the constructs capture distinct but related aspects of students' perceptions and behavior.

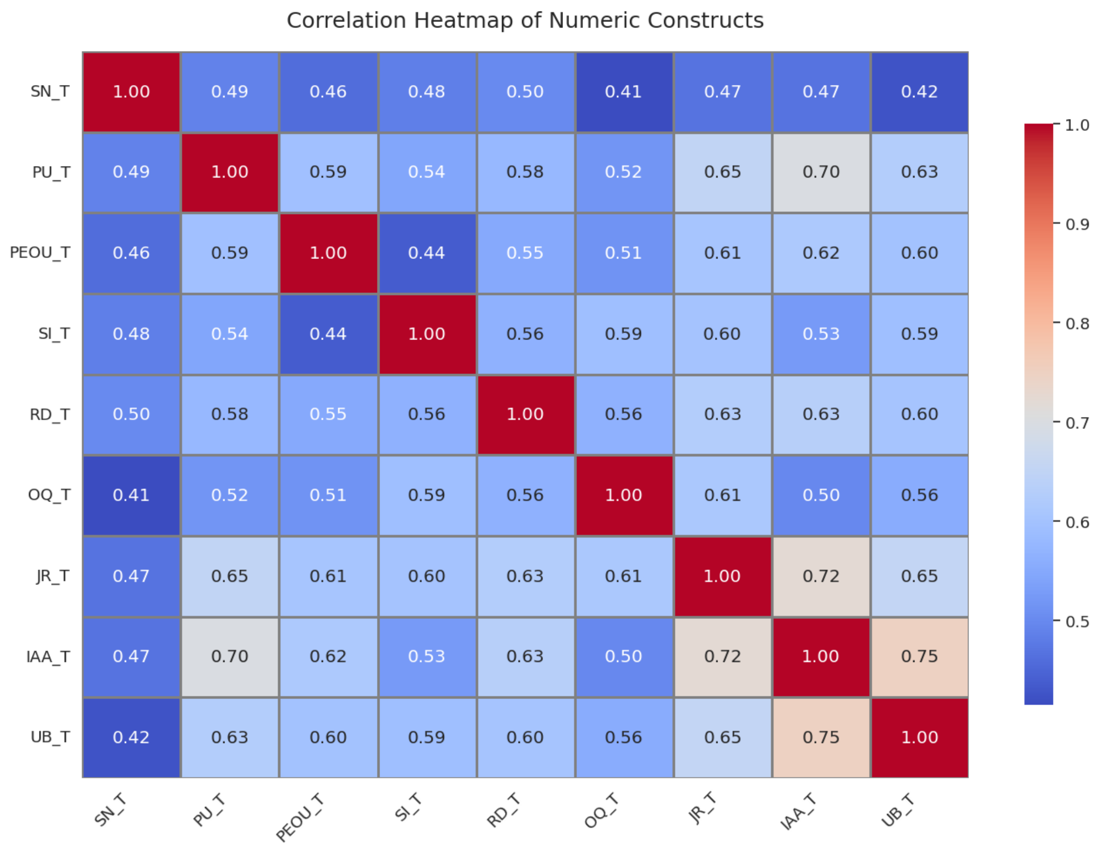

Figure 4.2: Correlation Heatmap of Numeric Constructs

4.3 Exploratory Trends and Multivariate Analysis

This section presents an exploration of trends in user behavior across different demographics and examines pairwise relationships among key constructs. Visualizations such as line plots and pairplots are used to reveal patterns and relationships.

4.3.1 Trends of User Behavior Across Demographics

This subsection illustrates how user behavior (`UB_T`) varies across different demographic groups, including Year of Study, Gender, and Student Status. Multi-line plots are used to examine combined trends.

User Behavior by Year of Study and Gender

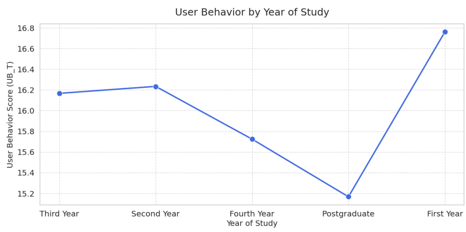

Figure 4.3: Line Plot of User Behavior (UB_T) by Year of Study

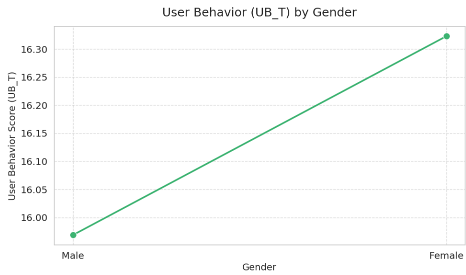

Figure 4.4: Line Plot of User Behavior (UB_T) by Gender

Figure 4.3 depicts the trend of User Behavior (UB_T) across different Years of Study. The plot shows that Third-Year students record the highest level of usage behavior, followed closely by Second- and Fourth-Year students, while First-Year and Postgraduate students report noticeably lower levels of usage. These observations suggest that engagement with generative AI tools increases as students become more advanced in their academic journey, possibly due to higher course demands and greater familiarity with AI-based learning support.

Figure 4.4 shows a comparison of User Behavior (UB_T) for Male and Female students. While both genders demonstrate a generally similar pattern, the line plot reveals a slightly higher level of usage for Male students throughout the observed range. This difference is not large, but it indicates that Male students in this sample are marginally more active in their use of generative AI tools compared to Female students.

User Behavior by Student Status

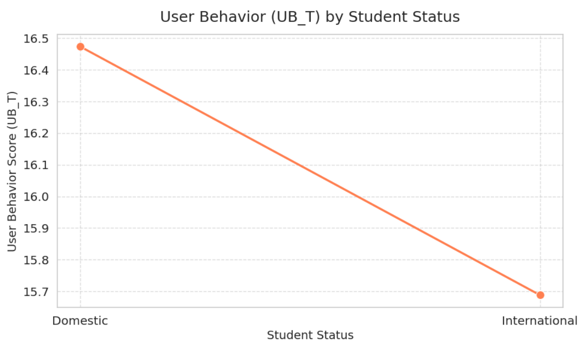

Figure 4.5: Line Plot of User Behavior (UB_T) by Student Status

Figure 4.5 illustrates the trend of User Behavior (UB_T) for Domestic and International students. The figure shows that Domestic students have slightly higher usage levels across the scale when compared to International students. This finding suggests that domestic students may face fewer linguistic or cultural barriers in using AI systems.

Multi-Demographic Trends of User Behavior

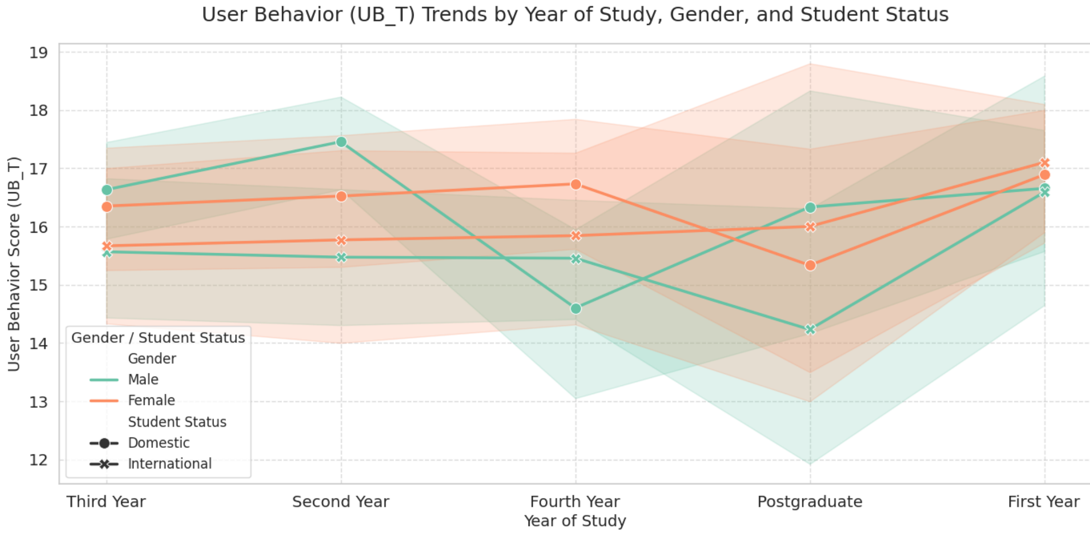

Figure 4.6: Multi-Line Plot of UB Trends by Year of Study, Gender, and Student Status

Figure 4.6 combines the three demographic variables (Year of Study, Gender, and Student Status) in a multi-line plot to provide a comprehensive overview of user behavior trends. The figure shows that Third-Year International Male students exhibit the highest usage of generative AI tools, whereas First-Year Domestic Female students record the lowest. The intersecting lines further highlight how the effect of one demographic variable (e.g., Year of Study) can vary depending on another factor (e.g., Gender), reinforcing the importance of considering demographic interactions in the interpretation of behavioral trends.

4.3.2 Pairwise Relationships

This subsection examines the pairwise relationships between selected numeric constructs, using a pairplot to visualize both distributions and interrelationships across Gender groups.

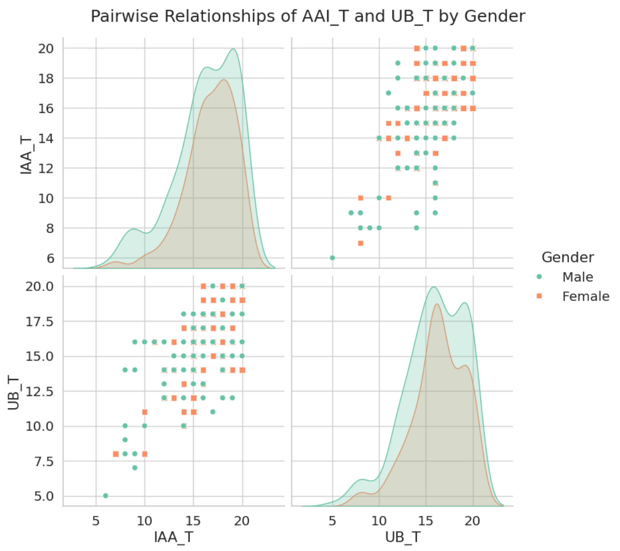

Figure 4.7: Pairwise Relationships of IAA and UB by Gender

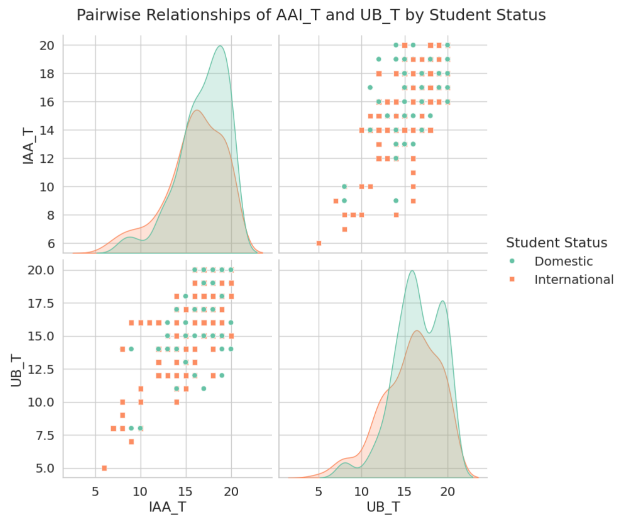

Figure 4.8: Pairwise Relationships of IAA and UB by Student Status

Figure 4.7 presents the pairwise relationships between intention to adopt AI (IAA_T) and User Behavior (UB_T), separated by Gender. The plot reveals a clear positive relationship between IAA and UB for both Male and Female students, meaning that higher positive attitudes toward generative AI are associated with a higher level of actual usage. The slopes for both Gender groups appear similar, indicating that the strength of this relationship does not differ substantially by Gender. This aligns with the earlier trend analysis and confirms that attitude is a consistent driver of usage behavior regardless of gender group.

Figure 4.8 displays the pairwise relationships between Intention to Adopt AI (IAA_T) and User Behavior (UB_T), separated by Student Status. Overall, a positive association between IAA and UB can be observed in both groups, indicating that higher intentions to adopt AI tools tend to correspond with higher levels of actual usage. However, the density areas show that Domestic students are slightly more concentrated toward the upper range of UB values when compared to their International counterparts. In other words, for similar levels of intention, Domestic students tend to exhibit marginally higher usage of generative AI tools. The slopes remain fairly parallel, suggesting that the strength of the relationship is comparable across the two status groups, although the overall usage level is visibly higher among Domestic students.

4.4 Assessing Measurement Model

Before interpreting the results of our study, it was necessary to carefully assess the measurement model. This step plays a crucial role in ensuring that the survey items used in this research accurately and consistently measure the theoretical constructs of interest. Without this verification, any subsequent analysis of relationships between constructs could be misleading.

Evaluating model measurement helps us determine how well the items represent the underlying latent variables, what gives solid ground to draw the study's conclusions based on trustworthy and valid information data. It also offers insights into the quality of the collected data, emphasizing both the strengths and potential limitations of the instrument. By methodically assessing the measurement properties, researchers can ensure that each construct is correctly operationalized and that the items used accurately reflect the conceptual meaning of the constructs. In this study, we focused on assessing reliability and convergent validity, two fundamental elements in establishing the robustness of the measurement model.

4.4.1 Reliability and Convergent Validity

Reliability and convergent validity are essential for verifying the quality of a measurement tool, such as the survey used in our study. Reliability shows how consistently the survey items measure the same underlying factor, ensuring that results remain stable and trustworthy across repeated measurements (Hair, Black, Babin, & Anderson, 2010). On the other hand, convergent validity evaluates whether multiple items are designed to measure the same concept, and it goes further by checking if the different items intended to assess that concept actually agree with each other and truly represent that idea (Hair et al., 2010, 2017).

To assess these key properties, we used four widely recognized criteria:

Item Loadings, Cronbach's Alpha (α), Composite Reliability (CR), and Average Variance Extracted (AVE) (Fornell & Larcker, 1981; Henseler et al., 2015). Analysis was performed using Partial Least Squares Structural Equation Modeling (PLS-SEM). Each criterion provides a different perspective on the quality of measurement, allowing for a comprehensive assessment (Hair et al., 2017).

The results of the reliability and convergent validity assessment are summarized in Table 4.3.

Cronbach's Alpha (α): For all constructs, Cronbach's alpha values exceeded the widely accepted threshold of 0.70, indicating strong internal consistency (Hair et al., 2010). One exception was the

Output Quality (OQ) construct, which had an alpha of 0.671, due to item OQ1, which measures the Accuracy and reliability of AI-generated responses; some respondents expressed concerns about AI output accuracy. Despite this, the item was retained due to its conceptual importance. The construct maintained a composite reliability of 0.807 and an AVE of 0.585, confirming acceptable reliability and convergent validity (Fornell & Larcker, 1981). Composite Reliability (CR): All constructs showed CR values above 0.70, with several indicating excellent reliability (Hair et al., 2017).
This demonstrates that the constructs consistently measure their intended theoretical concepts, reinforcing the robustness of the measurement model. Item Loadings: All retained items had factor loadings above the recommended minimum of 0.60, ensuring that each item contributes meaningfully to its respective construct (Hair et al., 2017).The specific values for each indicator's Outer Loading and Outer Weight, which confirm indicator reliability and relevance, are detailed in Appendix 6.5.2.
During refinement, one item from the Subjective Norms (SN) construct was removed due to a low factor loading; the remaining three SN items demonstrated strong loadings, strengthening the overall measurement model (Hair et al., 2010). Average Variance Extracted (AVE): All constructs exceeded the 0.50 threshold for AVE, confirming that the items collectively explained a sufficient portion of variance in their respective constructs (Fornell & Larcker, 1981).
This validates the convergent validity of the constructs and ensures items are appropriately interrelated. In summary, the measurement model exhibits both reliability and convergent validity, providing a solid foundation for subsequent structural model analysis. By retaining meaningful items and removing weaker indicators, the model accurately represents theoretical constructs and allows for valid interpretation of relationships among variables (Hair et al., 2010, 2017).

4.4.2 Discriminant Validity

Discriminant validity is an essential aspect of measurement models in structural equation modeling (SEM), ensuring that each construct is distinct from the others, meaning the items used to measure one concept do not overlap with those measuring a different concept (Fornell & Larcker, 1981; Hair et al., 2017). It ensures that no construct is excessively correlated with another from which it is theoretically expected to differ. Discriminant validity is essential because it guarantees that each construct retains its unique theoretical and empirical identity, thereby enhancing the accuracy of findings and the reliability of interpretation in research studies (Henseler et al., 2015).

Table 4.3: Reliability and Convergent Validity of Constructs

Construct	Items	Loadings	α	CR (a)	CR (c)	AVE
Adoption of Use	IAA1	0.805	0.851	0.851	40.899	0.691
	IAA2	0.881				
	IAA3	0.826				
	IAA4	0.811				
Job Relevance	JR1	0.770	0.729	0.731	0.847	0.649
	JR2	0.808				
	JR3	0.837				
Output Quality	OQ1	0.655	0.671	0.746	0.807	0.585
	OQ2	0.781				
	OQ3	0.846				
Perceived Ease of Use	PEOU1	0.844	0.794	0.797	0.879	0.707
	PEOU2	0.835				
	PEOU3	0.844				
Perceived Usefulness	PU1	0.747	0.754	0.757	0.844	0.575
	PU2	0.721				
	PU3	0.800				
	PU4	0.763				
Result Demonstrability	RD1	0.729	0.731	0.750	0.847	0.650
	RD2	0.847				
	RD3	0.837				
Students' Image	SI1	0.761	0.824	0.835	0.876	0.586
	SI2	0.793				
	SI3	0.824				
	SI4	0.707				
	SI5	0.736				
Subjective Norms	SN1	0.825	0.710	0.723	0.837	0.632
	SN2	0.817				
	SN3	0.739				
User Behavior	UB1	0.869	0.804	0.820	0.884	0.718
	UB2	0.871				
	UB3	0.799				

Note: α = Cronbach's Alpha, CR (a) = rho_a, CR (c) = rho_c, AVE = Average Variance Extracted

Table 4.4: Cross-Loadings of Measurement Model Items

Item	IAA	JR	OQ		PU		SI	SN	UB
IAA1	0.805	0.609	0.478	0.491	0.609	0.564	0.412	0.445	0.601
IAA2	0.881	0.613	0.479	0.490	0.579	0.532	0.389	0.417	0.602
IAA3	0.826	0.602	0.388	0.566	0.552	0.443	0.325	0.436	0.714
IAA4	0.811	0.584	0.565	0.507	0.578	0.596	0.610	0.436	0.628
JR1	0.550	0.770	0.557	0.448	0.517	0.522	0.439	0.437	0.531
JR2	0.614	0.808	0.458	0.559	0.526	0.526	0.464	0.464	0.552
JR3	0.583	0.837	0.557	0.457	0.542	0.483	0.574	0.267	0.545
OQ1	0.224	0.394	0.655	0.300	0.257	0.303	0.376	0.126	0.346
OQ2	0.308	0.428	0.781	0.416	0.402	0.367	0.492	0.302	0.405
OQ3	0.646	0.613	0.846	0.491	0.577	0.674	0.528	0.411	0.515
PEOU1	0.505	0.538	0.450	0.844	0.518	0.478	0.398	0.410	0.563
PEOU2	0.454	0.457	0.441	0.835	0.503	0.432	0.338	0.429	0.499
PEOU3	0.593	0.534	0.478	0.844	0.511	0.476	0.410	0.410	0.559
PU1	0.548	0.452	0.432	0.339	0.747	0.430	0.400	0.375	0.386
PU2	0.506	0.456	0.422	0.391	0.721	0.474	0.350	0.431	0.405
PU3	0.541	0.552	0.423	0.517	0.800	0.424	0.448	0.346	0.537
PU4	0.522	0.521	0.475	0.573	0.763	0.444	0.517	0.400	0.570
RD1	0.366	0.400	0.453	0.421	0.374	0.729	0.480	0.350	0.538
RD2	0.565	0.581	0.512	0.443	0.520	0.847	0.410	0.422	0.548
RD3	0.590	0.534	0.566	0.469	0.499	0.837	0.485	0.421	0.520
SI1	0.363	0.496	0.470	0.381	0.447	0.378	0.761	0.266	0.434
SI2	0.439	0.553	0.452	0.488	0.540	0.404	0.793	0.232	0.500
SI3	0.386	0.453	0.507	0.293	0.366	0.451	0.824	0.234	0.413
SI4	0.378	0.388	0.417	0.240	0.324	0.445	0.707	0.231	0.291
SI5	0.417	0.413	0.516	0.284	0.451	0.489	0.736	0.224	0.369
SN1	0.485	0.397	0.433	0.394	0.497	0.442	0.285	0.825	0.394
SN2	0.386	0.353	0.239	0.423	0.373	0.319	0.186	0.817	0.376
SN3	0.361	0.411	0.265	0.363	0.325	0.420	0.266	0.739	0.383
UB1	0.723	0.590	0.458	0.587	0.627	0.541	0.402	0.406	0.869
UB2	0.668	0.583	0.550	0.571	0.542	0.614	0.511	0.438	0.871
UB3	0.538	0.540	0.428	0.465	0.410	0.522	0.457	0.383	0.799

Note: IAA = Intention to Adopt AI, JR = Job Relevance, OQ = Output Quality, PEOU = Perceived Ease of Use, PU = Perceived Usefulness, RD = Result Demonstrability, SI = Students' Image, SN = Subjective Norms, UB = User Behavior. Highest loading for each item is shown in bold.

In this study discriminant validity was assessed using three complementary analytical methods: the *Fornell-Larcker criterion*, *cross-loadings testing*, and the *Heterotrait-Monotrait ratio of correlations (HTMT)*. All of these methods provides a distinct perspective on construct distinctiveness, ensuring a rigorous and multi-layered validation process.

Fornell-Larcker Criterion: The first method employed was the Fornell-Larcker criterion (Fornell & Larcker, 1981), which posits that discriminant validity is achieved when the square root of the average variance extracted (AVE) for each construct is greater than the highest correlation of that construct with any other construct in the model. Essentially, this criterion asserts that each construct should share more variance with its own items than with items of any other construct.

As illustrated in Table 4.6, The diagonal values of the correlation matrix, which represent the square roots of AVE, are consistently greater than the corresponding off-diagonal values correlations, this confirm that all constructs in the model demonstrate adequate discriminant validity according to this established criterion, providing confidence in the uniqueness of each construct.

Cross-Loadings: Second, cross-loadings of all measurement items were analyzed to confirm that each item loads more heavily on its intended construct than on any other construct. (Hair et al., 2017). Table 4.4 presents the results of this analysis, showing that each item's loading on its assigned construct is consistently higher than its loading on other constructs, which indicates that each questionnaire item accurately captures the specific theoretical construct it was designed to measure, supporting the distinctiveness of constructs and reinforcing the validity of the measurement instrument.

Heterotrait-Monotrait (HTMT) Ratio: Third, the HTMT ratio, a more stringent and contemporary approach to assessing discriminant validity (Henseler et al., 2015), was applied to evaluate the degree of potential overlap between constructs. HTMT values exceeding 0.85 (conservative threshold) or 0.90 (liberal threshold) indicate possible discriminant validity concerns. As shown in Table 4.5, all HTMT values were below the liberal threshold of 0.90, except for two construct pairs: Adoption of Use (IAA) and User Behavior (UB), and Adoption of Use (IAA) and Job Relevance (JR), which recorded values of 0.915 and 0.919, respectively. Although these values slightly exceed the conventional threshold, further examination using bias-corrected confidence intervals revealed that none included the critical value of 1.00, indicating that these correlations do not compromise discriminant validity. This outcome reinforces the conclusion that all constructs in the model are sufficiently distinct from each other.

Overall, the results from these three complementary methods: the Fornell-Larcker criterion, cross-loadings, and the HTMT ratio—show that the measurement model has acceptable discriminant validity across all constructs. This enhances the reliability and strength of the model, making sure that each construct can be confidently seen as a distinct theoretical entity. These results are particularly significant in this study, which examines the adoption of generative AI in higher education, as they confirm that the relationships among variables are meaningful, clear, and not confounded by overlapping constructs.

Table 4.5: Heterotrait-Monotrait (HTMT) Ratio for Discriminant Validity

	IAA	JR	OQ		PU		SI	SN	UB
JR	0.919								
OQ	0.670	0.885							
PEOU	0.747	0.794	0.710						
PU	0.872	0.882	0.742	0.776					
RD	0.799	0.857	0.823	0.722	0.777				
SI	0.620	0.777	0.803	0.542	0.701	0.735			
SN	0.664	0.674	0.509	0.659	0.687	0.684	0.404		
UB	0.915	0.879	0.740	0.797	0.790	0.865	0.648	0.639	

IAA = Intention to Adopt AI, JR = Job Relevance, OQ = Output Quality, PEOU = Perceived Ease of Use, PU = Perceived Usefulness, RD = Result Demonstrability, SI = Students' Image, SN = Subjective Norms, UB = User Behavior

Table 4.6: Latent Variable Correlations (Fornell-Larcker Criterion)

	IAA	JR	OQ		PU		SI	SN	UB
IAA	0.831								
JR	0.725	0.805							
OQ	0.574	0.648	0.765						
PEOU	0.619	0.609	0.544	0.841					
PU	0.697	0.656	0.578	0.607	0.758				
RD	0.641	0.634	0.636	0.551	0.583	0.806			
SI	0.521	0.611	0.617	0.456	0.570	0.562	0.765		
SN	0.522	0.485	0.402	0.494	0.510	0.495	0.310	0.795	
UB	0.767	0.675	0.566	0.644	0.632	0.659	0.536	0.483	0.869

Note: Square root of AVE on diagonal. Correlations below diagonal.

4.5 Assessing Structural Model

Assessing the structural model is necessary to verify its adequacy, stability, and predictive ability before interpreting the relationships between constructs, which is essential for confirming that the hypothesized relationships among variables are both statistically valid and theoretically meaningful (Hair et al., 2017).

We assessed the structural model of this study by examining two key aspects: assessing multicollinearity using the variance inflation factor (VIF) and examining the predictive explanatory power through the coefficient of determination (R^2), this dual evaluation ensures that the model is free from statistical redundancy and can explain a significant portion of variance in the dependent constructs.

4.5.1 Assessment of Multicollinearity:

Multicollinearity occurs when two or more predictor variables are highly correlated and move together, which can distort regression estimates, inflate standard errors, and hinder the interpretability of results (Kline, 2016).

We examined the VIF values for all predictor constructs to identify and address this issue, where a VIF value above 5.0 indicates potential multicollinearity concerns, and values exceeding 10 pose serious threats to the model's validity, as suggested by (Hair et al., 2017). As presented in Table 4.7, all VIF values fell within the range of 1.426 to 2.587, which are well below the conservative threshold of 5.0. These findings confirm that multicollinearity does not pose a threat in the model and each predictor construct contributes uniquely to the explanation of its corresponding dependent construct.

Absence of multicollinearity in our proposed model ensures that the statistical estimates are reliable and that the relationships between constructs can be interpreted with confidence.

4.5.2 Predictive Explanatory Power (R^2):

The second step in our model structural assessment was the evaluation of its predictive explanatory power using R^2 values. The coefficient of determination (R^2) reflects the proportion of variance in the dependent variables that is explained by their predictor variables, serving as an indicator of the model's explanatory strength. According to Hair et al. (2017), R^2 values of 0.19, 0.33, and 0.67 can be interpreted as weak, moderate, and strong explanatory power, respectively (Hair et al., 2017).

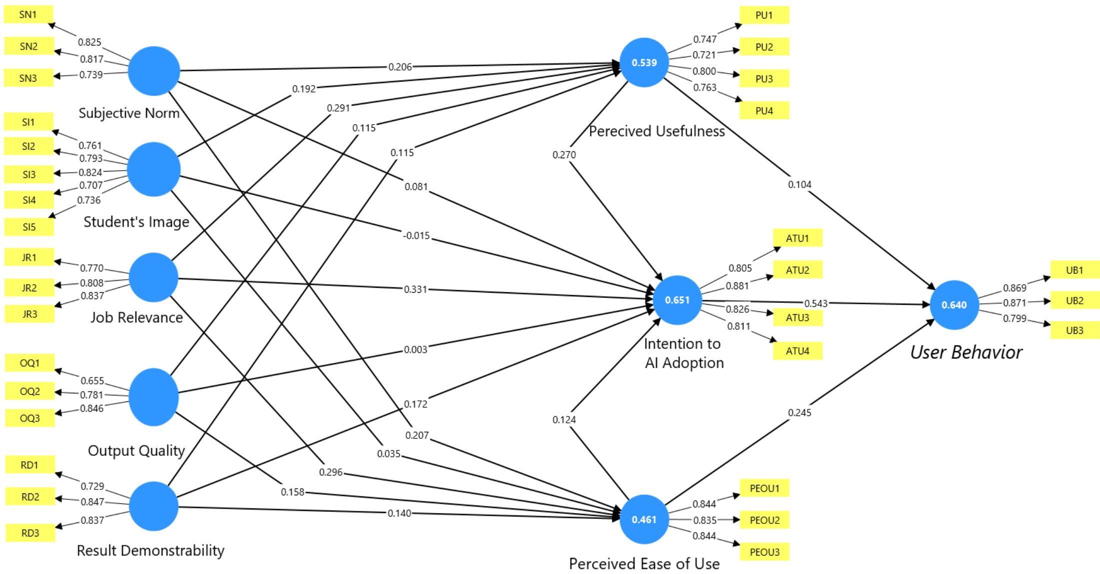

Figure 4.9: Conceptual Framework Implemented in SmartPLS

In this study, several important findings emerged from the analysis (see Table 4.7 and Figure 4.9: Structural Model Results (VIF and R²)). First, the model explains 64.0% of the variance in Usage Behavior (UB) through three predictors: Intention to Adopt AI (IAA), Perceived Ease of Use (PEOU), and Perceived Usefulness (PU). This R^2 value of 0.640 indicates a strong level of explanatory power, suggesting that these three constructs collectively provide a robust explanation of students' actual usage behavior. Second, Perceived Ease of Use (PEOU) is explained with an R^2 value of 0.461, meaning that 46.1% of its variance is accounted for by Job Relevance (JR), Output Quality (OQ), Result Demonstrability (RD), Student's Image (SI), and Subjective Norms (SN). This level of explanatory power falls within the moderate range, indicating that these antecedent variables have a significant influence on how students perceive the ease of using AI-based tools.

Furthermore, Intention to Adopt AI (IAA) shows an R^2 value of 0.651, indicating strong predictive power, which means that 65.1% of the variance in IAA is explained by a combination of predictors, including JR, OQ, PEOU, PU, RD, SI, and SN. This result highlights the strength of the model in explaining students' intentions, a key element in adoption studies.

Perceived Usefulness (PU) achieved an R^2 value of 0.539, with most variance explained by Job Relevance (JR) and Output Quality (OQ). This indicates moderate to strong explanatory power and underscores the importance of these constructs in shaping students' perceptions of usefulness. The structural model demonstrated consistent predictive power across all dependent constructs, with R^2 values exceeding recommended thresholds. These findings confirm that the proposed model is statistically robust and conceptually meaningful, providing a reliable framework for understanding causal relationships among constructs. Absence of multicollinearity and the significant difference explained further support the validity and real-world relevance of the observed relationships.

Table 4.7: Structural Model Results (VIF and R^2)

Relationship	VIF	R^2
Dependent Variable: User Behavior (UB)		
IAA → UB	2.207	0.640
PEOU → UB	1.796	
PU → UB	2.157	
Dependent Variable: Perceived Ease of Use (PEOU)		
JR → PEOU	2.305	0.461
OQ → PEOU	2.210	
RD → PEOU	2.159	
SI → PEOU	1.909	
SN → PEOU	1.426	
Dependent Variable: Intention to Adopt AI (IAA)		
JR → IAA	2.587	0.651
OQ → IAA	2.271	
PEOU → IAA	1.961	
PU → IAA	2.291	
RD → IAA	2.212	
SI → IAA	1.990	
SN → IAA	1.566	
Dependent Variable: Perceived Usefulness (PU)		
JR → PU	2.305	0.539
OQ → PU	2.210	

4.5.3 Testing Hypotheses

The relationships among constructs were examined using path coefficients expressed as standardized regression weights (β), their associated t-values, p-values, and effect sizes (f^2). Statistical significance was determined through the bootstrapping technique with 5,000 resamples, following the guidelines of(Hair et al., 2017). In addition to significance testing, The inclusion of effect sizes offered a more complete evaluation by indicating not just whether a relationship exists but also the extent of its practical significance. (Cohen, 2013) emphasized that effect size thresholds of 0.02, 0.10, and 0.35 correspond to small, medium, and large effects, respectively. This dual consideration of significance and effect size ensures that the findings are not interpreted solely on the basis of statistical thresholds but are also grounded in their substantive importance. The detailed results of hypothesis testing are presented in Table 4.8, and the discussion below organizes the findings into groups of related constructs for clarity.

Influence of Subjective Norm (SN). The first set of hypotheses addressed the role of Subjective Norm (SN) in shaping perceptions and behavioral intentions. The findings indicate that SN had a significant positive effect on Perceived Usefulness (PU) (H1: $\beta = 0.206$, $t = 4.490$, $p < 0.001$, $f^2 = 0.064$), with an effect size that falls within the small to medium range. This highlights that peer and social influence play a noticeable role in shaping whether students perceive AI tools as beneficial. SN also influenced Intention to Adopt AI (IAA) (H2: $\beta = 0.081$, $t = 1.992$, $p = 0.046$, $f^2 = 0.012$), though the effect was relatively small. Similarly, SN was found to have a significant impact on Perceived Ease of Use (PEOU) (H3: $\beta = 0.207$, $t = 3.798$, $p < 0.001$, $f^2 = 0.056$). These results collectively suggest that social and normative pressures, while varying in strength, consistently influence students' attitudes and beliefs about AI adoption, with stronger influence on PU and PEOU than on direct intention.

Influence of Student's Image (SI). The second group of hypotheses investigated the role of Student's Image (SI). The results show that SI significantly affected PU (H4: $\beta = 0.192$, $t = 4.264$, $p < 0.001$, $f^2 = 0.042$), an effect that can be categorized as small to medium. This indicates that students' perception of how adopting AI may enhance their image or status positively shapes their beliefs about its usefulness. However, SI did not significantly influence IAA (H5: $\beta = -0.015$, $t = 0.388$, $p = 0.698$, $f^2 = 0.000$) or PEOU (H6: $\beta = 0.035$, $t = 0.605$, $p = 0.545$, $f^2 = 0.000$).

These findings suggest that while SI can shape perceptions of usefulness, it does not directly motivate students' behavioral intention or their perception of ease of use. The rejection of H5 and H6 highlights that image-related considerations are more peripheral in this context and may only matter when tied to perceptions of usefulness rather than effort expectancy.

Influence of Job Relevance (JR). Job Relevance (JR) emerged as one of the strongest predictors across multiple constructs. The results show that JR significantly influenced PU (H7: $\beta = 0.291$, $t = 5.195$, $p < 0.001$, $f^2 = 0.080$), IAA (H8: $\beta = 0.331$, $t = 5.299$, $p < 0.001$, $f^2 = 0.121$), and PEOU (H9: $\beta = 0.296$, $t = 4.169$, $p < 0.001$, $f^2 = 0.070$). With effect sizes ranging from moderate to approaching large, these findings underscore the critical importance of relevance to academic and professional tasks in shaping both attitudinal and perceptual variables. In other words, when students find AI tools closely aligned with their academic or job-related needs, they are more likely to view them as useful, easy to use, and worth adopting.

Influence of Output Quality (OQ). The influence of Output Quality (OQ) was less pronounced but still noteworthy. OQ significantly predicted PU (H10: $\beta = 0.115$, $t = 2.214$, $p = 0.027$, $f^2 = 0.013$) and PEOU (H12: $\beta = 0.158$, $t = 2.256$, $p = 0.024$, $f^2 = 0.021$), though both with small effect sizes. By contrast, its effect on IAA (H11: $\beta = 0.003$, $t = 0.057$, $p = 0.954$, $f^2 = 0.000$) was negligible and statistically non-significant, leading to the rejection of H11. Taken together, these results suggest that while students care about the quality of system outputs in forming perceptions of usefulness and ease of use, this factor does not directly translate into behavioral intentions.

Influence of Result Demonstrability (RD). The role of Result Demonstrability (RD) showed a mixed pattern. RD did not significantly predict PU (H13: $\beta = 0.115$, $t = 1.884$, $p = 0.060$, $f^2 = 0.013$), but it did significantly influence both IAA (H14: $\beta = 0.172$, $t = 2.868$, $p = 0.004$, $f^2 = 0.039$) and PEOU (H15: $\beta = 0.140$, $t = 2.514$, $p = 0.012$, $f^2 = 0.017$). These significant relationships, though small in effect size, indicate that when students can clearly observe and communicate the benefits of AI tools, they are more inclined to adopt them and to view them as easier to use. The rejection of H13, however, highlights that demonstrability alone does not directly shape perceptions of usefulness.

Core UTAUT Relationships. The core relationships posited by the Technology Acceptance Model (UTAUT) were strongly supported by the findings. PU significantly influenced IAA (H16: $\beta = 0.270$, $t = 5.415$, $p < 0.001$, $f^2 = 0.092$), reflecting a medium effect. Similarly, PEOU exerted a significant effect on IAA (H17: $\beta = 0.124$, $t = 2.459$, $p = 0.014$, $f^2 = 0.022$), though with a smaller magnitude. These findings reinforce the centrality of PU and PEOU as key determinants of user intentions in the TAM framework, consistent with decades of research in the technology adoption literature.

Determinants of Usage Behavior (UB). The final set of hypotheses explored the predictors of actual system use. UB was significantly predicted by PU (H18: $\beta = 0.104$, $t = 2.467$, $p = 0.014$, $f^2 = 0.014$) and PEOU (H19: $\beta = 0.245$, $t = 5.543$, $p < 0.001$, $f^2 = 0.093$), both statistically significant with effect sizes ranging from small to medium. Most notably, IAA emerged as the strongest predictor of UB (H20: $\beta = 0.543$, $t = 10.521$, $p < 0.001$, $f^2 = 0.371$), representing a large effect size. This result highlights the pivotal role of intention in driving actual usage behavior, underscoring that students' willingness and commitment to adopt AI technologies is the most powerful driver of whether they ultimately use them.

Overall Summary. In total, 16 out of the 20 proposed hypotheses were supported. By considering both statistical significance and effect sizes, the findings provide a more nuanced picture of the relationships among constructs. The results highlight the importance of social influence, job relevance, and the core TAM constructs, while also noting weaker or context-dependent factors such as Student's Image. Collectively, these findings lend strong support to the proposed structural model and its ability to explain the dynamics of technology acceptance and use among students.

4.5.4 Mediation Analysis

To complement the direct effects analysis, mediation testing was carried out using bootstrapping with 5,000 resamples, following the approach outlined by Preacher and Hayes (2008) and recommended in PLS-SEM studies by (Hair et al., 2017). Mediation was assessed by examining whether indirect effects were statistically significant and whether their strength indicated partial or full mediation. The results of these tests are presented in Table 4.9, and the discussion below organizes the findings according to each antecedent construct.

Table 4.8: Hypothesis Testing Results (Direct Effects)

H#	Relationship				p	Decision	f²
H1	SN → PU	0.206	0.046	4.490	0.000***	Supported	0.064
H2	SN → IAA	0.081	0.041	1.992	0.046*	Supported	0.012
H3	SN → PEOU	0.207	0.055	43.798	0.000***	Supported	0.056
H4	SI → PU	0.192	0.045	4.264	0.000***	Supported	0.042
H5	SI → IAA	−0.015	0.039	0.388	0.698	Not Supported	0.000
H6	SI → PEOU	0.035	0.058	0.605	0.545	Not Supported	0.000
H7	JR → PU	0.291	0.056	5.195	0.000***	Supported	0.080
H8	JR → IAA	0.331	0.062	5.299	0.000***	Supported	0.121
H9	JR → PEOU	0.296	0.071	4.169	0.000***	Supported	0.070
H10	OQ → PU	0.115	0.052	2.214	0.027*	Supported	0.013
H11	OQ → IAA	0.003	0.049	0.057	0.954	Not Supported	0.000
H12	OQ → PEOU	0.158	0.070	2.256	0.024*	Supported	0.021
H13	RD → PU	0.115	0.061	1.884	0.060	Not Supported	0.013
H14	RD → IAA	0.172	0.060	2.868	0.004**	Supported	0.039
H15	RD → PEOU	0.140	0.056	2.514	0.012*	Supported	0.017
H16	PU → IAA	0.270	0.050	5.415	0.000***	Supported	0.092
H17	PEOU → IAA	0.124	0.050	2.459	0.014*	Supported	0.022
H18	PU → UB	0.104	0.042	2.467	0.014*	Supported	0.014
H19	PEOU → UB	0.245	0.044	5.543	0.000***	Supported	0.093
H20	IAA → UB	0.543	0.052	10.521	0.000***	Supported	0.371

Note: ***p ¡ 0.001, **p ¡ 0.01, $*p < 0.05$; SN = Subjective Norms, SI = Students' Image, JR = Job Relevance, OQ = Output Quality, RD = Result Demonstrability, PU = Perceived Usefulness, PEOU = Perceived Ease of Use, IAA = Intention to Adopt AI, UB = User Behavior

Mediation pathways of Subjective Norm (SN). The results revealed consistent evidence of partial mediation. Specifically, the pathway SN $\rightarrow$ PU $\rightarrow$ IAA (H1, H16) was significant ($\beta = 0.056$, $t = 3.487$, $p < 0.001$), indicating that perceived usefulness partly carries the influence of social norms into behavioral intention. A similar partial mediation effect was observed in the sequential chain SN $\rightarrow$ PU $\rightarrow$ IAA $\rightarrow$ UB (H1, H16, H20; $\beta = 0.030$, $t = 3.309$, $p = 0.001$), showing that normative influence on actual usage behavior is transmitted indirectly through both usefulness and intention. Mediation through PEOU also emerged, albeit weaker, with SN $\rightarrow$ PEOU $\rightarrow$ IAA (H3, H17; $\beta = 0.026$, $t = 2.137$, $p = 0.033$) and SN $\rightarrow$ PEOU $\rightarrow$ UB (H3, H19; $\beta = 0.051$, $t = 2.881$, $p = 0.004$). These findings collectively reinforce that social influence exerts its impact primarily through cognitive appraisals of usefulness and ease of use, rather than directly.

Mediation pathways of Student's Image (SI). For SI, the mediation patterns were more nuanced. The pathway SI $\rightarrow$ PU $\rightarrow$ IAA (H4, H16) was significant ($\beta = 0.052$, $t = 3.131$, $p = 0.002$), representing a case of full mediation since the direct effect of SI on IAA was non-significant. This means that students' image considerations affect adoption only by shaping their perception of usefulness. However, mediation through IAA into UB (H5, H20) and through PEOU into either IAA or UB (H6, H17; H6, H19) was not significant. Thus, image appears to matter only when it informs perceived usefulness, not ease of use or direct intention.

Mediation pathways of Job Relevance (JR). Job Relevance showed the strongest and most consistent mediated effects. The PU pathway was significant for both IAA (H7, H16; $\beta = 0.079$, $t = 3.767$, $p < 0.001$) and UB (H7, H18; $\beta = 0.030$, $t = 2.338$, $p = 0.019$). Similarly, sequential mediation through PU and IAA to UB (H7, H16, H20) was also significant ($\beta = 0.043$, $t = 3.579$, $p < 0.001$). Mediation through PEOU followed the same pattern (H9, H17; H9, H19), suggesting that job relevance shapes both usefulness and ease of use, which then drive intention and usage. These findings underline the central role of relevance as a driver of adoption, operating indirectly through core UTAUT constructs.

Mediation pathways of Output Quality (OQ). Unlike JR, the mediation effects of OQ were mostly non-significant. For example, OQ $\rightarrow$ PU $\rightarrow$ IAA (H10, H16) narrowly missed significance ($p = 0.051$), and other pathways involving PU and IAA (H10, H16, H20; H10, H18; H11, H20) were not significant. Only one pathway, OQ $\rightarrow$ PEOU $\rightarrow$ UB (H12, H19), showed partial mediation ($\beta =$

0.039, $t = 2.077$, $p = 0.038$). This suggests that while students care about system quality, its influence does not strongly transmit through usefulness or intention.

Mediation pathways of Result Demonstrability (RD). RD displayed a mixed pattern. Mediation through IAA into UB (H14, H20; $\beta = 0.094$, $t = 2.827$, $p = 0.005$) was significant, but pathways through PU or PEOU were non-significant (H13, H16; H13, H18; H15, H17). Interestingly, RD $\rightarrow$ PEOU $\rightarrow$ UB (H15, H19) showed partial mediation ($\beta = 0.034$, $t = 2.254$, $p = 0.024$), suggesting that demonstrability can ease use perceptions that indirectly shape behavior. Overall, RD seems to matter most when students translate observable outcomes into stronger adoption intentions.

Core mediations of PU and PEOU. Finally, the core UTAUT constructs exhibited expected mediation roles. PU significantly mediated the relationship between IAA and UB (H16, H20; $\beta = 0.147$, $t = 5.107$, $p < 0.001$), while PEOU mediated IAA's impact on UB (H17, H20; $\beta = 0.067$, $t = 2.403$, $p = 0.016$). These pathways confirm that students' behavioral intention is a crucial mechanism translating both usefulness and ease of use perceptions into actual system usage.

Overall summary. In total, the mediation analysis shows that many relationships are not merely direct but operate through one or more core constructs. The strongest mediated pathways were observed for Job Relevance and PU, while Output Quality displayed weak or absent mediation. These findings highlight that UTAUT's cognitive appraisals (PU, PEOU, IAA) are essential mechanisms through which external variables exert their influence on adoption and usage.

Table 4.9: Test Results of Mediation Effects

H#	Relationship				p	Decision
H1,16	SN → PU → IAA	0.056	0.016	3.487	0.000***	Partial mediation
H1,16,20	SN → PU → IAA → UB	0.030	0.009	3.309	0.001**	Partial mediation
H1,18	SN → PU → UB	0.021	0.010	2.117	0.034*	Partial mediation
H2,20	SN → IAA → UB	0.044	0.022	1.989	0.047*	Partial mediation
H3,17	SN → PEOU → IAA	0.026	0.012	2.137	0.033*	Partial mediation
H3,17,20	SN → PEOU → IAA → UB	0.014	0.007	2.086	0.037*	Partial mediation
H3,19	SN → PEOU → UB	0.051	0.018	2.881	0.004**	Partial mediation
H4,16	SI → PU → IAA	0.052	0.017	3.131	0.002**	Full mediation
H4,16,20	SI → PU → IAA → UB	0.028	0.009	3.043	0.002**	Partial mediation
H4,18	SI → PU → UB	0.020	0.009	2.158	0.031*	Partial mediation
H5,20	SI → IAA → UB	−0.008	0.021	0.387	0.699	Not Supported
H6,17	SI → PEOU → IAA	0.004	0.008	0.548	0.584	Not Supported
H6,19	SI → PEOU → UB	0.009	0.015	0.588	0.557	Not Supported
H7,16	JR → PU → IAA	0.079	0.021	3.767	0.000***	Partial mediation
H7,16,20	JR → PU → IAA → UB	0.043	0.012	3.579	0.000***	Partial mediation
H7,18	JR → PU → UB	0.030	0.013	2.338	0.019*	Partial mediation
H8,20	JR → IAA → UB	0.180	0.042	4.275	0.000***	Partial mediation
H9,17	JR → PEOU → IAA	0.037	0.016	2.233	0.026*	Partial mediation
H9,17,20	JR → PEOU → IAA → UB	0.020	0.009	2.200	0.028*	Partial mediation
H9,19	JR → PEOU → UB	0.072	0.021	3.472	0.001***	Partial mediation
H10,16	OQ → PU → IAA	0.031	0.016	1.954	0.051	Not Supported
H10,16,20	OQ → PU → IAA → UB	0.017	0.009	1.947	0.052	Not Supported
H10,18	OQ → PU → UB	0.012	0.008	1.449	0.147	Not Supported
H11,20	OQ → IAA → UB	0.002	0.027	0.057	0.955	Not Supported
H12,17	OQ → PEOU → IAA	0.020	0.014	1.432	0.152	Not Supported
H12,19	OQ → PEOU → UB	0.039	0.019	2.077	0.038*	Partial mediation
H13,16	RD → PU → IAA	0.031	0.017	1.810	0.070	Not Supported
H13,18	RD → PU → UB	0.012	0.009	1.314	0.189	Not Supported
H14,20	RD → IAA → UB	0.094	0.033	2.827	0.005**	Partial mediation
H15,17	RD → PEOU → IAA	0.017	0.010	1.728	0.084	Not Supported
H15,19	RD → PEOU → UB	0.034	0.015	2.254	0.024*	Partial mediation
H16,20	PU → IAA → UB	0.147	0.029	5.107	0.000***	Partial mediation
H17,20	PEOU → IAA → UB	0.067	0.028	2.403	0.016*	Partial mediation

Note: ***p ¡ 0.001, **p ¡ 0.01, *p ¡ 0.05; Hypothesis numbers correspond to the path links in the mediation chain (e.g., H1, H16 refers to the path from SN to IAA via PU)

4.6 T-test Analysis

In this study, independent samples t-tests were conducted to investigate whether significant differences existed in students' perceptions of generative AI based on two demographic variables: gender (male vs. female) and student status (domestic vs. international). By examining these differences, the study aims to provide a deeper understanding of how demographic characteristics may shape students' attitudes toward generative AI technologies. Such insights are crucial for educators, institutional leaders, and policymakers seeking to design interventions that are both inclusive and sensitive to the needs of different student groups.

The analysis is organized into two main subsections. The first subsection (4.6.1) presents findings for gender-based comparisons, while the second subsection (4.6.2) focuses on comparisons between domestic and international students. Each subsection incorporates descriptive statistics and inferential test results, allowing for a balanced interpretation of central tendencies, variability, and statistical significance.

Supplementary figures showing the mean and median values of each construct are provided in Appendix 6.5.2.

4.6.1 Gender Differences in Students' Perceptions

Table 4.10 summarizes the descriptive statistics for male and female students across all constructs, while Table 4.11 reports the results of independent samples t-tests. Overall, the findings show no statistically significant gender differences across the measured constructs, as none of the p-values dropped below the standard 0.05 significance level. Nevertheless, the descriptive data offer nuanced insights into subtle variations that may still be important for understanding the broader context of AI adoption.

For example, the construct *Perceived Ease of Use* (PEOU) approached significance ($t = -1.663$, $p = 0.097$, effect size = -0.174). Female students reported slightly higher ease of use compared to their male peers, suggesting that women may perceive generative AI tools as marginally more user-friendly. A similar near-significant trend emerged for *Result Demonstrability* (RD) ($t = -1.955$, $p = 0.051$, effect size = -0.205), with female students again reporting somewhat stronger perceptions. While these differences were not statistically significant, they point to potential gendered patterns of engagement with AI that may warrant further exploration in future studies.

The remaining constructs such as *Perceived Usefulness* (PU), *Subjective Norm* (SN), *Job Relevance* (JR), and *Attitude Toward Use* (IAA) showed very small mean differences across genders, with effect sizes close to zero. This consistency reinforces the idea that male and female students, in this sample, generally hold similar views about the utility, quality, and relevance of generative AI tools in their academic contexts.

It is important to emphasize that null results are valuable in their own right. The lack of significant gender differences suggests that generative AI may be perceived as broadly accessible and equally relevant across gender groups, reducing concerns about gender-based disparities in adoption. Nonetheless, the near-significant results for PEOU and RD remind us that subtle dynamics may still exist and could surface in larger samples or different cultural contexts.

Table 4.10: Group Descriptives by Gender

Variable	Group	N				
SN	Male	223	14.8	15.0	2.61	0.175
	Female	155	14.8	15.0	2.89	0.232
PU	Male	223	16.4	17.0	2.79	0.187
	Female	155	16.5	17.0	2.75	0.221
PEOU	Male	223	11.9	12.0	2.35	0.157
	Female	155	12.3	12.0	2.25	0.181
SI	Male	223	18.2	18.0	4.12	0.276
	Female	155	18.7	19.0	3.73	0.299
RD	Male	223	11.7	12.0	2.29	0.153
	Female	155	12.1	12.0	1.79	0.144
OQ	Male	223	11.0	11.0	2.44	0.163
	Female	155	11.1	11.0	2.21	0.178
JR	Male	223	11.8	12.0	2.29	0.153
	Female	155	12.1	12.0	2.07	0.166
IAA	Male	223	16.3	17.0	3.27	0.219
	Female	155	16.7	17.0	2.59	0.208
UB	Male	223	16.0	16.0	3.21	0.215
	Female	155	16.3	16.0	2.80	0.225

Note: Group 1 = Male, Group 0 = Female. SD = Standard Deviation, SE = Standard Error.

Table 4.11: Independent Samples T-Test Results by Gender

Variable	t		p			
SN	−0.149	376	0.882	−0.0425	0.285	−0.0156
PU	−0.539	376	0.590	−0.1563	0.290	−0.0564
PEOU	−1.663	376	0.097	−0.4013	0.241	−0.1739
SI	−1.331	376	0.184	−0.5516	0.415	−0.1391
RD	−1.955	376	0.051	−0.4292	0.219	−0.2045
OQ	−0.273	376	0.785	−0.0670	0.246	−0.0285
JR	−1.206	376	0.229	−0.2778	0.230	−0.1261
ATU	−1.540	376	0.124	−0.4844	0.315	−0.1610
UB	−1.109	376	0.268	−0.3540	0.319	−0.1160

Note: T-values are from an Independent Samples T-Test comparing male and female groups. H_a : $\mu_{\text{male}} \neq \mu_{\text{female}}$.

Table 4.12: Group Descriptives by Student Status (Domestic vs International)

Variable	Group	N				
SN	Domestic	205	15.1	15.0	2.61	0.182
	International	173	14.5	15.0	2.83	0.215
PU	Domestic	205	16.9	17.0	2.47	0.173
	International	173	16.0	16.0	3.02	0.230
PEOU	Domestic	205	12.5	13.0	2.09	0.146
	International	173	11.6	12.0	2.48	0.188
SI	Domestic	205	18.4	19.0	4.13	0.288
	International	173	18.4	19.0	3.78	0.288
RD	Domestic	205	12.1	12.0	1.98	0.138
	International	173	11.6	12.0	2.22	0.169
OQ_T	Domestic	205	10.9	11.0	2.25	0.157
	International	173	11.1	11.0	2.46	0.187
JR_T	Domestic	205	12.1	12.0	2.08	0.145
	International	173	11.6	12.0	2.32	0.176
IAA_T	Domestic	205	16.9	18.0	2.74	0.191
	International	173	15.9	16.0	3.24	0.247
UB_T	Domestic	205	16.5	16.0	2.78	0.194
	International	173	15.7	16.0	3.30	0.251

4.6.2 Differences by Student Status: Domestic vs. International

The second analysis examined whether perceptions of generative AI differed between domestic and international students. Table 4.12 provides descriptive statistics for each group, while Table 4.13 presents the t-test results. Unlike the gender-based comparisons, several significant differences emerged here, highlighting meaningful contrasts between the two groups.

Domestic students consistently reported higher scores than international students on several constructs. Specifically, domestic students rated *Perceived Usefulness* (PU) significantly higher ($t = 3.160$, $p = 0.002$, effect size = 0.326), indicating a stronger belief in the academic value of generative AI tools. Similarly, they rated *Perceived Ease of Use* (PEOU) higher ($t = 3.568$, $p < 0.001$, effect size = 0.368), suggesting that domestic students felt more confident and comfortable in navigating AI technologies.

The construct *Result Demonstrability* (RD) also showed a significant difference ($t = 2.352$, $p = 0.019$, effect size = 0.243), with domestic students perceiving AI benefits as more visible and easily communicated. Likewise, domestic students scored higher on *Job Relevance* (JR) ($t = 2.246$, $p = 0.025$, effect size = 0.232), underscoring a stronger belief that AI tools align with their current or future academic and professional tasks. Most notably, *Attitude Toward Use* (ATU) ($t = 3.076$, $p = 0.002$, effect size = 0.318) and *Usage Behavior* (UB) ($t = 2.510$, $p = 0.013$, effect size = 0.259) were also significantly higher for domestic students, reflecting greater enthusiasm and actual engagement with AI technologies.

In contrast, no significant differences were observed for constructs such as *Student Image* (SI) or *Output Quality* (OQ), with both groups reporting similar views. Interestingly, the construct *Subjective Norm* (SN) approached significance ($t = 1.898$, $p = 0.059$, effect size = 0.196), hinting at a possible trend where domestic students may feel slightly stronger social pressure or peer endorsement for AI use.

Taken together, these findings highlight that international students may face more barriers whether cultural, linguistic, or technological—that could inhibit their perceptions of usefulness, ease of use, and alignment of AI tools with academic tasks. The consistent pattern of higher ratings by domestic students suggests that international students may benefit from additional institutional support, such as targeted training workshops, culturally sensitive resources, and peer mentoring programs.

By addressing these disparities, institutions can promote a more equitable adoption of AI technologies, ensuring that both domestic and international students are equally empowered to leverage these tools in their academic journeys.

Table 4.13: Independent Samples T-Test Results by Student Status (Domestic vs International)

Variable	t		p			
SN	1.8975	376	0.059	0.5316	0.280	0.195 89
PU	3.1600	376	0.002**	0.8932	0.283	0.326 23
PEOU	3.5677	376	<.001***	0.8391	0.235	0.368 33
SI	−0.0795	376	0.937	−0.0326	0.410	−0.008 21
RD	2.3520	376	0.019*	0.5085	0.216	0.242 82
OQ	−0.8264	376	0.409	−0.2003	0.242	−0.085 32
JR	2.2457	376	0.025*	0.5083	0.226	0.231 85
IAA	3.0763	376	0.002**	0.9465	0.308	0.317 60
UB	2.5096	376	0.013*	0.7853	0.313	0.259 09

Note: T-values are from an Independent Samples T-Test comparing Domestic and International students. $H_a : \mu_0 \neq \mu_1$. Significance: ***p¡0.001, **p¡0.01, *p¡0.05. [a] Levene's test significant (p¡0.05), equal variances not assumed.

4.7 Conclusion

This chapter presented the empirical findings and analysis of data collected to examine students' acceptance and adoption of generative AI tools, where it began by introducing the dataset and describing the characteristics of the respondents, followed by a detailed presentation of descriptive statistics.

The demographic profile revealed a balanced representation across gender, academic level, and discipline, providing a solid foundation for interpreting behavioral trends. The summary of constructs showed consistently high mean values for perceived usefulness and ease of use, suggesting a generally positive perception of generative AI tools among students and a strong tendency to view them as supportive of academic performance and efficiency.

Exploratory trends and multivariate analysis provided a deeper understanding of usage behavior and its variations across demographic groups. The results indicated that younger students and those in technology-focused disciplines demonstrated higher engagement and confidence in using generative AI, while pairwise relationships among key constructs confirmed strong positive correlations between perceived usefulness, behavioral intention, and facilitating conditions. These results highlight that both cognitive beliefs and contextual factors jointly shape students' adoption behavior in higher education environments.

The measurement model assessment confirmed the reliability and validity of all constructs, as evidenced by high Cronbach's alpha, composite reliability, and average variance extracted (AVE) values. Discriminant validity analysis further ensured that each construct represented distinct theoretical dimensions. In the structural model assessment, the absence of multicollinearity confirmed the robustness of the estimation, while the model's explanatory power (R2) for behavioral intention and actual use was found to be strong. Hypothesis testing supported most of the proposed relationships within the integrated UTAUT–TAM2 framework, confirming that performance expectancy, effort expectancy, social influence, and facilitating conditions significantly influence behavioral intention and actual usage. Mediation analysis further demonstrated that behavioral intention partially mediates the effects of cognitive and contextual factors on actual usage, thereby reinforcing the theoretical soundness and predictive validity of the model.

The final section examined group differences through independent samples t-tests. The analysis revealed statistically significant gender-based differences in perceived usefulness, social influence, and behavioral intention, with male students reporting slightly higher scores, while differences between domestic and international students were comparatively small.

These findings suggest that variations in exposure and academic experience, rather than nationality, play a more defining role in shaping students' engagement with generative AI tools. Overall, this chapter provided a comprehensive analysis that validated the measurement and structural models, confirmed the hypotheses, and offered empirical support for the integrated framework guiding the study. The results collectively demonstrate that students' adoption of generative AI tools is shaped by a dynamic interplay of cognitive evaluations, social influences, and institutional conditions. Building on these findings, the next chapter discusses their broader implications, connects them to existing literature, and outlines recommendations for policy, pedagogy, and future research.

Chapter 5 Discussion

5.1 Introduction

This chapter interprets the findings in light of the research questions and the literature. It explains how social influence works here, including the roles of subjective norms and student image, and how the cognitive drivers; job relevance, usefulness, ease of use, output quality, and result demonstrability feed into intention and behavior. It then focuses on the mediation pathways that connect social and cognitive factors, and reflects on demographic differences in the Bangladeshi engineering context. The chapter also states the main theoretical contributions and answers to the research questions before closing with a brief conclusion.

5.2 Situating the Findings

The structural model results confirmed the robustness of the integrated TAM2–UTAUT model, with 16 of 20 hypotheses supported. The model explained 64% of the variance in usage behavior, a substantial explanatory power in acceptance research. Among the findings, three themes stand out: (1) Job Relevance emerged as the most powerful external driver, shaping usefulness, ease of use, and intention; (2) Attitude and Intention to Adopt AI served as the pivotal mechanism translating beliefs into behavior; and (3) Subjective Norms strongly shaped perceptions of usefulness and usability, reflecting the collectivist academic environment.

The sections that follow unpack these findings in detail, organized around cognitive, social, interactive, and demographic factors, before synthesizing theoretical and practical implications.

5.3 Social Influences on Adoption (RQ1)

5.3.1 Subjective Norms: The Weight of the Collective

The findings confirmed that Subjective Norms (SN) strongly shape adoption pathways. SN enhanced PU, PEOU, and IAA, demonstrating that peer and institutional endorsement fosters perceptions of AI as both useful and easy to use,in other words, when students observe positive attitudes and responsible use among classmates or instructors, they are more likely to perceive AI tools as useful and manageable in their learning activities.

This addresses RQ1 by confirming that adoption decisions are socially embedded. In a collectivist academic environment like Bangladesh, students place weight on what peers and instructors endorse (Asag et al., 2024; Shahzad, Xu, & Asif, 2024). However, the modest direct effect on intention suggests that SN primarily works through cognitive reappraisal, rather than exerting strong direct pressure.

This indirect mechanism aligns with the argument by Foroughi, Senali, et al. (2024) and Asag et al. (2024), who observed that peer encouragement and instructor guidance increase students' confidence and trust in generative AI, which in turn improves perceived usefulness. At the same time, the limited direct impact on behavioral intention contrasts with findings from Western contexts (Strzelecki, 2024; Yilmaz et al., 2024), where individual autonomy and innovation tendencies amplify direct peer influence. This divergence underscores the contextual sensitivity of social influence and highlights how collectivist settings translate social expectations into cognitive adaptation rather than direct behavioral conformity.

5.3.2 Student Image: The Limits of Symbolic Motivation

By contrast, Student Image (SI) only enhanced PU, without significant effects on IAA or PEOU. This indicates that symbolic motivations, such as appearing competent through AI use, are less influential in driving actual adoption.

This finding answers RQ1 by showing that while students recognize a reputational benefit, they prioritize practical and task-related drivers. Symbolic motives matter less in a pragmatic student community, contrasting with workplace settings where prestige plays a larger role (Shrivastava, 2025), the current results indicate that in the student community, especially within Bangladeshi higher education, the primary concern is functional effectiveness rather than social signaling. This supports Du and Lv (2024) and Cabero-Almenara et al. (2024), who found that students' engagement with AI tools is shaped more by perceived academic relevance and learning utility than by status enhancement. From a theoretical perspective, this weaker influence of SI aligns with the TAM2 extension, where image is expected to operate indirectly through perceived usefulness rather than serving as a direct determinant of intention (Venkatesh & Davis, 2003). In this study, that indirect path is evident—students perceive AI as useful when its adoption aligns with positive academic reputations or instructor approval—but symbolic motivation alone is insufficient to trigger behavioral change.

Culturally, this also reflects the pragmatic orientation of Bangladeshi students, who tend to evaluate technologies based on academic productivity, reliability, and instructor endorsement rather than the desire for social recognition. Unlike in Western or corporate environments, where innovation is often tied to personal distinction, students in this context appear motivated by collective performance norms and task-based outcomes. This observation aligns with the cross-cultural evidence from Sobaih et al. (2024) and Tiwari et al. (2024), who emphasize that collectivist learners interpret technology adoption less as a status symbol and more as a shared academic resource.

Overall, while the image construct contributes modestly to perceived usefulness, its limited direct influence on behavioral intention indicates that symbolic appeal alone cannot sustain adoption. Instead, the evidence suggests that students prioritize functional benefits, trust, and peer validation as stronger and more consistent motivators for using generative AI tools in their academic routines.

5.4 Cognitive Drivers of Adoption (RQ2)

5.4.1 Job Relevance as the Cornerstone of Adoption

One of the most salient findings concerns the dominant role of Job Relevance (JR). JR exerted significant influence on Perceived Usefulness (PU) ($\beta = 0.291, p < 0.001$), Perceived Ease of Use (PEOU) ($\beta = 0.296, p < 0.001$), and Intention to Adopt AI (IAA) ($\beta = 0.331, p < 0.001$). These medium-to-large effects indicate that students' engagement with generative AI tools is primarily driven by how strongly they perceive these technologies as aligned with their academic and professional pathways.

This finding directly addresses RQ2, suggesting that adoption is grounded in students' awareness of AI's capacity to enhance practical outcomes such as problem-solving, research, programming, and report preparation. In engineering education—where learning is inherently task-oriented—AI systems that support employability and professional competence are more readily internalized as legitimate learning aids (Baharin et al., 2024; Siriwardena, Abeywickrama, Sandika, & Vidanapathirana, 2024).

The pivotal role of JR corroborates earlier work emphasizing that perceived task alignment is central to technology adoption in technical and applied disciplines (Baroni, Calegari, Scandolari, & Celino, 2022b; Bernabei et al., 2023). By simultaneously reinforcing both usefulness and usability perceptions, JR functions as a *cornerstone predictor*, confirming that adoption peaks when AI tools are seamlessly integrated into the authentic tasks students must master for their future careers.

5.4.2 Validating the TAM Pathway in the GenAI Era

The results also reaffirm the continuing relevance of the Technology Acceptance Model (TAM) in the generative AI context. Perceived Usefulness (PU) significantly predicted both intention ($\beta = 0.270, p < 0.001$) and behavior ($\beta = 0.104, p = 0.014$), while Perceived Ease of Use (PEOU) influenced intention ($\beta = 0.124, p = 0.014$) and behavior ($\beta = 0.245, p < 0.001$).

Although PU was the stronger determinant of intention, PEOU had a more pronounced effect on actual usage, revealing that sustained behavioral engagement depends not only on perceived value but also on operational simplicity. This dynamic reflects the original TAM proposition that cognitive evaluations of usefulness precede affective confidence in ease of use (Davis, 1989), while extending it to AI tools such as ChatGPT and Gemini. In practice, this underscores that even among digitally skilled engineering students, the consistent use of generative AI hinges on the extent to which the interface and outputs remain intuitive and reliable.

5.4.3 The Nuanced Role of Output Quality and Result Demonstrability

Further insights emerged regarding the subtle influence of Output Quality (OQ) and Result Demonstrability (RD) on adoption. OQ positively affected PU ($\beta = 0.115, p = 0.027$) and PEOU ($\beta = 0.158, p = 0.024$), but its direct effect on IAA was insignificant ($\beta = 0.003, p = 0.954$).

This suggests that while students value accurate, contextually relevant, and coherent responses, such quality improvements alone do not directly alter willingness to adopt. Instead, OQ operates indirectly through its influence on usefulness and ease of use perceptions (Baroni et al., 2022b; Ganescu & Passerat-Palmbach, 2024).

Conversely, RD showed a distinct behavioral route, significantly influencing IAA ($\beta = 0.172, p = 0.004$) and PEOU ($\beta = 0.140, p = 0.012$), but not PU ($\beta = 0.115, p = 0.060$). This finding implies that students' adoption behavior is strengthened when AI outcomes are demonstrable and visible to peers or instructors. In collectivist academic cultures, the ability to display results publicly may enhance perceived legitimacy and confidence in use, encouraging continued engagement (Asag et al., 2024). Together, these results emphasize that system-related features shape adoption indirectly—by influencing the cognitive pathways that precede behavioral commitment.

5.4.4 Attitude and Intention as Cognitive Gateways

Finally, Intention to Adopt AI (IAA) emerged as the strongest determinant of User Behavior (UB), exhibiting a large and significant effect ($\beta = 0.543, p < 0.001$). This outcome confirms that affective and attitudinal responses remain the central psychological gateways through which beliefs are translated into concrete actions. Students who feel positively inclined toward generative AI are substantially more likely to engage with it consistently, independent of demographic or contextual variations.

This reinforces the foundational TAM claim that attitudes mediate the belief–behavior link (Davis, 1989), while extending it to a new technological domain where creativity, automation, and interactivity converge. Practically, these findings underscore the importance of cultivating positive student attitudes through guided exposure, structured demonstrations, and authentic task integration—ensuring that generative AI tools are perceived not as external aids but as natural extensions of academic inquiry and skill development.

5.5 Interactions and Mediation Pathways (RQ3)

5.5.1 Intention as the Central Mechanism

Intention to Adopt AI (IAA) emerged as the strongest single predictor of User Behavior (UB), reaffirming its central function as the *gateway between belief and action*. This directly addresses RQ3, illustrating that adoption unfolds through a sequential process in which external influences first shape cognitive appraisals, which then reinforce attitudes and ultimately produce observable behavioral engagement. Such staged progression is consistent with established technology-acceptance logic (Rana et al., 2024; Venkatesh & Davis, 2003) and reinforces that IAA is not a peripheral construct but a cognitive bridge linking perception to practice.

5.5.2 Key Mediation Pathways

The mediation analysis uncovered several indirect routes through which external constructs influence user behavior, confirming that adoption is largely shaped by interdependent cognitive and attitudinal mechanisms rather than by direct effects alone.

- SN $\rightarrow$ PU $\rightarrow$ IAA $\rightarrow$ UB ($\beta = 0.030$): Social Norms (SN) influenced usage indirectly, consistent with evidence of peer-mediated technology adoption (Mustofa, Kuncoro, Atmono, Hermawan, et al., 2025). Partial mediation was evident, indicating that social cues not only enhance perceived usefulness but also exert a modest direct effect on both intention and behavior.

- JR $\rightarrow$ IAA $\rightarrow$ UB ($\beta = 0.180$): The strongest pathway, underscoring Job Relevance (JR) as the cornerstone of adoption. Both PU and PEOU serve as mediators, emphasizing JR's function in shaping perceptions of usefulness and usability key drivers of sustained behavioral engagement.

- SI $\rightarrow$ PU $\rightarrow$ IAA ($\beta = 0.052$): Full mediation was observed, showing that Student Image (SI) influences intention only through cognitive interpretation of usefulness. The absence of a direct link highlights that image-based motivations are translated into action only when internalized as genuine value (Foroughi, Iranmanesh, et al., 2024).

- OQ $\rightarrow$ PEOU $\rightarrow$ UB ($\beta = 0.039$): Higher Output Quality (OQ) improves ease of use, which subsequently enhances behavioral engagement (Camilleri, 2024). However, its effect through PU or IAA was minimal, indicating that quality influences adoption more through practical interaction than through attitudinal belief formation.

- RD $\rightarrow$ IAA $\rightarrow$ UB ($\beta = 0.094$) and RD $\rightarrow$ PEOU $\rightarrow$ UB ($\beta = 0.034$): Result Demonstrability (RD) strengthens both intention and usability perceptions, translating into higher actual use. This reflects the motivational impact of observable, shareable outcomes, particularly in socially cohesive academic cultures (Asag et al., 2024).

- PU $\rightarrow$ IAA $\rightarrow$ UB ($\beta = 0.147$) and PEOU $\rightarrow$ IAA $\rightarrow$ UB ($\beta = 0.067$): Core TAM constructs mediate the intention–behavior pathway, confirming that cognitive evaluations of usefulness and simplicity remain essential psychological mechanisms through which students' intentions manifest as concrete engagement.

Overall, the mediation results reveal that adoption is not a simple linear progression but an interactive process of cognitive reinforcement. Full mediation was evident for constructs like Student Image, whereas partial mediation characterized Social Norms, Job Relevance, Output Quality, and Result Demonstrability. These findings reaffirm that cognitive appraisals particularly PU, PEOU, and IAA serve as the central conduits through which external and contextual influences shape students' adoption of generative AI tools.

5.6 Demographic and Contextual Insights

5.6.1 Gender Dynamics and Digital Equity

Independent-sample t-tests revealed no significant gender differences across any major constructs, suggesting that digital equity is emerging among Gen Z learners (Bagdi, Bulsara, Sankar, & Sharma, 2023). Both male and female students reported comparable perceptions of usefulness, ease of use, and intention to adopt AI, indicating that generative systems are increasingly perceived as universally accessible resources rather than gendered technologies.

This partially answers RQ4 while adding nuance to earlier questions (RQ1–RQ3) by showing that gender may no longer act as a strong conditioning factor in technology adoption. This finding contrasts with earlier studies that identified persistent digital divides but aligns with recent evidence reporting minimal gender-based variation in generative AI use (Asag et al., 2024). It suggests that evolving academic norms, equal access to digital tools, and social exposure have collectively narrowed historical disparities in technology engagement.

5.6.2 Domestic vs. International Students

In contrast, statistically significant differences were observed between domestic and international students, with domestic participants reporting higher mean scores for PU, PEOU, JR, IAA, and UB. These differences likely stem from several contextual conditions:

- Curriculum alignment: Domestic students may find that AI tools align more naturally with local course structures and assessment expectations, enabling easier integration into their learning routines.
- Language and cultural barriers: International students might encounter challenges in engaging with predominantly English-based AI interfaces and prompts, affecting their comfort and confidence levels (Karakas, 2023).
- Familiarity with academic norms: Domestic students may possess a clearer understanding of institutional expectations surrounding ethical AI use and assessment integrity (Shahzad, Xu, & Asif, 2024).

These contextual disparities highlight the importance of targeted support for international learners, including AI literacy programs, multilingual scaffolding, and culturally responsive orientation. Enhancing these supports can help bridge the adoption gap and ensure more equitable participation and benefit from generative AI technologies across diverse student groups. In doing so, institutions can foster an inclusive ecosystem where AI serves as a shared educational tool rather than a stratifying force.

5.7 Trends and Pairwise Relationships

5.7.1 Demographic Influences on User Behavior

Observed patterns indicate that students' engagement with generative AI tools reflects an interplay between academic experience, gender, and student status. Third-Year students demonstrated the highest levels of usage, likely due to increased academic pressure and greater familiarity with digital learning tools. Similar findings have been observed in other studies, where senior students exhibited higher reliance on AI for managing workload and enhancing performance efficiency (Baharin et al., 2024; Bernabei et al., 2023). In contrast, lower adoption among First-Year and Postgraduate students may point to transitional barriers or differing academic priorities during these stages (Alzoubi, 2024).

Gender-based variations were relatively minor, with male students reporting slightly higher engagement than female students, consistent with patterns in previous AI adoption studies (Almogren et al., 2024; Foroughi, Iranmanesh, et al., 2024). This convergence suggests an encouraging trend toward digital equity, implying that both genders perceive the usefulness and manageability of AI tools in comparable ways. In other words, when students observe responsible and effective use of AI among peers or instructors, they are more likely to view these tools as beneficial and legitimate components of learning environments.

Student status also played a subtle role. Domestic students tended to engage more with AI tools compared to international students, possibly due to greater linguistic comfort, contextual familiarity, and access to localized resources (Anik & Rahman, 2025; Chowdhury, 2025). International students, despite positive attitudes, may experience additional cultural or academic barriers in transferring intention into regular usage. The intersection of these demographic factors, being a Third-Year, International, Male student showing the highest usage, and First-Year, Domestic, Female students the lowest—demonstrates that these variables do not act in isolation but collectively shape adoption patterns. Such intersections reaffirm that behavioral trends emerge through the compound influence of social positioning, experience, and perceived task relevance (Bhatia & Dassani, 2025; Cabero-Almenara et al., 2024).

5.7.2 Pairwise Relationships Between Attitude and Behavior

Pairwise plots between Intention to Adopt AI (IAA) and User Behavior (UB) further revealed a strong, positive relationship across gender and study-level groups. The consistency of this association suggests that favorable attitudes reliably translate into actual usage, confirming the robustness of the integrated TAM–UTAUT framework in predicting behavioral adoption (Acosta-Enriquez, 2024; Venkatesh & Davis, 2003). The alignment across gender categories reinforces the notion of digital parity in adoption, showing that students' perceptions of usefulness and ease of use similarly inform behavioral outcomes regardless of gender.

However, differences based on student status were more pronounced. Domestic students displayed higher behavioral engagement at comparable attitude levels, suggesting that contextual factors such as familiarity with institutional systems and cultural learning habits strengthen the intention–behavior link. International students, while positive in attitude, may encounter uncertainties related to academic-integrity guidelines or linguistic precision when using generative AI tools (Dietrich & Grassini, 2025).

Overall, these results indicate that although attitudes remain a primary predictor of behavior, the demographic and contextual environment modulate how intentions manifest as active use. The pairwise approach complements statistical testing by visualizing the underlying dynamics of adoption, revealing that similar attitudes can yield different behavioral expressions depending on students' experience, environment, and self-efficacy. In this way, trend visualization and relational analysis together provide a more nuanced understanding of behavioral dynamics surrounding the adoption of generative AI tools in higher education.

5.8 Theoretical Contributions

This study advances the theoretical understanding of technology acceptance in higher education by integrating social and cognitive perspectives within the context of generative AI adoption. It offers three interconnected contributions that extend existing frameworks and refine the interpretation of behavioral adoption among engineering students.

1. Validation of the Integrated TAM–UTAUT Framework: The empirical model accounted for 64% of the variance in User Behavior (UB), demonstrating that the integration of the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) provides a strong explanatory foundation for predicting generative AI adoption. This alignment supports the notion that cognitive appraisals such as perceived usefulness and ease of use are reinforced by social drivers like peer norms and institutional influence (Acosta-Enriquez, 2024; Rana et al., 2024; Venkatesh & Davis, 2003). The findings thus affirm that social and cognitive determinants operate in tandem, enriching the explanatory scope of acceptance models in technology-mediated learning environments.

2. Emphasizing Job Relevance as the Cornerstone Factor: Among external determinants, Job Relevance (JR) emerged as the most influential construct, underscoring the importance of aligning generative AI tools with authentic academic and professional tasks. This outcome reinforces previous evidence that the perceived congruence between technology features and disciplinary requirements plays a decisive role in shaping both intention and continued use (Bernabei et al., 2023; Camilleri, 2024). In the engineering context, students are more likely to adopt AI tools when they perceive direct contributions to their coursework, problem-solving efficiency, and employability, positioning JR as a key motivational anchor for sustained behavioral engagement.

3. Advancing Insights on Mediation Pathways: The analysis further clarifies that the effects of social influence, perceived quality, and demonstrability on adoption are not primarily direct but operate through cognitive and attitudinal channels. In this sense, perceived usefulness and ease of use act as cognitive gateways that transform social cues into meaningful behavioral intentions, echoing theoretical refinements proposed by recent acceptance studies (Cabero-Almenara et al.,

2024; Foroughi, Iranmanesh, et al., 2024). This mediation structure highlights that students' engagement with generative AI is not a passive reaction to peer behavior but a reflective process of internal evaluation, trust formation, and contextual reasoning.

Overall, these theoretical contributions reposition technology acceptance within a contextualized socio-cognitive paradigm, suggesting that adoption of generative AI in education results from the convergence of perceived task relevance, social validation, and cognitive appraisal. The integrated approach developed in this study therefore extends the explanatory reach of existing frameworks and provides a foundation for future comparative and longitudinal investigations in similar multicultural and resource-constrained academic environments.

5.9 Answers to the Research Questions

RQ1: What is the role of social influence, particularly subjective norms and student image, in shaping engineering students' adoption of generative AI?

The findings indicate that subjective norms (SN) significantly influenced students' perceptions of usefulness, ease of use, and intention to adopt generative AI. Peer recommendations and faculty encouragement served as strong enablers of adoption, particularly by shaping positive attitudes. By contrast, student image (SI) exerted a limited effect: while it enhanced perceived usefulness, it did not significantly affect intention or actual usage. This suggests that collective social cues were more influential than prestige-driven motivations in the adoption process.

RQ2: How do cognitive appraisals (usefulness, usability, job relevance, quality, demonstrability) drive adoption?

Cognitive factors emerged as the strongest predictors of adoption. Perceived usefulness (PU) and perceived ease of use (PEOU) directly increased intention and usage behavior, confirming their central role. Job relevance (JR) was the most powerful driver, strongly influencing usefulness, ease of use, and intention. Output quality (OQ) and result demonstrability (RD) shaped adoption indirectly by improving perceptions of usability and confidence. Overall, the results affirm that adoption was primarily driven by functional and task-oriented evaluations.

RQ3: How do social and cognitive factors interact through mediation pathways to shape intention and Usage Behavior?

The study revealed that adoption followed a multi-stage process mediated by cognitive constructs. Intention to adopt (IAA) emerged as the single strongest predictor of actual behavior. Mediation analyses showed that:

- SN influenced usage indirectly through PU and IAA.
- JR had the most substantial mediated effect on usage, especially via intention.
- OQ and RD shaped behavior through usability and demonstrability, reinforcing confidence.

These pathways highlight intention as the central gateway through which social and cognitive factors translate into practical usage of generative AI. Importantly, this dynamic was most evident in academic contexts: students used generative AI to tackle complex problem-solving, assist with coding, and support the development of academic assignments. Thus, social encouragement and cognitive appraisals did not just shape perceptions but directly enabled concrete applications of AI in students' academic lives.

RQ4: How do demographic differences (e.g., gender and international vs. domestic student status) affect perceptions, intentions, and Usage Behavior of generative AI?

The demographic analysis found that gender differences were negligible, with male and female students demonstrating similar acceptance levels. However, a significant divide was observed between domestic and international students. Domestic students reported higher levels of perceived usefulness, ease of use, job relevance, result demonstrability, intention, and behavior. This points to cultural, linguistic, and contextual factors as barriers for international students, suggesting the need for more inclusive support.

5.10 Conclusion

In summary, this study shows that cognitive, social, and contextual factors jointly shape generative AI adoption. Cognitive drivers such as job relevance, usefulness, and ease of use provide the foundation, while subjective norms reinforce perceptions in a collectivist setting. Intention emerges as the pivotal gateway to behavior, confirming TAM's enduring relevance.

Demographic analysis highlights the convergence of gendered perceptions and the divergence between domestic and international students, offering fresh insights into equity and accessibility. Theoretically, the research validates and extends integrated TAM-UTAUT frameworks to a multicultural, resource-constrained higher education context. Practically, it points educators, policymakers, and developers toward strategies that emphasize relevance, usability, and supportive learning environments.

Chapter 6 Conclusion, Implications and Future Research Directions

6.1 Introduction

This chapter turns from interpretation to implications and the way forward. It first presents the theoretical and practical implications for researchers, educators, administrators, and developers. Then it discusses the study's limitations methodological and theoretical—and explains how they shape the scope of the results. Next, it lays out future research directions, including broader comparisons, stronger methods, and deeper work on demographic and contextual differences. The chapter closes with concluding remarks that recap the purpose, the research questions, and the contribution of the study to understanding generative AI adoption in higher education. Building on the interpretation of the study's findings presented in the previous chapter, this chapter explores the broader implications of the study's findings. It considers how the insights from this research contribute to academic theory, inform practical strategies for various stakeholders, and highlight important limitations that should be addressed in future research. The chapter also outlines specific directions for extending this work, offering a roadmap for scholars and practitioners who aim to deepen understanding of generative AI adoption in higher education.

6.2 Implications

6.2.1 Theoretical Implications

This study offers several important contributions to the academic literature on technology adoption, where it extends established models, clarifies the interplay between social and cognitive drivers, and demonstrates the value of contextualized research in understanding new, disruptive technologies like generative AI.

Validating and Extending the UTAUT–TAM Model in a Novel Context

A central theoretical contribution lies in validating the robustness of an integrated UTAUT–TAM framework for understanding the adoption of generative AI in a non-Western, engineering-focused academic environment. The model explained 64% of the variance in usage behavior, indicating strong explanatory power.

This finding is significant because most prior applications of UTAUT and TAM have been conducted in Western contexts or in relation to more mature technologies. By successfully applying this hybrid model to generative AI in a multicultural Bangladeshi university, the study confirms its relevance and adoptability to emerging technologies and diverse cultural settings. This reinforces calls in the literature for extending and testing established models across varied socio-cultural contexts (Asag et al., 2024; Feng, Yu, Tan, Dai, & Li, 2025).

Highlighting the Interplay of Social and Cognitive Constructs

Another key theoretical insight is the clarification of how social influence and cognitive evaluation interact in shaping adoption. The findings show that Subjective Norms (SN) significantly influenced both Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), and also had a small but significant direct effect on Intention to Adopt AI (IAA).

Similarly, Job Relevance (JR) significantly influenced PU and PEOU, and had a strong direct impact on IAA, with a pattern that shows social cues and task evaluations support each other instead of functioning separately. Adoption is a complex, multi-stage process in which external signals (e.g., peer endorsement, curriculum alignment) enhance cognitive appraisals, which in turn influence intention and behavior. This detailed view enriches the theoretical landscape by highlighting that social and cognitive factors are interconnected elements in the adoption process, not isolated areas. (Mustofa et al., 2025; Sobaih et al., 2024).

6.2.2 Practical Implications

Beyond theoretical contributions, the study offers concrete, evidence-based recommendations for educators, university administrators, and AI tool developers. These implications are particularly relevant for higher education institutions in multicultural and resource-constrained contexts, where the integration of generative AI poses both opportunities and challenges.

For Educators and Curriculum Designers

One of the strongest findings was that Job Relevance (JR) emerged as a central driver of adoption, influencing PU, PEOU, and IAA. This underscores the importance of embedding generative AI within authentic academic and professional tasks, such as simulations, coding assignments, and design projects. When students see clear alignment between AI tools and their future career tasks, their motivation to adopt and use these tools increases significantly.

Equally important, the role of Subjective Norms (SN) highlights that peer and faculty endorsement are powerful levers. Policies should therefore encourage collaborative learning environments and promote peer mentoring programs that can help strengthen positive norms around responsible AI use, promote engagement, and decrease uncertainty.

For University Administrators and Policymakers

The study found that Intention to Adopt AI (IAA) was the strongest predictor of Usage Behavior (UB), which has critical policy implications, as institutions must actively shape students' attitudes and intentions toward AI through clear, transparent guidelines for ethical use. Showcasing positive uses of generative AI in coursework can foster constructive attitudes that translate into meaningful engagement. For example, encouraging students to reflect on and disclose their AI use in assignments can promote responsible integration.

Perceived Ease of Use (PEOU) also significantly influenced both IAA and UB, aligning with previous studies emphasizing that usability is a crucial factor, as was ensured by Asag et al. (2024), so universities should provide user-friendly platforms, orientation sessions, peer-led training, and continuous technical support to ensure a positive user experience. Small but impactful interventions such as micro-training sessions on prompt design, hands-on workshops, and quick-start guidescan boost student confidence and lower barriers to entry.

The demographic analysis showed that domestic students reported significantly higher levels of PU, PEOU, JR, RD, IAA, and UB compared to international students. This highlights the need for culturally inclusive policies that address language and cultural barriers. Institutions should offer multilingual resources, tailored workshops, and culturally responsive training to help international students participate equally. (Asag et al., 2024).

Finally, the indirect effects of Output Quality (OQ) and Result Demonstrability (RD) indicate that making AI's value visible and reliable is essential for maintaining engagement. Universities can achieve this by providing access to high-quality tools, incorporating verification steps into coursework, and promoting critical reflection on AI-generated content. These measures not only build trust but also prevent over-reliance by encouraging reflective and ethical use.

For AI Tool Developers

Output Quality (OQ) and Result Demonstrability (RD) have large indirect effects, suggesting that students will continue to use AI more when its output is trustworthy and its benefits are evident. Developers have to prioritize making AI output more accurate, transparent, and explainable to foster trust. Additionally, features such as confidence scores or explainable AI modules can be added to aid learners to analyze and reflect on AI-generated content. These features will help facilitate learning goals along with reducing the danger of over-reliance.

6.3 Limitations

Despite offering new insights into generative AI adoption in Bangladesh, this study inevitably carries several limitations that must be acknowledged. Recognizing these boundaries is essential, not only to situate the validity of the current findings but also to chart clear pathways for future scholarship.

6.3.1 Methodological Constraints

The first limitation lies in the methodological design. Because this research employed a cross-sectional survey, the findings cannot establish causality and may be subject to response biases inherent in self-reported data. This concern has been raised in similar research. For example, (Strzelecki, 2024), in a PLS-SEM study on ChatGPT adoption, cautioned that the correlational nature of such surveys, combined with reliance on student self-reports, can introduce distortions in interpretation. While our model provides valuable associations, longitudinal or experimental designs would allow future studies to trace how adoption behaviors evolve over time and under varying conditions. Moreover, supplementing self-reports with objective usage metrics (such as log data or system analytics) could validate the reliability of responses and enrich our understanding of Usage Behavior.

6.3.2 Generalizability

A second limitation concerns the generalizability of the findings. The data were collected from a single engineering university in Bangladesh, which limits the extent to which results can be applied across other cultural or institutional settings. Prior scholarship has shown that student acceptance of AI is not uniform worldwide. For instance, (Ravšelj et al., 2025), in a large-scale study involving over 23,000 students globally, documented significant variations in students' perceptions depending on socio-demographic and geographic factors . Similarly, Dietrich and Grassini (2025) found that the determinants of ChatGPT adoption differed substantially between students and teachers, reinforcing the importance of diverse contexts (Dietrich & Grassini, 2025). Against this backdrop, our findings should be interpreted as context-specific rather than universally applicable. To test the robustness of the model, comparative research across universities, disciplines, and countries including both public and private institutions would be particularly valuable.

6.3.3 Theoretical Scope

While the integrated UTAUT/TAM2 model proved useful in capturing key drivers of adoption, it necessarily excluded other constructs that may be relevant in educational contexts. Recent reviews indicate that performance expectancy and perceived usefulness often emerge as the most powerful predictors of adoption intentions (Asag et al., 2024; Xue et al., 2024).
Constructs like trust, ethical concerns, or anxiety have been shown to influence AI adoption in other studies; Dietrich and Grassini (2025) emphasized how some students' reluctance arose from ethical doubts or anxiety about relying on AI. Furthermore, alternative theoretical perspectives, including the Theory of Planned Behavior or Diffusion of Innovation, have been employed to shed light on adoption dynamics. Bhatia and Dassani (2025) pointed to innovation bias and herding effects as important drivers of ChatGPT use, suggesting that enriching future models with such constructs could offer a more comprehensive view of adoption pathways.

In summary, while this study provides important contributions to the literature, its limitations remind us that adoption of generative AI is a multi-faceted process shaped by methodological, contextual, theoretical, and demographic factors. Addressing these through innovative designs and broader samples will help build a richer, more nuanced understanding of how students navigate this disruptive technology.

6.4 Future Research Directions

Addressing the limitations we discuss in section 6.3 opens up a range of promising avenues for further research.

6.4.1 Expanding Research Approaches and Perspectives

A mixed-method study is particularly worthwhile, as Xue et al. (2024) emphasized, because capturing the ultimate richness of technology adoption in higher education requires bringing together diverse groups, mixed methodologies and theoretical perspectives. For example, combining survey research with qualitative interviews, focus groups, or diary studies will allow future scholars to capture both the breadth and depth of students' experiences with generative AI.

Longitudinal or intervention-based studies, such as tracking students before and after structured AI training, could also clarify the causal effects of AI adoption on learning outcomes. Moreover, exploring the interplay between digital inequality and institutional support is essential. Feng et al. (2025), for instance, highlighted how differences in access to high-speed internet or faculty guidance significantly shape adoption trajectories (Feng et al., 2025). By broadening samples, diversifying methods, and expanding theoretical lenses, future research can move toward a more comprehensive and generalizable understanding of generative AI adoption in higher education.

6.4.2 Adopting Advanced Methodologies

Future studies can employ longitudinal or experimental designs to establish causal relationships between constructs. As (Xue et al., 2024) argues, integrating diverse groups, mixed methodologies, and theoretical perspectives is crucial for a comprehensive understanding of technology adoption in higher education.

6.4.3 Expanding the Research Scope

The findings should be tested across various universities, countries, and educational disciplines, with comparative studies such as cross-country or cross-cultural surveys, to determine whether the model applies to non-engineering groups, private versus public institutions, and different regions. This will improve the generalizability and strength of the theoretical framework.

6.4.4 Broadening the Theoretical Framework

Future studies could also explore additional factors such as trust, ethical perceptions, or AI-related anxiety. Applying other theories, like the Theory of Planned Behavior (TPB) or Diffusion of Innovation, could further enhance understanding of adoption processes. As (Xue et al., 2024) and (Bhatia & Dassani, 2025) indicate, combining these views can help clarify individual differences in AI acceptance.

6.4.5 Investigating Demographic and Individual Differences

Ultimately, demographic and individual factors warrant further study using other frameworks to uncover additional findings. While this study found no gender differences, other research suggests that variables such as academic major, prior experience with AI, socioeconomic status, or rural/urban background may influence acceptance. (Ravšelj et al., 2025). Large-scale surveys and qualitative case studies can reveal how study habits, cultural assumptions, or digital inequality influence AI use. Following students as they go through AI training can potentially demystify causal effects on learning outcomes. Additionally, the investigation of institutional support factors, such as high-speed internet connectivity or faculty mentoring, can provide a clearer image of how generative AI is being integrated into higher education. (Feng et al., 2025).

6.5 Conclusion

6.5.1 Recapitulation of the Purpose and Research Questions

The main goal of this study was to explore the adoption and use of generative AI tools among engineering students at a Bangladeshi multicultural university. The study aimed to explain cognitive as well as social factors associated with the acceptance of technology, besides examining demographic differences in adoption behavior. Based on an extended UTAUT–TAM framework, the study integrated constructs such as perceived usefulness, perceived ease of use, job relevance, output quality, result demonstrability, subjective norms, and student image to explain students' intentions and behaviors toward generative AI.

6.5.2 Final Conclusion

The study makes a significant contribution to understanding the adoption of generative AI in higher education by validating and extending the UTAUT–TAM2 framework. The research highlights the dominant role of cognitive appraisals, while also demonstrating the importance of social norms and mediation pathways in shaping adoption.

Key positive outcomes include the identification of job relevance as the most influential driver of adoption, the confirmation of intention as the strongest predictor of usage, and the recognition of domestic–international student disparities that must be addressed for equitable integration of AI.

Practical recommendations emphasize the importance of embedding AI into authentic academic tasks, providing accessible training and technical support, fostering ethical guidelines, and ensuring culturally inclusive strategies. Limitations include the reliance on self-reported, cross-sectional data from a single university, which constrains generalizability.

Looking ahead, future research should adopt longitudinal and mixed-methods approaches, expand to diverse institutional and cultural contexts, and integrate additional constructs such as trust and ethical perceptions. By doing so, subsequent studies can build a richer, more generalizable understanding of how generative AI can be responsibly and effectively integrated into higher education.

In sum, this thesis demonstrates that while generative AI offers transformative potential for engineering education, its adoption depends on a careful balance of cognitive, social, and contextual factors. With intentional policies and inclusive practices, universities can move beyond sporadic use toward structured, responsible, and equitable integration of generative AI into academic and professional life.

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Appendices

Initial Version of the Survey

Table 6.1: Measurement Items for Constructs (Table A)

Construct	Items / Questions	Source
Subjective Norms (SN)	SN1 Students at my educational institution think that using AI-powered tools like ChatGPT, Google Gemini, or Bing CoPilot is beneficial for learning. SN2 My peers frequently use AI-powered tools for learning that influences my perception of AI tools. SN3 Recommendations from classmates or friends to use AI tools for learning influence my attitude towards it. SN4 Educators at my institution encourage students to use AI-powered chatbots as learning aids.	(Baharin et al., 2024; Khoa et al., 2020; Venkatesh & Davis, 2000, 2003)
Perceived Usefulness (PU)	PU1 I believe that using AI-powered tools enhances my learning experience. PU2 AI-powered tools are effective for helping me understand difficult concepts. PU3 AI-powered tools help to improve my academic performance. PU4 I believe that utilizing AI-powered tools will significantly contribute to my academic success.	(Baharin et al., 2024; Khoa et al., 2020; Venkatesh & Davis, 2000)

Construct	Items / Questions	Source
Perceived Ease of Use (PEOU)	PEOU1 Interacting with AI-powered tools is intuitive and user-friendly. PEOU2 I find it easy to navigate and use features offered by AI-powered tools. PEOU3 I find it easy to learn how to use AI-powered tools for my study.	(Khoa et al., 2020; Venkatesh & Davis, 2000)
Student Image (SI)	SI1 Using AI-powered tools enhances my reputation as a tech-savvy student. SI2 I feel more confident in my academic abilities when I use AI-powered tools for learning. SI3 When my friends and classmates see me using AI-powered tools for educational purposes, their perceptions about me improve. SI4 Ethical considerations influence my decision to use AI-powered tools in my learning pursuits. SI5 Using AI-powered tools aligns with ethical principles and positively impacts my social image within the educational community.	(Khoa et al., 2020; Patterson et al., 2024; Venkatesh & Davis, 2000)

Table 6.2: Measurement Items for Constructs (Table B)

Construct	Items / Questions	Source
Result Demonstrability (RD)	RD1 It is easy for me to showcase the benefits of using AI-powered tools to my peers and educators. RD2 I can easily demonstrate how AI-powered tools have helped me in my academic achievements. RD3 Sharing my positive experiences with AI-powered tools encourages others to use them for learning purposes.	(Baharin et al., 2024; Khoa et al., 2020; Patterson et al., 2024; Venkatesh & Davis, 2000)

Continued on next page

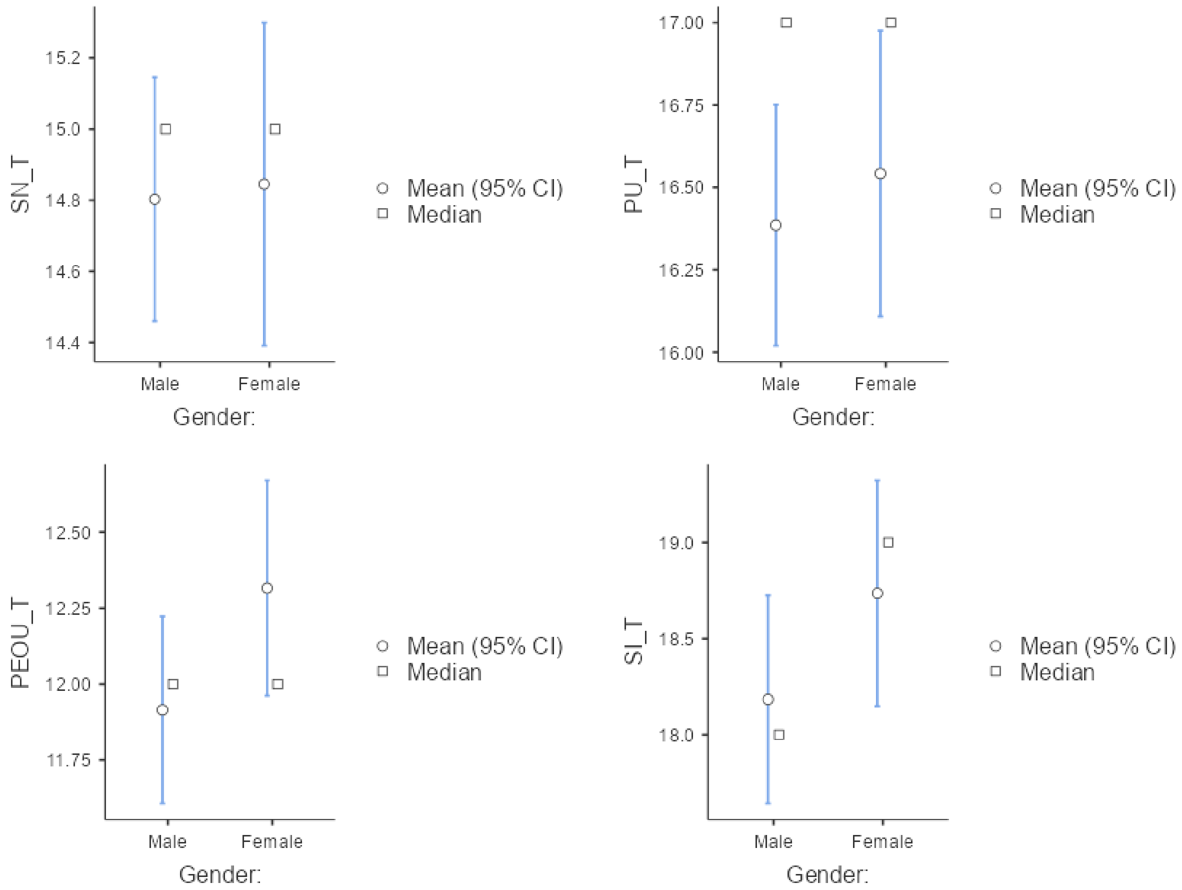
Construct	Items / Questions	Source
Output Quality (OQ)	OQ1 The responses generated by AI-powered tools are accurate and reliable. OQ2 I trust the information provided by AI-powered tools to be helpful and relevant to my studies. OQ3 Using AI-powered tools improves the quality of the resources available to me for learning purposes.	(Baharin et al., 2024; Khoa et al., 2020; Patterson et al., 2024; Venkatesh & Davis, 2000)
Job Relevance (JR)	JR1 Integrating AI-powered tools into my studies aligns with my academic goals and objectives. JR2 I find AI tools are valuable for completing my tasks and responsibilities. JR3 AI-powered tools contribute significantly to achieving my learning outcomes and objectives.	(Khoa et al., 2020; Venkatesh & Davis, 2000)
Intention to Adopt AI (IAA)	IAA1 I am willing to adopt AI-powered tools as a learning aid. IAA2 I want to continue using AI-powered tools for my studies. IAA3 I will use AI-powered tools for my studies if I get the opportunity. IAA4 I will encourage others to use AI-powered tools for their studies.	(Baharin et al., 2024; Khoa et al., 2020; Patterson et al., 2024; Venkatesh & Davis, 2000, 2003)
User Behavior (UB)	UB1 I use AI-powered tools for various tasks and activities in my learning and study. UB2 My overall experience of using AI-powered tools for academic work is satisfactory. UB3 I frequently use AI-powered tools. UB4 I have bookmarked or saved the AI-powered tools or their websites in my browser/homepage/Desktop for easy access to them.	(Khoa et al., 2020; Patterson et al., 2024; Venkatesh & Davis, 2003)

Outer Loadings and Outer Weights of Measurement Items

Table 6.3: Outer Loadings and Outer Weights of All Constructs

#	Indicator		
1	IAA1 ←IAA	0.805	0.297
2	IAA2 ←IAA	0.881	0.293
3	IAA3 ←IAA	0.826	0.314
4	IAA4 ←IAA	0.811	0.300
5	JR1 ← JR	0.770	0.392
6	JR2 ← JR	0.808	0.439
7	JR3 ← JR	0.837	0.410
8	OQ1 ← OQ	0.655	0.274
9	OQ2 ← OQ	0.781	0.395
10	OQ3 ← OQ	0.846	0.605
11	PEOU1 ← PEOU	0.844	0.402
12	PEOU2 ← PEOU	0.835	0.364
13	PEOU3 ← PEOU	0.844	0.423
14	PU1 ← PU	0.747	0.309
15	PU2 ← PU	0.721	0.306
16	PU3 ← PU	0.800	0.346
17	PU4 ← PU	0.763	0.356
18	RD1 ← RD	0.729	0.335
19	RD2 ← RD	0.847	0.444
20	RD3 ← RD	0.837	0.453
21	SI1 ← SI	0.761	0.267
22	SI2 ← SI	0.793	0.329
23	SI3 ← SI	0.824	0.235
24	SI4 ← SI	0.707	0.213
25	SI5 ← SI	0.736	0.261
26	SN1 ← SN	0.825	0.479
27	SN2 ← SN	0.817	0.410
28	SN3 ← SN	0.739	0.365
29	UB1 ← UB	0.869	0.440
30	UB2 ← UB	0.871	0.409
31	UB3 ← UB	0.799	0.328

Independent Samples t-Test Results by Gender and Student Status



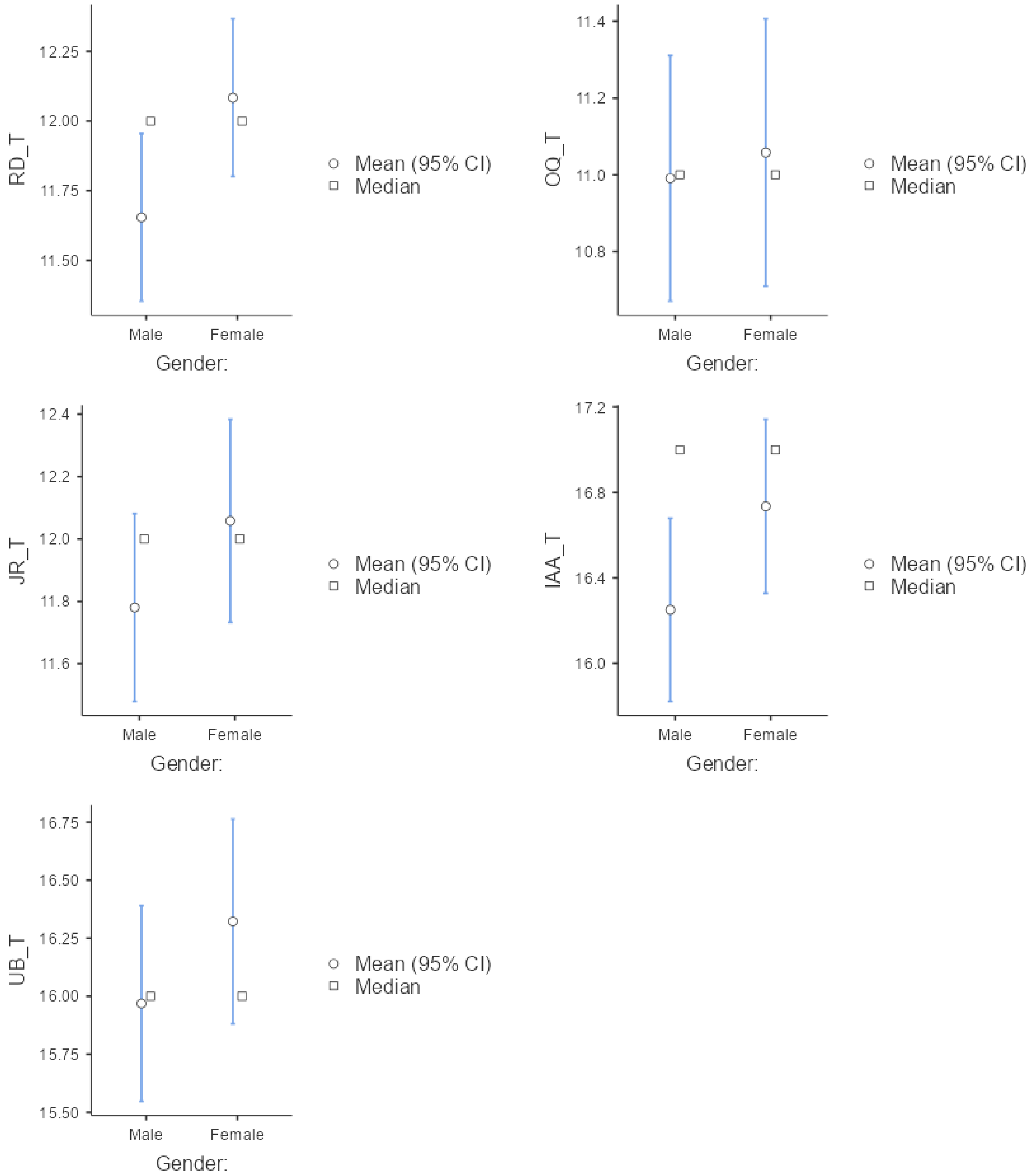
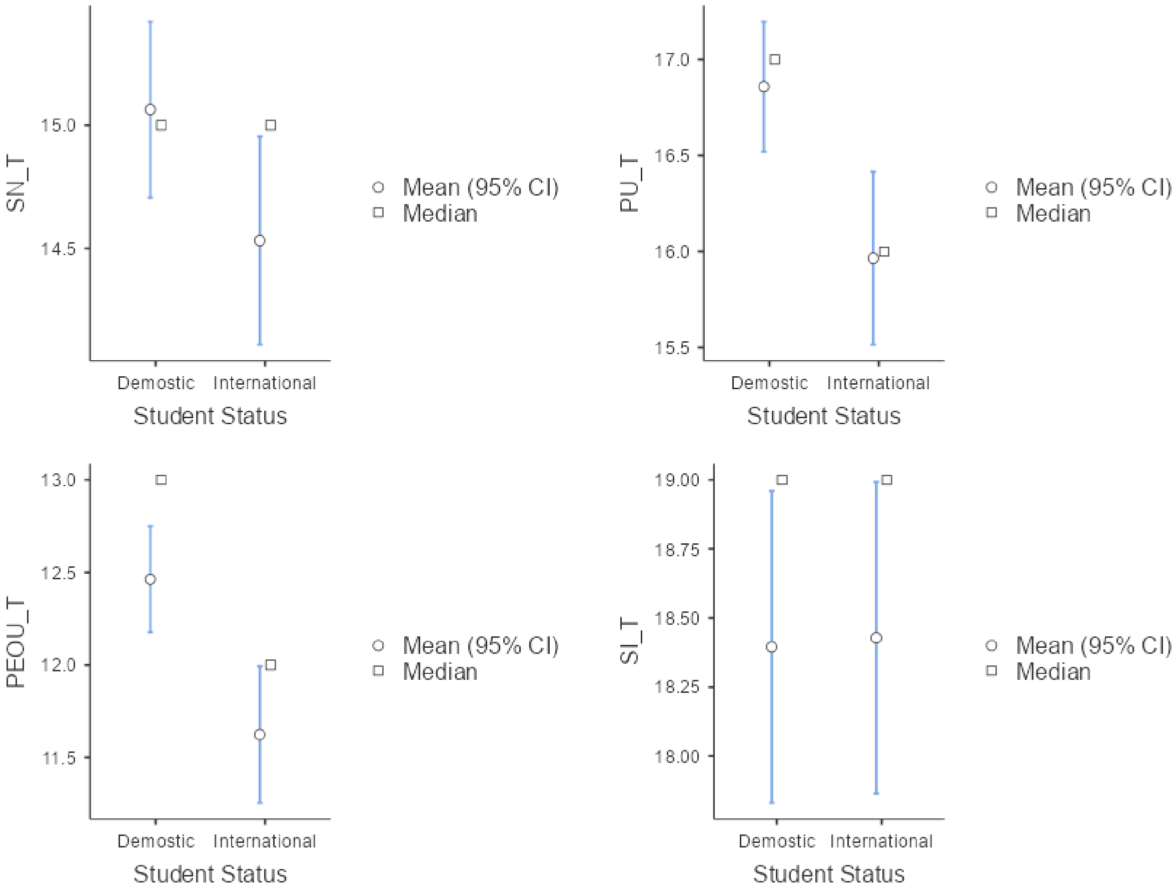
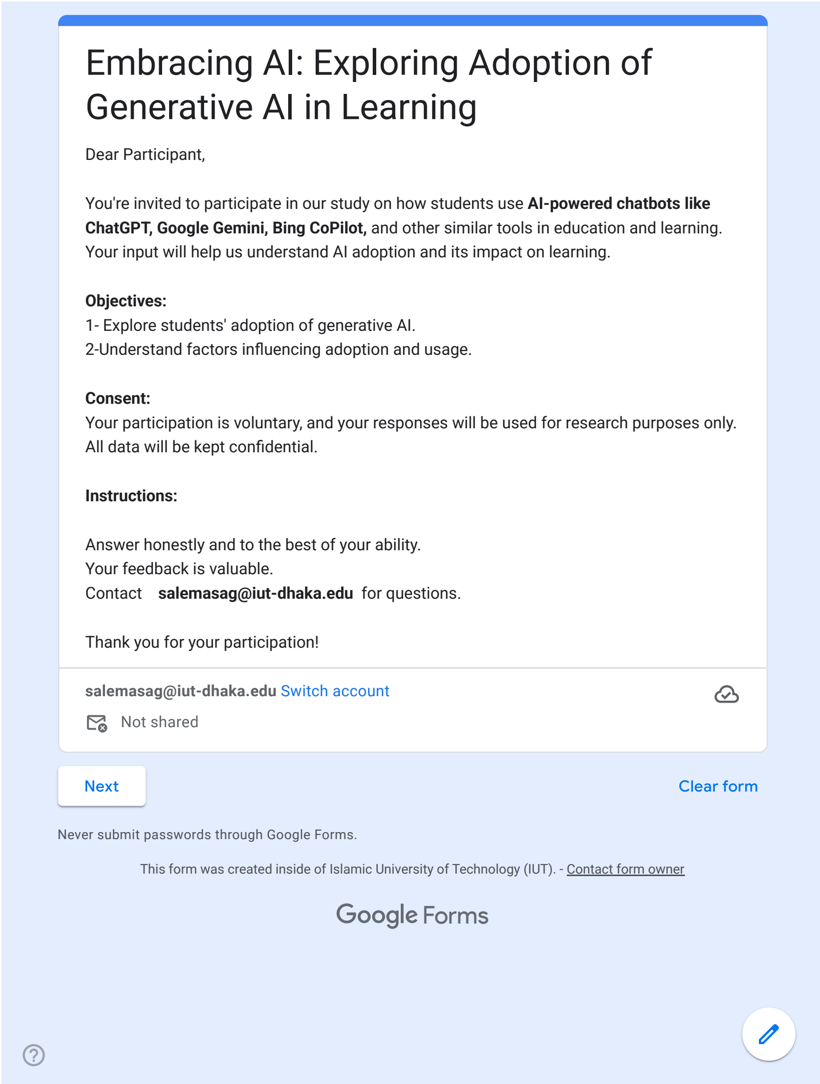


Figure 6.1: Mean and median values of constructs from independent samples t-test by gender.


SN_T
15.0
14.5
Demostic
International
Student Status
Mean (95% CI)
Median
PU_T
17.0
16.5
16.0
15.5
Demostic
International
Student Status
Mean (95% CI)
Median
PEOU_T
13.0
12.5
12.0
11.5
Demostic
International
Student Status
Mean (95% CI)
Median
SI_T
19.00
18.75
18.50
18.25
18.00
Demostic
International
Student Status
Mean (95% CI)
Median

Participant Consent Form



Embracing AI: Exploring Adoption of Generative AI in Learning

Dear Participant,

You're invited to participate in our study on how students use **AI-powered chatbots like ChatGPT, Google Gemini, Bing CoPilot,** and other similar tools in education and learning. Your input will help us understand AI adoption and its impact on learning.

Objectives:
1- Explore students' adoption of generative AI.
2-Understand factors influencing adoption and usage.

Consent:
Your participation is voluntary, and your responses will be used for research purposes only. All data will be kept confidential.

Instructions:

Answer honestly and to the best of your ability.
Your feedback is valuable.
Contact **salemasag@iut-dhaka.edu** for questions.

Thank you for your participation!

salemasag@iut-dhaka.edu Switch account

Not shared

Next

Clear form

Never submit passwords through Google Forms.

This form was created inside of Islamic University of Technology (IUT). - Contact form owner

Google Forms

Figure 6.2: Participant Consent Form

Note:This study was conducted following the ethical guidelines and institutional regulations of the Islamic University of Technology (IUT). The research protocol was reviewed and approved by the Committee for Advanced Studies and Research (CASR) during its 57th meeting held on 21st August 2025 at the Board Room of IUT under the Chairmanship of the Vice-Chancellor. All procedures involving participants were conducted with full compliance to institutional standards for ethical research.

Ethical Clearance, Approval, and Funding (Ref. No: CASR/57/2025/01/Proc-001)

22 AUG 2025
Serial No. 4608
PART of 96th Academic Council

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Ref. No.: CASR/57/2025/01/Proc/001

Date: 22 August 2025

Proceedings of the 57th CASR

The 57th meeting of the Committee for Advanced Studies and Research (CASR) began its deliberations in both physical and virtual mode on **21st August 2025**, at 10:00 AM at the Board room of IUT under the Chairmanship of the Vice-Chancellor of IUT.

The following members were present at the meeting:

1.	Prof. Dr. Mohammad Rafiqul Islam	Vice-Chancellor, IUT
2.	Dr. Hissein Araby Nour	Pro Vice-Chancellor, IUT
3.	Prof. Dr. Md. Anayet Ullah Patwari	Dean, FET, IUT
4.	Prof. Dr. Md. Tarek Uddin	Dean, FSTE, IUT
5.	Prof. Dr. Md. Rezaul Karim	Head, BTM Department, IUT
6.	Prof. Dr. Md. Abdullah Al Mamun	Head, TVE Department, IUT
7.	Prof. Dr. Mohammad Ahsan Habib	Head, MPE Department, IUT
8.	Prof. Dr. Shakil Mohammad Rifaat	Head, CEE Department, IUT
9.	Prof. Dr. Md. Hasanul Kabir	Head, CSE Department, IUT
10.	Prof. Dr. Syed Iftekhar Ali	Head, EEE Department, IUT
11.	Dr. Md. Abul Kalam Azad	Head, N Sc Department, IUT
12.	Prof. Dr. Md. Rezwanul Karim	Head, IEE, IUT
13.	Dr. Abdullahel Bari	Chairman, Ananda Group, Dhaka
14.	Prof. Dr. Mohammad Kaykobad	Distinguished Professor, BRAC University
15.	Prof. Dr. Md. Shamsul Hoque	Professor, Department of Civil Engineering, BUET

At the beginning of the meeting, the Chairman welcomed all the members of the Committee and thanked the external CASR members for attending the meeting. Then, the Chairman took up the agenda one by one and declared the floor open for deliberations. After detailed discussions, the following resolutions were adopted:

Agenda & Resolutions of the 57th CASR meeting:

Agenda Item No. 01: Confirmation of Minutes of the 56th CASR meeting

The **56th meeting** of the Committee for Advanced Studies and Research (CASR) was held on **22nd May 2025** physically under the chairmanship of the Vice-Chancellor. The minutes of the meeting were circulated among the members of the CASR. Therefore, it is placed for confirmation.

Resolution 1: The Minutes of the 56th CASR meeting were approved with the following amendment in Resolution 4(e) (ii) is given below:

	Status: Full-Time		Course and their success in academic Courses: A case of IUT.	
03	Name: Mazen Abdulwahab Mahyoub Salem Asag Stu ID: **221031403** Status: Full-Time	Course completed: **45.00** Credits Current CGPA: **3.91**/4.00 Supervisor: Dr. Md. Abdullah Al Mamum	Engineering Students' Acceptance and Use of Generative AI: The Role of Social Influence and Cognitive Dynamics.	Printing and Binding (As per rule)

Resolution 6(b): The CASR approved the thesis proposals with the following remarks as stated below:

Sl.	Student Details	Approved Thesis Title	Remarks	Approved Budget
03	Name: Mazen Abdulwahab Mahyoub Salem Asag Std ID: **221031403**	Engineering Students' Acceptance and Use of Generative AI: The Role of Social Influence and Cognitive Dynamics.	Approved with the following modifications: -Reference style needs to be revised, -Budget needs to be revised -Overall formatting needs to be revised.	Printing and Binding (As per rule)

57th CASR: **21 of 22**

Figure 6.3: Official CASR Ethical Clearance and Funding Approval Letter (Ref. No: CASR/57/2025/01/Proc-001)