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An Investigation of Students' Perception of Generative AI as a Learning Tool in Computer Science and Engineering

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Dedication

I dedicate this thesis to some extraordinary individuals who have profoundly shaped my life, my late parents, whose unwavering love, support, and wisdom continue to guide and inspire me; my beloved husband, whose constant encouragement, patience, and unconditional love have been my greatest source of strength and motivation throughout this journey; and my family, whose kindness, love, and support have sustained me and made this achievement possible.

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Declaration of the author

This is to certify that the work presented in this thesis is an original work of me, Ida Njie, a student of the Department of Technical and Vocational Education (TVE), 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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List of Acronyms

AI (Artificial Intelligence)

AVE (Average Variance Extracted)

CSE (Computer Science and Engineering)

CB – SEM (Covariance – Based Structural Equation Modeling)

CVI (Content Validation Index)

CR (Composite Reliability)

GAN (Generative Adversarial Network)

GenAI (Generative Artificial Intelligence)

GAU (Generative AI Use)

HTMT (Heterotrait – Monotrait)

IUT (Islamic University of Technology)

IUG (Intention to use generative AI)

K – S (Kolmogorov – Smirnov)

PEOU (Perceived Ease of Use)

PU (Perceived Usefulness)

LO (Learning Outcome)

PLS – SEM (Partial Least Squares Structure Equation Modeling)

RQ (Research Question)

RMSEA (Root Mean Square Error of Approximation)

SEM (Structural Equation Modeling)

S – W (Shapiro – Wilk)

S – CVI (Scale – Level Content Validation Index)

SPSS (Statistical Package for the Social Sciences)

TAM (Technology Acceptance Model)

TPACK (Technological Pedagogical Content Knowledge)

UTG (University of the Gambia)

UI/UX (User Interface/User Experiences

VAEs (Variational Autoencoders)

VIFs (Variance Inflation Factors)

Abstract

The study investigates students' perception of generative AI as a learning tool in computer Science Engineering (CSE) with specific attention to two universities in two different regions: the University of The Gambia and the Islamic University of Technology in Bangladesh. The Technology Acceptance Model (TAM) positioned the research because there are four key inputs: perceived usefulness, perceived ease of use, and intention to use shape students' learning outcomes. The responses were analysed using descriptive statistics, validity and reliability testing, and structural equation modelling (SEM) after the data were collected through a structured survey. The results show that most students hold a positive view of generative AI, often describing it as helpful for their studies and relatively easy to use. At the same time, many raised concerns about ethical issues and the risk of depending too heavily on AI tools. The research, therefore, points to the need for clear training and guidance on how to apply these technologies responsibly in education. Finally, the study draws attention to the lack of research in South Asia and West Africa, suggesting that further work in these regions could deepen our understanding of how students experience AI in their academic journeys.

Chapter 1 Introduction

GenAI refers to Artificial intelligence that produces content, including text, pictures or code, with the assistance of Natural language processing to process and create natural human-like text. It is possible that these instruments can assist with creativity and decision-making in various fields, such as the study and employment (Bharti et al., 2024).

Researchers hold differing views on the role of GenAI. Some see it as a “workhorse” that handles repetitive tasks, others as a “language assistant” limited to text generation, and still others as a “research accelerator” that can speed up analysis and discovery. These perspectives highlight both the promise and the challenges associated with GenAI, including concerns about maintaining research integrity(Andersen et al., 2024).

In educational settings, students tend to view GenAI positively. They are aware of its capabilities and see it as a useful tool for improving understanding, developing skills, increasing confidence, and achieving meaningful learning outcomes. At the same time, they recognize potential concerns, such as ethical issues and over-reliance on AI tools (Aldossary et al., 2024).

This study focuses on exploring how Computer Science and Engineering (CSE) students perceived and used generative AI as a learning tool. This chapter began with the background of the study and then proceeded with the problem statement, research aims and objectives, scope and significance, after which it concluded with an overview of the thesis structure.

1.1 Background of the Study

The rapid development in Artificial Intelligence (AI) is changing the education sector, and, in this study, we specifically focus on the diffusion of Generative AI (GenAI) tools, such as ChatGPT and GitHub Copilot, and how they can generate original content, which is quickly being used in tertiary education. In the sphere of computer science and engineering, students also start developing a fine understanding of how GenAI can facilitate the learning processes. The results demonstrate that the majority of students consider GenAI an effective tool to reach academic success, especially when it comes to writing, correcting of grammar mistakes, and creating ideas (Liu et al., 2024a). Learning that GenAI has the possibility to create a more engaging educational experience as well as make them more employable, students advise that GenAI should and must serve as an add-on to the existing pedagogical approaches, not to be used to ignore them. In this regard, GenAI is typically considered as a secondary tool for achieving academic goals (Egeli et al., 2024). However, there are still some concerns connected with the issues of academic dishonesty, plagiarism, and privacy in the context (Arowosegbe et al., 2024).

In general, the picture is not bad when engineering learners envision GenAI in their academic and professional landscapes (Camacho-Zuñiga et al., 2024). The positive relationship with tools such as ChatGPT reflects this positive outlook, contrasting with the cautious approaches taken by some faculty members when it comes to GenAI integration in higher education (Guillén-Yparrea & Hernández-Rodríguez, 2024). Students appreciate GenAI in terms of prompting creativity, adopting multi-perspective approaches, and shaping them to fit a highly competitive and fast-changing job market (Altares-López et al., 2024).

Early adopters of GenAI, such as computer science and engineering students, recognize the potential transformative value, but have mixed professional implications and concerns about the long-term educational and career implications of GenAI. Already, these views are having an impact on the pedagogy of computer science, the design of computer science curriculum, and computer science policy (Smith et al., 2024). In learning to code, students tend to respond well to GenAI-generated feedback that incorporates their own code by describing it as very specific, clear and corrective. But they also state that they require additional improvement of such feedback (Zhang et al., 2024). Although using such tools is commonplace, students remain unaware of the historical origin and modern functionality of GenAI, which stresses the importance of new learning techniques and the expansion of multidisciplinary learning (Hutson & Jeevanjee, 2024).

1.2 Problem Statement

The integration of Generative Artificial Intelligence (GenAI) in higher education, particularly in computer science and engineering, is growing rapidly, with tools like ChatGPT and GitHub Copilot increasingly incorporated into learning and programming activities. Despite their growing prevalence, there is a limited understanding of how students perceive and interact with these tools. While GenAI has the potential to enhance learning outcomes, support complex problem-solving, and promote efficiency, it also raises concerns regarding critical thinking, creativity, academic integrity, and over-reliance on technology.

According to the existing literature, students recognize that GenAI can be useful in such activities: code assistance, idea generation, and customized learning, but research gaps remain regarding the actual effect of this technology on the learning process, skills acquisition, and academic growth on the long-term level. Additionally, there is a possibility that the knowledge gap, which exists before the use of these tools and access to them, might influence the perception and utilization pattern, which is not an extensively researched phenomenon. There is no simple way of developing proper embedding processes of these technologies in education in a responsible way unless the learning institutions have a clear vision as to how students learn using GenAI, struggle and progress.

In an attempt to bridge this gap, this research project will attempt to examine the perceptions, attitudes and experience of Computer Science and Engineering students regarding GenAI as a learning tool. By doing this, it tries to provide hints that can be employed to create pedagogical structures and policies to reap the maximum advantages of GenAI and react to its possible drawbacks and demerits in the context of higher education.

1.3 Aims and Objectives

This research aims to explore computer science and engineering students' perceptions of Generative AI as a learning tool. Specifically, it seeks to examine students' intentions to use GenAI for enhancing learning outcomes, assess the perceived usefulness and ease of use of these tools, and identify the types of GenAI applications most commonly employed to support academic performance. The study intends to provide insights into how GenAI can be effectively integrated into CSE education to maximize benefits for students.

1.3.1 Specific Objectives

- To assess computer science and engineering students' intention to use generative AI as a tool for enhancing their learning outcomes.
- To analyse the perceived usefulness of generative AI tools among computer science and engineering students.
- To evaluate the perceived ease of use of generative AI tools in supporting learning outcomes within computer science education.

- To identify the types of generative AI tools commonly used by computer science and engineering students to enhance their academic performance.

Research Questions

- What is the intention of computer science and engineering students to use generative AI tools for enhancing their learning outcomes?
- How do computer science and engineering students perceive the usefulness of generative AI tools in their academic learning?
- How do students evaluate the ease of use of generative AI tools in supporting their learning within computer science courses?
- What types of generative AI tools are commonly used by computer science and engineering students to improve their learning outcomes?

1.4 Scope of the Study

The focus of this study will be on students pursuing computer science and engineering at universities in The Gambia and Bangladesh. A purposive sampling technique will be employed to select at least one university from each country. Following this, participants will be chosen using convenience sampling. The study will involve participants from two institutions: the University of The Gambia (UTG) and the Islamic University of Technology (IUT). The objective of this comparative study is to explore the influence of regional diversity, like the educational context, access to technology, and cultural elements, on how students view the generative AI tools in computer science education. The overall population size is 700 students who are enrolled in the Islamic University of Technology (IUT), and the University of The Gambia (UTG), 400 students and 300 students respectively. The expected sample is 300, where 200 will be from the Islamic University of Technology (IUT) and 100 will be from the University of The Gambia (UTG).

1.5 Significance of the Study

The methodology to be used in this research study will be qualitative to gather and analyze the data regarding the objectives of the study in a systematic manner. Particularly, we will use a cross-sectional survey tool to determine the links between three major variables, namely the perceptions of Generative AI by students to use it in educational settings, the intention to use Generative AI to learn, and their ultimate impact on learning among learners who are enrolled in degree programs in Computer Science and Engineering. The survey is to be conducted among a heterogeneous group of respondents and enable us to collect adequate data about their perceptions and behavioural patterns regarding the introduction of Generative AI into their learning procedures. We believe that by performing statistical analysis, we will be able to identify meaningful trends and observations that would guide the effective application of technology in higher education.

1.6 Structure of the Thesis

This thesis is further subdivided into various distinct chapters so as to provide a brief and detailed summary of the study being presented. Chapter 1 has provided the background of the research. The background and aim and objectives of the study, as well as the problem statement thereof, have been determined. Chapter 2 is devoted to the deep analysis of the available literature and related studies, which provide the key findings and the methodology that can be used in regards to the topic of the ongoing research. Chapter 3 describes the research methodology to be employed in this study and entails the research design, data collection techniques, and data analysis procedures that will be employed to ensure the validity and reliability of the results.

The analysis and the results of the study will be presented in chapter 4 and will be discussed in-depth and provide an insight on the information gathered and its significance. The final point will be found lastly in Chapter 5 when the discussion of the findings will be conducted and the remarks concerning the possible direction of further research and the overall conclusions made as a result of studying this paper will be observed.

Chapter 2 Literature Review

2.1 Introduction

Generative Artificial Intelligence (GenAI) has turned out to be a disruptive technology that can generate a broad spectrum of output, including text-based solutions and non-text-based ones, including images, code, and simulations. Its application in the education sector offers fresh prospects of improving educational experiences in various fields such as in computer science and engineering. The perception of GenAI in students is of most significance, as it leads to the creation of AI literacy, incorporating practical suggestions on curriculum development, and preparing future graduates to work in the constantly changing world of technology. It is against this background that the current research focuses on the perceptions of students in Computer Science and Engineering (CSE) on the application of GenAI as a learning tool. The research falls within the two settings the University of The Gambia (UTG) and the Islamic University of Technology (IUT) in Bangladesh and hence offers perspectives of other cultures and educational setting.

2.2 Generative AI in Education

GenAI will likely bring about enormous change in the system of education due to its power to personalise learning, creating efficiency, and improving accessibility. GenAI can serve as a tool of encouraging creativity in students, engaging them in exploring and exercising their innovative abilities beyond the purpose of classical learning outcomes. GenAI has the potential to unlock the possibility of the production of unique content in many domains, whether it is programming and mathematics or storytelling. learners will be able to get out of merely consuming knowledge and actively contribute to the process of creation. Specifically, studying computer science, students will be able to use GenAI to explore different programming languages, algorithms, and problem-solving methods and enhance their technical skills as well as the skills of creative expression.

AI has transformed in the process of education and in the last two decades, its role has been drastically varied. The history of AI in learning can be described mainly by robots that were programmed to popular learning or teaching activities which somehow repetitive, but newer technologies are turning AI into a universal learning tool that can differentiate the learning procedures, knowledge construction or build out more inclusive learning settings (Coelho & Reis, 2023; Varynskyi et al., 2023). Wide distribution of deep learning modules has also improved the ability to host interaction and increased access and accessibility, especially via features like adaptive feedback systems and chatbots (Jsowd, 2023). Meanwhile, the issue of equity, the over-concentration of efforts, and ethical appropriateness remains relevant, and a measured approach to the integration is necessary (Ahmad et al., 2024).

This broader movement is also what the evolution of GenAI in the field of education bears the marks of. Early versions of algorithmic processes like GANs and VAEs that provided a foundation to large-scale language models like GPT are now widely incorporated in higher educational settings (Gatla et al., 2024; Yehia, 2024). In the future, GenAI will lead to a further revolutionization of teaching and learning due to such capabilities as offering such attributes as adaptive and equitable learning opportunities. Since GenAI makes the delivery of content and its reception personalised and supports various learner needs, it is likely to not only contribute to an increased level of learning outcomes but also help to decrease disparity in access to quality education (Hashmi & Bal, 2024; Sandhu et al., 2024).

2.2.1 Definition and Evolution

GenAI is gaining popularity as an education-altering aspect of education, and more specifically, as a writing aid. Research indicates that GenAI can be used to strengthen students in writing through its capacity to support the process of generating content, developing ideas and self-evaluation. Specifically, (Olszak & Krajka, 2024), conducted a quasi-experimental study of the influence of AI-based writing strategies on students of applied linguistics. These results will demonstrate not only that the implementation of various GenAI strategies can result in positive changes in the writing performance of students but also that the corresponding alterations of underlying, or rather, primary learning processes might seem to have an even greater potential than the focus on writing performance itself. In a similar line of thought, (Yang, 2024) explored the GenAI application in teaching writing and presented systematic instructions to create content, generate ideas, and review oneself. The research highlighted how GenAI feedback and scaffolding interventions can help students improve their writing habits, and hence, improve the delivery of instructions as well as the learning achievements. Taken together, these findings suggest the pedagogical opportunity in using GenAI as a writing assistant to embed critical engagement with text creation in text and rhetoric courses rather than automating writing through software.

On top of writing, GenAI-based code generation assistants have also demonstrated significant potential in helping first-time programmers by supplementing personalized and adaptive advice on how each student should learn. In (Poitras et al., 2024), cognitive apprenticeship principles were used in AI coding tools to reveal that a structured AI feedback mechanism can be used to instruct code readers, writers and revisers. Their research reproduced the result of the positive effects of AI assistance in skill building of programming, but they also observed the challenges of implementation fidelity. In an effort to complement these findings, (Garg & Rajendran, 2024), took the approach of GenAI together with structured prompts to assist novices in programming and data analysis. Their findings revealed marked results in improvement between pre and post-testing with almost half of the participants doing all the assigned tasks. These studies all point to the ability of GenAI to not only improve technical skills learning in the field of programming but also encourage people to persevere and self-regulate themselves

2.2.2 Applications in Education

GenAI or generative AI, is a recognized influential technology being used in schools that provides particular assistance with writing. Research indicates that GenAI has the capacity to improve the writing proficiencies of students through its ability to help generate content, develop ideas, and self-evaluate. A good example is (Olszak & Krajka, 2024), who explored the effects of AI-based writing methods on the student average of applied linguistics in a quasi-experiment. The results of their study show that GenAI-based strategies, when applied to enhance writing performance, not only enhance the students' writing performance but also transform their learning behaviour, proving the potential of GenAI to restructure academic writing learning. Likewise, (Yang, 2024) has focused on the pedagogical use of GenAI in curriculum development, where the functions of content development, thought process, and critical assessment became the structured solutions offered. The research focused on demonstrating how GenAI feedback and scaffolding may assist the students in the improvement of their writing patterns, thus improving the instruction and learning process through transition optimization. Taken together, these results suggest how GenAI can draw increased pedagogical interest to writing assistants as a constructive element that should help produce critical reflection on the topic of text manufacturing rather than replace human writing with automation.

Other than writing, GenAI-based coding assistants have been proven to be of significant value by assisting novice programmers in coding with a personalized, adaptive guidance process that fosters self-learning. The principles of cognitive apprenticeship were shown to be useful in the context of AI coding tools (Poitras et al., 2024) showed that systematic AI feedback can help novice learners navigate tasks in reading, writing and revising code. Their work proved the positive outcome of the use of AI assistants for acquiring programming skills, but also highlighted the experimental fidelity issues. In addition to this, (Garg & Rajendran, 2024) tried GenAI alongside structured prompts to assist novices in data analysis and programming. They documented a marked change in the pre-test and post-test scores, with almost half of the participants gaining correct scores in every activity they were assigned. These findings are all indicative of the fact that GenAI can not only augment technical skill development processes when it comes to programming, but also encourage self-regulation and persistence among the learners who tackle program development.

2.2.3 Advantages and Challenges

With GenAI, the future of education holds significant potential to be revolutionized, most notably, the areas of personalized learning, better student engagement, and administrative effectiveness. One of the main strengths is the ability to work with large datasets that reflect the different learning styles, performance scores as well as previous feedback and therefore facilitate the creation of personalized learning paths to individual students. The specificity of such personalization makes the learning much more effective and creates a sense of owning and being in control as the learner engages with the texts and activities that reflect their strengths and areas of improvement (Dhagare, 2024). In addition to personalization, GenAI will help to make learning experiences more interactive and engaging by designing simulations which could recreate the conditions of the real world and bring a theory and practice gap to students. Similarly, gamified texts have demonstrated their remarkable ability to raise motivation and engagement resulting in a higher level of participation and knowledge retention (Dhagare, 2024; Elmourabit et al., 2024). GenAI can also help in relieving the administration burden on a large scale by saving time on repetitive processes like grading and feedback generation, which creates time and allows educators to engage in more critical interactions with the students such as encouraging thoughtful discussion and collaborative problem-solving (Dhagare, 2024; Singh, 2024).

Although these aspects portray the potential positive impact of GenAI in the education sector, the presence of strong obstacles undermines and forces the slowdown of GenAI adoption on both sides. Issues of academic integrity are especially acute, as a considerable percentage of students think that the use of GenAI may be a breach of the academically recognized ethical principles and jeopardizes their academic status. This fear tends to obstruct the perceived gains of efficiency in writing, coding and problem-solving (Fawns et al., 2024; Johri et al., 2024). The second way that this problem is compounded by institutional ambiguity is the fact that unclear or inconsistent rules regarding what constitutes acceptable use of GenAI cause confusion amongst students in their uncertainty as to what constitutes acceptable practice (Fawns et al., 2024; Kanont et al., 2024). In addition, considerable structural disparities in schooling and digital divide and lingual barriers constrain the sanitary access. It is possible that those students with lower socioeconomic backgrounds or whose first language is not English will struggle with how to best use these tools, further exacerbating educational inequities (Kanont et al., 2024; Ma et al., 2024). A lack of knowledge concerning GenAI reliability is also an obstacle since most students do not trust the authenticity of AI-created content and have to go through multiple checks before it becomes an attractive option (Johri et al., 2024; Schultz, 2024). Collectively, these concerns point to both the future potential power and present disadvantages of GenAI in the field of education, in which it is already coming into use, but in an ethically irresponsible institutional and socio-technical environment.

2.3 Theoretical Framework

This study is guided by the Technology Acceptance Model TAM. The model is necessary because we can use it to assess and analyse the perception of computer science students towards generative AI as a learning instrument. By utilizing TAM, we may investigate numerous determinants that will contribute towards the attitude of students towards the adoption of generative AI, such as the perceived usefulness and the perceived ease of use. Such a framework will give us a better understanding of the motivations, concerns, and overall willingness of students to accept the use of generative AI, and will be able to inform the eventual strategy in terms of using generative AI in educational contexts.

2.3.1 Technology Acceptance Model (TAM)

Technology Acceptance Model (TAM), first coined by Davis (Davis, 1989a), is one of the most-used models that can be applied in the study of user adoption of any new technology. Basic in this, TAM points to two constructs that are available: Perceived Ease of Use (PEOU) and Perceived Usefulness (PU). PEOU indicates how much a user thinks that the use of a technology will be unstressful, whereas PU is the extent to which a technology is seen to improve efficiency or performance. Such constructs have been seen to have a profound impact on the attitudes, and thereafter the behavioral intentions of the technology user to adopt the technology (Teo et al., 2011; Varynskyi et al., 2023).

Over the past few years, TAM has been advanced by scholars, who have found it interesting to respond to the dynamics of technology adoption, which are growing in complexity. At that, attitude toward use ATU has been pointed out to mediate the relationship among the elements of PEOU, PU, and ITU, concluding that positive attitudes stimulate both the intention of using the device and the actual use (Or, 2024). Furthermore, the findings of some studies even indicate that PEOU can directly impact the actual use of the system, which contradicts the interpretation that intention is a single factor to decide adoption (Dr. Khalid Abdalmohsen F Alshammari, 2024) The perception of ease of use and usefulness has also been found to be based on contextual variables, including, but not limited to, computer anxiety, prior encounter, or cultural setting, and contextualizing TAM to a specific environment (Scherer, 2024).

Even though TAM has received a lot of utilization in various fields like healthcare, e-commerce and the field of financial technology (Jefdy Bawala & Tanaamah, 2024), its use has especially become prominent in educational research. Experiments reveal that TAM will provide insights in explaining how students receive state-of-the-art learning environments, e-tools of assessment, and, as of late, artificial intelligence–based systems (Teo et al., 2011). In the case of higher education, TAM gives an understanding of motivational and cognitive variables, which precondition students in the readiness to embrace the use of generative AI as a learning tool. With the analysis of both PEOU and PU, coupled with the emergent aspects of the theory, including attitudes, supportive institutional practices, and ethical issues, TAM can be considered an effective theoretical framework through which to examine how students interact with this fast-changing technology.

2.3.2 Application in Generative AI

The applicability of Technology Acceptance Model (TAM) to generative AI (GenAI) has contributed to the required insight into how people, particularly students and educators, can embrace the new forms of AI in learning institutions. Indeed, as shown in the previous literature, perceived ease of use and the perception of usefulness have been the most important motivation factors in the acceptance of GenAI ChatGPT and Midjourney in teaching and learning by defining how users value the connection between its usefulness and functionality (Shen et al., 2023). As an example, (Al-Abdullatif, 2024) suggests that the use of AI literacy which can be defined as informed awareness of the affordance and limitation of AI as well as intelligent TPACK integration could be used as mediating topics in terms of how teachers embrace GenAI. Such a result indicates the importance of not only technological proficiency but also the educational orienting of GenAI in relation to general instructional design. Consistently, (Sandhu et al., 2024) cite the importance of self-efficacy of users the confidence they have in terms of their technological abilities- and perceived effectiveness of genAI applications as the main factors contributing towards the engagement of students in the use of these tools. Remarkably, (Kanont et al., 2024) offer an analytical approach that reveals a negative correlation between the perceived ease of use and perceived usefulness indicators suggesting that the easier a GenAI tool is to use, the more users perceive its reduced importance, a factor that potentially stalls long-term usage.

Collectively, these results demonstrate the benefit of institutional programs that develop both technical and pedagogical skills in educators and students, as well as confronting the ethical dilemma of GenAI. Formal professional life learning courses, transparent regulatory policies, and systems allow professional and ethically responsible uptakes of GenAI tools hence not just tolerating but also enabling efficient adoption of GenAI tools in relevant learning behaviors (Al-Abdullatif, 2024).

2.4 Students' Perceptions of Generative AI

According to their global responses, it is expected that students will have an idea that generative AI (GenAI) can be used to improve the learning process as even the students will be aware of how the use of this technology will support communication, productivity, and knowledge acquisition.

A growing literature suggests that students are adopting technologies such as ChatGPT to assist in their studies by providing writing assistance and summarizing research papers, and using technologies to add clarity to more complicated ideas. These apps have enabled simplification of study processes, and such an innovation has been used to lead to improved learning outcomes as observed in (Liu et al., 2024b) and (Almassaad et al., 2024) studies. The students also give testimonies that GenAI simplifies the academic task, and they also comprehend the complex information better.

Despite these advantages, the concerns of academic integrity and reliability are a problem. The students are afraid of the risk of plagiarism and the fact that the excessive use of AI-generated work may make a negative mark on their own critical thinking abilities. As shown by empirical evidence by (Cabrera-Arnau, 2024) and (Saúde et al., 2024) alone, the prevalence of such concerns is not exclusive to the issue of dishonesty, but only to fear the lessening of cognitive workload of the learning processes. Also, research indicates that there is increasing sensitivity among the students since they see the need to possess a solid knowledge base as the application of GenAI continues to increase. Without such grounding, students may not be capable of critically analyzing and synthesizing AI outputs, and this may be an issue, as noted (Razmerita, 2024) and (Almassaad et al., 2024).

These statistics justify the requests to educational institutions in order to offer better regulations and education programs that will support the use of GenAI tools morally and critically.

Student accounts in South Asia and West Africa is one of the most missing in the existing literature. Whereas the research has been largely based on European, North American, and East Asian situations, very little has been conducted to explore the experiences of the European, North American, and East Asian students whose cultural, social, and institutional experiences can also play a dissimilating role to their perceptions and practices. The above gap incites the need to conduct additional studies on the topic of how generative AI can be utilized by bringing it to the learning experiences of South Asian and West African students in a fashion that would take into account their specific educational context and problematic scenarios within the educational process.

2.5 Conclusion

In conclusion, the current literature review has addressed the available literature on the topic of the generative AI (GenAI) role in education, not only by taking into account the conceptual argument behind it but also taking into consideration the theoretical framework, which characterizes the researchers surrounding it the Technology Acceptance Model (TAM). The review reports that students are inclined to view GenAI as a good experience because this technological tool can be instrumental in ensuring that the learning process becomes more personalized, more materials are available, and more complex issues are resolved. At the same time, its benefits are neutralized by the problems connected with academic integrity, ethical application and explanation of the institutional policies of its implementation. Students are eager to mention the importance of the ethical frameworks and pedagogical support to ensure that GenAI usage will be related to the training purposes and will be useful in meaningful learning.

In addition, the review notes that a research gap is present in regard to application of GenAI integration in local contexts, in South Asia and West Africa. In spite of the growing popularity of generative AI around the world, very little empirical studies have been performed to investigate how learners in such nations perceive and make use of generative AI instruments. The specified gap is a potentially worthwhile direction of the future research, as it would not only contribute to the elucidation of the cross-cultural perspective but also provoke more rational and contextually appropriate use of the generative AI in the educational environment in a new global setting.

Chapter 3 Methodology

3.1 Introduction

This chapter presents the research methodology employed in the study, outlining the research context, target population, sampling strategy, instrument design, and the procedures undertaken to establish reliability and validity. It also describes the data collection process and the methods of analysis. The study is guided by four research questions: (1) What is the intention of computer science and engineering students to use Generative AI tools for enhancing their learning outcomes? (2) How do these students perceive the usefulness of Generative AI tools in their academic learning? (3) How do students evaluate the ease of use of Generative AI tools in supporting their learning within computer science courses? and (4) What types of Generative AI tools are commonly used by computer science and engineering students to improve their learning outcomes? Collectively, these questions form the basis for exploring students' perceptions of Generative AI as a learning tool and provide a structured framework for examining its role in computer science and engineering education.

3.2 Research Approach

In this study, the research method is deductive which is based on the in-depth collection and analysis of empirical evidence to support preset theory and hypothesis. One starts at a more theoretical level and moves on to gathering data and analyze to prove or reject initial assumptions, respectively. Deduction is prospectively linked to quantitative research since, it permits assessment of theoretical assumptions, empirical connections to causation, and allows the likelihood of generalized conclusions to be drawn in terms of a systematic and systematic planning process.

The chosen instrument is deductive, as this research is based on the Technology Acceptance Model (TAM) that is used to investigate the perception of computer science and engineering students concerning Generative AI as a learning tool. In this way, hypotheses developed on explanation of the theory with the possible involvement of the statistical analysis can be formulated and tested.

Using this approach, the research will be unbiased to gauge the variables, and the research helps predictively deduce the thoughts of students, and it can also make evidence-based conclusions.

Therefore, the deductive method gives a rigorous procedure of quantitatively determining the nature of the perceptions, adoption and usefulness standard of computer science and engineering students on the use of Generative AI in the learning process.

3.3 Research Method

Research methods can be said to be systematic designs of strategies and procedures that provides a researcher with a system or a way through which data is collected, analyzed and interpreted in an objective manner. These ways guarantee the validity, reliability and accuracy of the results of research and they comply with the research goals. In general, research methods are defined as quantitative, qualitative, and mixed-methods research, which can be applied to answer the different kinds of research questions.

Quantitative measures deal with the number collection and statistically analysing data to give a disposal on the patterns, relationship, and trends. The methods frequently used within this category are surveys, experiment, and structured assessments, which enable a researcher to verify a hypothesis, predict the outcome, and make a generalizable conclusion. Qualitative methods, in their turn, are concerned with a lack of numerical data, such as textual material, images, or observations. Research methods such as interviews, focus groups and thematic analysis can be applied in identification of meanings, exploration of experiences, elimination of depth of views that were presented by the participants. A mixed-methods design is quite the opposite since it incorporates both quantitative and qualitative methods to gain a better, more comprehensive picture of the research problem by integrating numeric evidence and narrative data.

The study will be conducted on the basis of a quantitative research methodology, as it is consistent with the deductive approach presented earlier. The selection of quantitative approaches is also based on the main objective of the study of investigating how computer science and engineering students perceive Generative AI (GenAI) as a learning tool. In particular, this methodology would allow one to measure and statistically test conceptually important variables, including the intention to use, perceived usefulness, and perceived ease of use of generative AI tools as well as types of generative AI tools used, and learning outcomes. This research is able to derive standardized data that can be used in rigid statistical methods because it utilizes structured methods of data collection, especially surveys.

Quantitative approaches particularly suit the application of hypotheses that were formulated on the basis of the Technology Acceptance Model (TAM). In this study, the relationships between the perceived usefulness and intention to actually use, and the relationship between the intention to use and learning outcomes, will be examined. Such associations may be measured using methods, including the correlation, regression, path analysis so that the study may present evidence-based information on the role of GenAI in education.

Furthermore, quantitative research typically requires a relatively large sample and this therefore increases the generalizability of the findings of the study to a larger group of students in computer science and engineering. With the use of standardized research tools and statistical methods, this methodology reduces biasness, and the quality of results can be characterized as reliable and objective. Finally, the quantitative approach will enable the researcher to produce a strong, replicable and generalizable study that could form the guiding principles of practice and policy frameworks on the use of GenAI tools in higher education.

3.4 Population and Sample

3.4.1 Population and Participants

The research had a wide range of participants, which were undergraduate and postgraduate students on the Computer Science and Engineering (CSE) programs. The study subjects were selected in one of the two institutions of higher learning namely Islamic University of Technology (IUT), Bangladesh and the University of The Gambia (UTG). The number of students participating in the study was 300, 200 students were enrolled at the IUT and 100 students were enrolled at the UTG.

Composition wise the survey was fully filled by about 291 respondents who were considered in the analysis. The sample population was a large one, and students of different nationalities were included. The sample at IUT included both the domestic and international students whereas at UTG only the domestic students were involved. The mean age of the participants was 24.2 years, mode of 22 years and standard deviation of 5.3 years; the age of participants was between 17 to 46 years old.

There was a gender distribution that indicated that most of the respondents were males (64.3%), and female students were 36 percent of the sample population. This gender imbalance reflects broader trends often observed in computer science and engineering disciplines. Overall, the diversity in age, nationality, and academic level provided a robust basis for examining perceptions of generative AI tools within computer science education.

3.4.2 Sampling Techniques

This paper has utilized a research method that used a cross-sectional research design, that is, at one moment of time in relation to the population of university students. Cross-sectional surveys are very effective when capturing the perception, attitude, and intended behavior of the population in terms of cost- and time-efficiency (Setia, 2016). A self-report questionnaire was used to investigate the perceptions and desires of the students about using the Generative AI (GenAI) as a tool to learn. Self-report questionnaires are more popular in the educational and technology adoption studies, typically because self-report enables researchers to gather standardized data regarding variables of intention to use and perceived usefulness, perceived ease of use, and the actual tool adoption (Podsakoff & Organ, 1986).

The convenience sampling was utilized to choose respondents. Also called snowball method, this non-probability method entails the recruitment of participants out of convenience and accessibility to the researcher (Etikan, 2016). Despite the drawbacks associated with convenience sampling in terms of the representativeness of research findings, the approach is still commonly advised to use in higher education research due to its simplicity of application, performance, and costs (Bornstein et al., 2013). In order to overcome the possible weaknesses, a large sample size (N = 300) was aimed at to make results more robust and reliable.

The researchers have chosen two universities as a target population purposively IUT, based in Bangladesh and UTG, based in Gambia. This purposive sampling promoted diversity within the research sample since IUT has both international and domestic students whereas UTG only has domestic students. This kind of variation adds richness to the observation because it brings to the fore how culture and academic environments vary across cultures. The benefit is that it was able to select the appropriate sample leading to the adaptation of the research instrument to an efficient and objective process of data collection in line with the research objectives.

3.5 Survey Questionnaire Development

A structured questionnaire was used as the main source of primary data collection tools in the study, with specific care taken to ensure that it was highly clear, valid and consistent with research objectives. The questionnaire had 21 items and it was structured in each conceptual research model in six sections.

The demographic data related to the respondents, such as the age, gender, academic level, and affinity to the university, were obtained in Section 1.

The independent variable: Generative AI Tool Use (GAU) was measured in Section 2.

Section 3 was a measure of the mediating variable: Perceived Usefulness (PU).

The mediating variable was tested in section 4 namely Perceived Ease of Use (PEOU).

Section 5 addressed the discussion concerning the moderating variable: Intention to Use Generative AI (IUG).

Section 6 was about the dependent variable which is Learning Outcomes (LO).

All the constructs/items were adapted based on proven instruments in other works to increase reliability and comparability (Venkatesh & Davis, 2000a). Each question was read on a five-point Likert scale strongly disagreeing to strongly agree (1-5). Likert-type scales are well-known and accepted as a valid way of measuring the attitude and perceptions of the respondent (Joshi et al., 2015).

The survey tool was structured in a tabular form in terms of clarity and simplicity of responding. Table 1 presents a summary of the questionnaire, including item statements, construct categories, and coding adopted for analysis. The systematic adaptation and refinement of items from prior studies ensured both content validity and alignment with the study's theoretical framework.

Table 1 contains items for Generative AI Use and the coding adopted for easy analysis. out of four items, three were used for this study.

Table 1: *Items for Generative AI Used*

Construct	Items	Coding
Generative AI Used (GAU)	Which generative AI do you frequently use? (ChatGPT, Copilot GitHub, Gemini, Alpha code).	GAU1
	Which of the generative AI tools do you find most beneficial for your studies?	GAU2
	Which platforms do you access generative AI tools (mobile apps, desktop applications, and online platforms)?	GAU3

Likewise, Table 2 contains the items for Perceived Usefulness, along with the coding for easy analysis. These items were adopted from David (Davis, 1989b). Five items were adopted for this study, and all five were selected.

Table 2: Items for Perceived Usefulness

Construct	Items	Coding
Perceived Usefulness (PU)	I find generative AI tools to be a valuable resource for exam preparation.	PU1
	I find generative AI useful in doing all my academic tasks	PU2
	I believe generative AI tools significantly contribute to my understanding of course material.	PU3
	I believe that using generative AI enhances my academic performance.	PU4
	I believe Generative AI tools help me understand complex concepts better	PU5

Table 3 contains the items for Perceived Ease of Use. Four items were adopted for this study, and all four were selected.

***Table 3**: Items for Perceived Ease of Use*

Construct	Items	Coding
Perceived Ease of Use	I find it easy to use generative AI tools for my studies.	PEOU1
	I find it easy to incorporate generative AI tools into my learning process.	PEOU2
	Generative AI tools make it easy to interact with peers for academic purposes.	PEOU3
	I require minimal assistance to use generative AI tools effectively.	PEOU4

Table 4 contains items for Intention to use Generative AI and the coding adopted for easy analysis. out of five items, three were used for this study.

***Table 4:** Items for Intention to Use Generative AI*

Construct	Items	Coding
Intention to Use Generative AI (IUG)	I intend to use generative AI tools in my future studies.	IUG1
	I would recommend generative AI tools to my peers for academic purposes.	IUG2
	I plan to continue using generative AI tools in my future academic endeavours.	IUG4

Table five includes items for Learning Outcomes They had six items, and all were adopted for this study.

Table 5: *Items for Learning Outcome*

Construct	Items	Coding
Learning Outcome (LO)	Using generative AI tools has improved my grades.	LO1
	Generative AI tools have enhanced my understanding of course materials.	LO2
	I feel more confident in my academic abilities after using generative AI tools.	LO3
	Using generative AI tools has made my learning experience more enjoyable.	LO4
	I have gained a deeper understanding of complex topics through the assistance of generative AI tools.	LO5
	I feel that my critical thinking skills have developed as a result of using generative AI tools.	LO6

3.6 Content Validation of Survey Instrument

To ensure the reliability and appropriateness of the instrument, all items used in this study were adapted from established literature and subsequently subjected to expert validation. The validation of the content was done to test the transparency, usefulness and sampling of the items included in the questionnaire used in assessing the constructs of interest. Content validity is a very vital stage in developing an instrument because it makes sure that the survey is well sufficient to describe the theoretical and research goals (Polit & Beck, 2006a).

This was carried out according to the directions of Content Validity Index (CVI), which is a popular measure of the consistency of the assessments of the experts or scholars regarding the importance of the survey items. Namely, the overall Scale-level Content Validity Index (S-CVI) was computed to define the validity of the instrument in totality. The methodology is in line with the guidelines in the ABC of Content Validation and calculation of CVI (Department of Medical Education, School of Medical Sciences, Universiti Sains Malaysia, MALAYSIA & Yusoff, 2019).

In this study, the questionnaire would be sent to four academic experts, all of whom were the faculty members in the Department of Technical and Vocational Education at the Islamic University of Technology. These professionals were asked to complete the rating of each of the 24 items by using a four-point Likert scale with the gradations 1 (Not Relevant) - 4 (Highly Relevant). The responses of the experts have been positive overall with no more than satisfactory scores. Further, functional feedback was given after which a few remaking was completed to enhance the clarity and contextual appropriateness of some of the items.

The assessment proved that the item interrogated the instrument in terms of content validity. The analysis of the CVI also confirms the idea that the instrument is suitable to assess the perception of generative AI as a learning tool of students. The content validation process aimed to evaluate the clarity, relevance, and representativeness of the questionnaire items in measuring the constructs of interest. Content validity is a crucial step in instrument development, as it ensures that the survey adequately reflects the theoretical framework and research objectives (Polit & Beck, 2006b).

The process followed the guidelines of the Content Validity Index (CVI), which is widely recognized for assessing the degree of agreement among experts on the relevance of survey items. Specifically, the Scale-level Content Validity Index (S-CVI) was used to determine the overall validity of the instrument. The approach is consistent with the principles outlined in the ABC of Content Validation and CVI calculation (Department of Medical Education, School of Medical Sciences, Universiti Sains Malaysia, MALAYSIA & Yusoff, 2019).

For this study, the questionnaire was distributed to four academic experts, all of whom were faculty members of the Department of Technical and Vocational Education at the Islamic University of Technology. These experts were requested to rate each of the 24 items on a four-point Likert scale, ranging from 1 (Not Relevant) to 4 (Highly Relevant). The experts' feedback was generally positive, with all items receiving satisfactory ratings. In addition, constructive comments were provided, which led to minor revisions to improve the clarity and contextual suitability of certain items.

The evaluation process confirmed that the instrument met the required standards of content validity. The results of the CVI analysis further support the conclusion that the instrument is appropriate for measuring students' perceptions of generative AI as a learning tool.

3.7 Data collection procedure

The study utilized cross sectional survey to collect the data of the target population. The popularity of educational research in cross-sectional surveys is related to the possibilities to collect research data at a particular time since cross-sectional surveys provide an opportunity to collect data by assessing perceptions, attitudes, and behaviors (Huyler & McGill, 2019). In order to increase participation and make the process convenient to the respondents, questionnaires were run in two modes; an online version through the use of Google forms and the hard copy. Google Forms was considered because of the ease of use, affordability, minimal data entry errors due to the automatization factor, the ease of tracking responses in real time and the ease of exporting the responses to statistical databases. It was also eminently suited to its distribution method, which was through mails and in social media, which enabled its distribution in a large multi-site student population. Before asking them to complete the questionnaire, we informed them of a small description of the aim of the study and that their participation was on a voluntary basis. Also, the anonymity and confidentiality again were stressed to make sure that no identities could be made out, and that ethical guidelines were adhered to.

A research pilot test on the survey tool was done on 15 students to sort out the issue of clarity, readability and fitness of the tools. Pilot testing is an important aspect of survey research since it increases reliability and aids in removing any possible ambiguity or complexity that may be realized during full deployment of the survey (Dillman et al., 2014). The comments made during this pilot stage informed a revision of the questionnaire so that it broadly became more effective.

At the Islamic University of Technology (IUT), survey links were circulated on various student social media sites, and printed forms were also distributed by the researcher on visits to the Department of Computer Science and Engineering (CSE), academic buildings and student dormitories. This again was used at the University of The Gambia (UTG), where the research team was able to distribute the printed copies to the students in classrooms, libraries, and to student common area.

The students which accepted to participate would be directed to fill in the questionnaire and hand it in right at the moment to the researcher/research assistant present in the venue. The response rate was large since data collection lasted three months and two weeks. The printed questionnaires had 100 percent completion rate. A total number of valid responses obtained was 291; IUT contributed 202 responses, whereas UTG 89 responses.

3.8 Theoretical Framework and Research Model Development

The theoretical perspective of this research is the Technology Acceptance Model (TAM), which has been applied widely in understanding acceptance and use of technology especially in education (Davis, 1989b; Venkatesh & Davis, 2000b). According to TAM, the perceived usefulness (PU) and perceived ease of use (PEOU) of the technology is considered as the major influence on the intention of the users to adopt the technology and the adoption itself eventually leads to the actual usage and the results. In this research setting, the employment of Generative AI (GAU) is used as an independent variable, showing how and how often students use AI tools in learning. The dependent variable is learning outcomes (LO) that measures effectiveness of GAU in enhancing student performance. The perceived usefulness (PU) and perceived ease of use (PEOU) are believed to be mediating factors/ variables that explain how GAU influences students’ intention to use AI tools and subsequent learning outcomes. Also, intention to use Generative AI (IUG) is considered as a moderating one, the desire and readiness of the students to use Generative AI in learning processes. Based on this framework, eight hypotheses are postulated; H1 postulates a positive effect of GAU on LO; H2 and H3 postulate effect of GAU on PU and PEOU respectively; H4 investigates the effect of PEOU on PU; H5 and H6 investigates the effect of PU and PEOU on IUG; and H7 and H8 investigates the effect of PU and IUG on LO. This model supports those that have already been generated indicating how PU and PEOU can influence behavioral intentions and academic performance (Teo et al., 2011; Venkatesh et al., 2003). By including GAU, PU, PEOU, and IUG in one model, the present study offers an organized framework to consider in order to assess how student perceptions and behavioral intentions can lead to improved learning results concerning Generative AI. The proposed conceptual framework does not only permit empirical testing of such relationships but also provides a practically valuable understanding on how to best interrelate AI tools in learning educators and policymakers may pursue. In short, the hypothesis that will be examined in Chapter 4 to fulfil the objectives of this research goes as follows:

H1: Generative AI Used (GAU) → Learning Outcome (LO)

H2: Generative AI Used (GAU) → Perceived Usefulness (PU)

H3: Generative AI Used (GAU) → Perceived Ease of Use (PEOU)

H4: Perceived Ease of Used (PEU) → Perceived Usefulness (PU)

H5: Perceived Usefulness (PU) → Intention to Use Generative AI(IUG)

H6: Perceived Ease of Used (PEU) → Intention to Use Generative AI(IUG)

H7: Perceived Usefulness (PU) → Learning Outcome (LO)

H8: Intention to Use Generative AI(IUG) → Learning Outcome (LO)

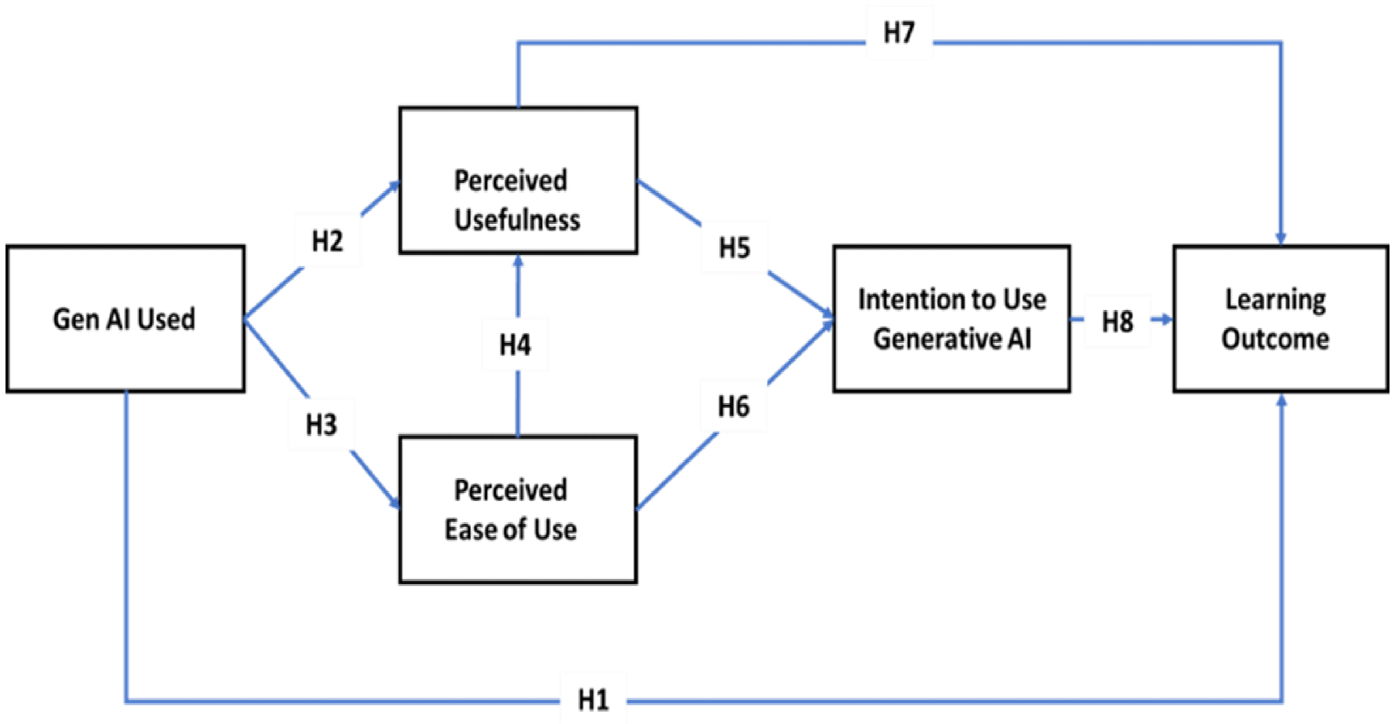


***Figure 1**: Theoretical Framework*

3.9 Data Preparation and Analysis Techniques

3.9.1 Data Preparation

The survey is aimed at gathering data of computer science and engineering students and was distributed online using Google Forms and physically as well. The original sample size was 300 persons; however, in performing a data screening process, it was established that there were six left-over physical responses, and three of the overall responses were invalid since they had contained all items with the same choice, that of strongly agreeing. These nine responses were deleted, to ensure that the study is valid and reliable. As a result, the overall sample to be performed was 291 students (202 and 89 representing IUT and UTG respectively), a complete and correct figure to work with in the analysis.

Cleaning of the data is also important as it ensures that the required data do not have any anomaly prior to any statistical analysis. Thus, data handling (including filtering) was important in this work. Descriptive statistics were used to describe participant attributes with the aim of giving a general picture of the sample characteristics. Structural equation modeling (SEM) was used in hypothesis testing and evaluation of the model. It was found that the measurement model was rigorously evaluated and the theoretical model was tested based on the model fit indices on its ability to explain the actual data. In this process one more response was expurgated in revision, and three more were eliminated as inconsistent, leaving 287 sound samples to be analyzed. These precautionary steps guaranteed that data on which the analysis was based is both reliable and accurate, and can thus mean robust and meaningful findings.

3.9.2 Data Analysis Techniques

The survey data was computed and analyzed with the help of IBM SPSS and SmartPLS, which are the most popular data analysis tools applied in such areas as social sciences and education research studies (Gaur & Gaur, 2009; Rahman & Muktadir, 2021) PSS was utilized in descriptive statistics, reliability testing, and preliminary data screening, to identify clearly the demographic characteristics of all the participants and the general response characteristics. The Analysis of Structural Equation Modeling (SEM) was conducted using SmartPLS, which is highly applicable in the study of complicated relations between measured and latent variables to evaluate hypotheses and model fitness, especially in researches that use data that are not representative of normal distributions or where the sample size is small (Hair et al., 2019). The use of SPSS and SmartPLS made the study very thorough as the measures of the statistical summary had statistical accuracy and reliability, whereas the test of the hypothesized model, incorporating path coefficients, mediating and moderating effects, and model validity, was rigorously tested. This twofold methodology contributed to strengthening the validity of the conclusions and gaining insights into the abovementioned key research questions of the study, which were aimed at investigating the intentions of computer science and engineering students to use generative AI tools to improve their learning outcomes (RQ1), the perceived usefulness of generative AI tools in academic learning (RQ2), the perceived effectiveness of generative AI tools in the learning process within the field of computer sciences (RQ3), and finally the types of generative AI tools that the students frequently use to boost their learning outcomes (RQ4).

3.10 Funding and Ethical Considerations

This research will be carried out within the regulations of the Committee of Advanced Studies and Research (CASR) of the Islamic University of Technology and approved on the 20 th November

2024 (Ref. No. ....). The study was conducted in accordance to policies and procedures stipulated by the university to govern the processes of carrying out any research given that the ethical standards were observed in all phases. Ethical issues were also addressed well, i.e., the consent of all participants was explained and informed, confidentiality and anonymity were maintained, and all data was treated with a lot of care not to misuse or violate privacy. All funding and resources used in carrying out this study were funded exclusively by the Islamic University of Technology. No financial or material assistance was offered by an external organisation that could possibly inhibit or jeopardise the integrity or lack of biasness about the research findings. This statement underscores the behest of carrying out the study in total independence, objectiveness, and in an ethical manner.

3.11 Conclusion

In conclusion, this chapter has presented the stringent methodological approach taken in the study which includes the study design, the population and sample selection, the instrument development, the collection of data as well as data analysis. A cross-sectional survey design was used, combining the use of online (Google Forms) with a printed questionnaire in order to regulate the convenience, participation, and accuracy of the data collected. The survey was well designed by questioning pertinent questions of a previous study and carefully guarded of all probable confusions, readable questions and most importantly, reliable. Data screening and cleaning activities were applied to ensure the validity of the data collection leading to 291 valid responses of the students of both the Islamic University of Technology (IUT) and the University of The Gambia (UTG). The ethics of the research, such as informed consent, confidentiality, and validity of the university regulations, were well taken into account during the research. The data analysis was carried out by using the IBM SPSS and SmartPLS, and the collected data were analysed using descriptive statistics and structural equation modeling which helps in answering research questions on how students perceived, intended to use, and used generative AI tools to enhance learning outcomes. Explicit planning and conducting of such methodological processes lay a solid ground to the validity, reliability, and credibility of the research and thus the findings and interpretations of the same are both relevant and dependable.

Chapter 4 Results and Data Analysis

4.1 Introduction

In this chapter interpretation and statistical analysis of the survey data collected in potion will be provided in details. The main study that is going to be conducted is to study the perception of Computer Science and Engineering (CSE) students towards the usage of generative AI (GenAI) as a learning tool whereas the relationships between the key constructs such as perceived usefulness, perceived ease of use, and intention to use GenAI to enhance learning outcomes. It will also measure the relationships between the variables to support their model and find empirical data supporting the propositions of the theoretical framework.

The descriptive statistics of the type and demographics of the study participants will be described first. This is then followed by discussion of the validity and the reliability indicated by research tool to ensure the accuracy and the consistency of elements that are measured. Structural equation modeling (SEM) is applied to determine the relationship between the latent variables and also to determine the value of mediating perceived usefulness and ease of use. In general, the chapter helps to develop a thorough assessment of the collection of survey data and offers insights into the factors influencing CSE students' acceptance and utilization of generative AI as an educational tool.

4.2 Descriptive Analysis

4.2.1 Description of Demographic Information

The demographic data of the research population can be represented using the 291 people, among which 202 were done in IUT, and 89 of them were done at UTG. In terms of gender, male respondents constituted the highest number with 64.3% (187) and females 35.7% (104). The rate of domestic student enrollment was also high as the sample mainly included domestic students under their own names, 83.8% (244). With reference to academic level, the proportion of master students in the sample was small with 4.8% (14), implying that majority of participants were undergraduate students.

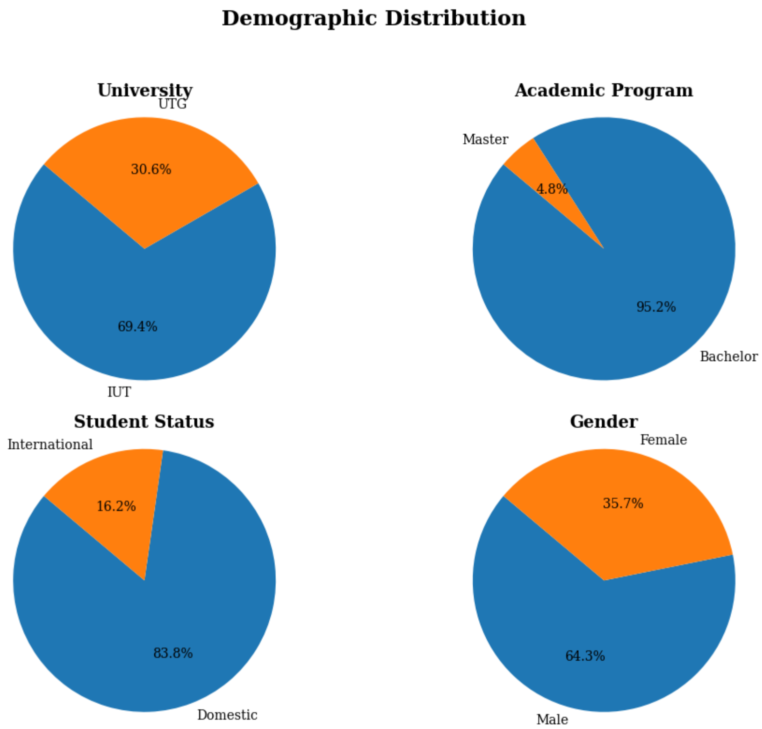


Figure 2: Demographic Distribution

When examining the usage of AI tools, ChatGPT was overwhelmingly the most frequently used, with 92.4% (269) of respondents reporting it as their primary tool. This dominance was mirrored in perceived benefits for academic studies, where 91.8% (267) of participants identified ChatGPT as the most beneficial. Other specialised tools showed significantly lower usage and perceived usefulness; GitHub Copilot was used by 4.8% (14) and also considered beneficial by the same percentage, while Gemini was used by 2.8% (8) and seen as beneficial by 3.4% (10). Alpha Code was not used or considered beneficial by any participant.

Table 6: Demographic Distribution

Demographic Factor	Category	Frequency	Percentage
University	IUT	202	69.40%
	UTG	89	30.60%
Academic Program	Bachelor	277	95.20%
	Master	14	5%
Student Status	Domestic	244	83.80%
	International	47	16.20%

Gender	Male	187	64.30%	
	Female	104	36%	
Age				***Mean***: 24.2 years **SD**: 5.3 years **Range**:17-46 years **Mode**: 22 years

Regarding access platforms, there was a nearly even split between mobile applications and desktop applications. Mobile apps were preferred by 42.6% (124) of respondents, closely followed by desktop applications at 40.2% (117). Online platforms were the least favoured, with only 17.2% (50) of participants choosing this method. This distribution suggests that while the choice of AI tools is heavily skewed towards ChatGPT, students access these tools through a variety of platforms, with mobile and desktop applications being the dominant modes.

4.2.2 AI Tool Usage Descriptive Statistics

The descriptive analysis of the use of AI tools of the 291 students who participated in the investigation showed a spectacular concentration in the preference of the tools, with ChatGPT as the overwhelmingly preferred platform. More than 92.4% of students (n = 269) indicated that they used ChatGPT, which is why not only the most widely used tool but also the most actively estimated in terms of perceived academic value as 91.8% of them said that this tool was useful in their studies. By contrast, GitHub Copilot was utilized by 4.8% (n = 14) and Gemini by 2.8% (n = 8) with Alpha Code showing no usages whatsoever. These numbers highlight a major imbalance in adoptions with the low Diversity Index of 0.14, which implies that there is little diversity of tools that are used within the sample. The reason behind the high popularity of ChatGPT can be explained by the fact that it was introduced early and it can be used in various academic settings, which is in line with prior studies indicating that it is useful in education. (Fornell & Larcker, 1981) (Yildirim-Erbasli & Bulut, 2023).

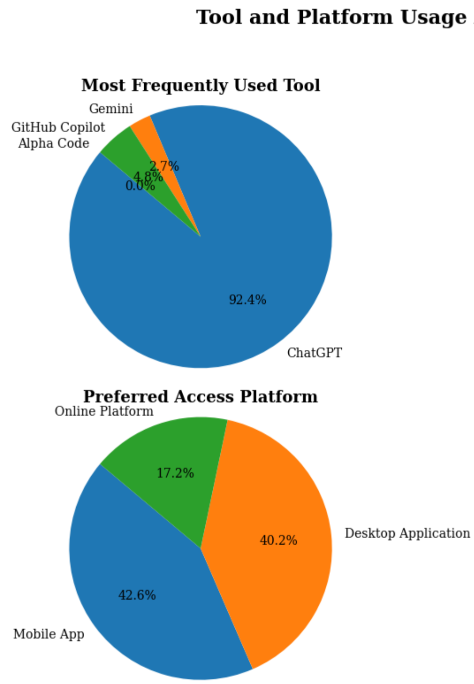


Figure 3: Tools and Platform Usage among Students

Regarding pattern of accessing the platform, the information indicated an almost equal response between mobile and desktop usage. The most frequently used access point was mobile apps, with the cited percentage of 42.6% (n = 124) respondents, and desktop applications in the second position (40.2% or 117). The use of online platforms through web browsers was less, and only 17.2% (n = 50) chose this way. The Platform Parity Index of 0.83 indicates that there is good balance between mobile and desktop preference and this could be an indicator of students using mobile gadgets to learn their academic stuff in a quicker and less intensive manner and desktop computer to learn in a more intensive manner like programming and writing. The agreement between the use of the tools and their perceived usefulness was especially high with GitHub Copilot that retained the same value in terms of both use and usefulness (4.8%). This implies that even though it is not popularly embraced, it has a particular useful purpose to the individuals working in more technical or developmental field.

Table 7: Tools and Platform Usage among Students

Category	Items	Frequency	Percentage
Most Frequently Used Tool	ChatGPT	269	92.40%

	Gemini	8	2.80%
	GitHub Copilot	14	4.80%
	Alpha Code	0	0%
Most Beneficial for Studies	ChatGPT	267	91.80%
	Gemini	10	3.40%
	GitHub Copilot	14	4.80%
	Alpha Code	0	0%
Preferred Access Platform	Mobile App	124	42.60%
	Desktop Application	117	40.20%
	Online Platform	50	17.20%

In order to further understand these trends, there was cross-tabulation of the tool usage by gender, whereby there was a consistent trend of usage of ChatGPT by male (92.1%), as well as female (93.2%), students, with slight variations in the use of GitHub Copilot and Gemini. Also, there was no statistically significant difference between AI tool adoption by IUT and UTG students, chi-square test, $\chi^2(2) = 1.24$, $p = .532$. This means that affiliation to the university did not make a significant impact on the choice of tools. The correlation between the selection of the AI tool and the preferred access platform was also identified as weak (Cramer's V = 0.18), indicating that students might be inclined to some access platform, but not to the tool applied. Taken together, the results indicate a strong ChatGPT as the AI tool of preference in the academic settings, reached via numerous platforms, and appreciated due to its educational assistance to the various student groups.

4.2.3 Descriptive Statistics of TAM Construct Items

The descriptive statistics of Technology Acceptance Model (TAM) constructs indicate the interesting trends in the responses of the students in the four fundamental variables: Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Intention to Use (IUG), and Learning Outcomes (LO). On the whole, the participants had positive attitudes towards AI tools in education, as most items have high mean scores. Under the Perceived Usefulness construct, PU2 (Useful in academic work) was given the highest mean score of 4.35, with PU5 (Helps understand complex concepts) coming in closely with 4.21. This implies that the use of AI tools in improving academic output and learning is well-known by the students. PU4 ("Improves studying performance) had the lowest mean within this construct at 3.95, though still above the midpoint of the scale, reflecting generally positive sentiment.

Table 8: 4.2.3 Descriptive Statistics of TAM Construct Items

Construct	Item	Question	Mean	Std. Error	Median	Std. Deviation	Skewness	Kurtosis
Perceived Usefulness (PU)	PU1	Valuable for exam preparation	412.00%	0.045	4	0.87	-0.82	0.93
	PU2	Useful for academic tasks	435.00%	0.039	5	0.76	-1.15	1.87
	PU3	Contributes to understanding	408.00%	0.047	4	0.91	-0.75	0.62
	PU4	Enhances academic performance	395%	0.051	4	0.98	-0.63	0.31
	PU5	Helps understand complex concepts	421.00%	0.043	4	0.84	-0.95	1.24
Perceived Ease of Use (PEOU)	PEOU1	Easy to use for studies	402.00%	0.048	4	0.93	-0.71	0.58
	PEOU2	Easy to incorporate	387.00%	0.052	4	1.01	-0.58	0.12
	PEOU3	Easy to interact with peers	365%	0.057	4	1.11	-0.42	-0.35
	PEOU4	Requires minimal assistance	378.00%	0.054	4	1.05	-0.51	0.07
Intention to Use (IUG)	IUG1	Intend to use in future	428.00%	0.041	4	0.8	-1.03	1.52
	IUG2	Recommend to peers	415.00%	0.044	4	0.86	-0.88	1.08
	IUG3	Plan to continue using	4.22	0.043	4	0.84	-0.97	1.35
Learning Outcomes (LO)	LO1	Improved grades	3.89	0.053	4	1.03	-0.55	0.05
	LO2	Enhanced understanding	4.17	0.044	4	0.85	-0.91	1.19
	LO3	Increased confidence	3.95	0.051	4	0.98	-0.63	0.31
	LO4	More enjoyable learning	4.02	0.049	4	0.95	-0.72	0.65
	LO5	Deeper understanding	4.11	0.046	4	0.89	-0.81	0.89
	LO6	Developed critical thinking	3.82	0.055	4	1.07	-0.47	-0.18

In the case of Perceived Ease of Use, there was more variation in the responses. PEU1 rated the highest in this category and had a mean of 4.02 (Easy to use to studies) and PEOU3 (Easy to interact with peers) had the lowest mean score of 3.65. It means that, though the tools can be used by students with ease at the individual level, the incorporation into the collaborative work can be a bit more complicated. Intention to Use construct had high levels of response with IUG1 (Intend to use in future) and IUG3 (Plan to continue using) having means of 4.28 and 4.22 respectively. Such results indicate the high possibility of further use and recommendation by students.

Regarding Learning Outcomes, the most rated item was the LO2 (Enhanced understanding) with the mean of 4.17, which means that students believe that these tools can be of serious help in gaining an understanding. Nevertheless, LO6 ("Developed critical thinking") scored the lowest in this group with an average of 3.82, which indicates a low level of encouraging deeper analytical abilities. The range of standard deviations of all items yielded between 0.76 and 1.11 with a moderate variability of the responses. All the items had negative skew (between -0.42 and 1.15) which means that the majority of students expressed their answers on the positive end of the scale. Also, the kurtosis was moderate (-0.35 to 1.87), which indicated the distributions were not skewed excessively, which might have extreme values.

These findings coupled with each other reinforce the reliability and interpretability of the data with the most perceptions in the domains of usefulness and future intent. Despite being rated with a positive perception ease of use and learning outcomes, they were more varied and reported certain areas of improvement especially on ease of peer interaction and developing critical thinking. The analysis will be based on complete cases (N=291) based on a five-point Likert scale with 1 indicating strong disagreement, and 5 indicating strong agreement. The general pattern of the responses proves that there is a positive tendency towards AI tools, which is expected according to the TAM framework.

4.2.4 Reliability and Descriptive Statistics of TAM Constructs

Analysis of the theoretical constructs Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Intention to Use (IUG), and Learning Outcomes (LO) showed that the theoretical constructs had a high level of reliability and positive perception among the student sample. The four constructs had Cronbach alpha values exceeding the recommended value of 0.85 which is good to excellent internal consistency. In particular, Learning Outcomes were found to be the most reliable (a =

0.92), then closely followed by Perceived Usefulness (a = 0.91) and Intention to Use (a = 0.88), and slightly lower but still strong reliability was also shown by Perceived Ease of Use (a = 0.86). These findings support the hypothesis that the survey questions were able to maintain consistency in the measurement of the constructs among the sample.

According to the Descriptive statistics, students were the most agreeable with statements that concerned their Intention to Use AI tools (M = 4.22, SD = 0.76) and this depicts a patient desire to keep on using generative AI in their further academic work. Perceived Usefulness was rated high as well (M = 4.14, SD = 0.73), which indicates that students were relatively aware of the usefulness of AI tools in facilitating their learning activities. Conversely, the Perceived Ease of Use had the lowest rating among all four constructs (M = 3.83, SD = 0.87), but at least, the values remain within the positive range, which means that people are generally comfortable with AI tools, but with higher variation and the opportunity to be improved. The mean score of Learning Outcomes was 3.99 (SD = 0.81) which indicated rather positive attitudes towards the influence of AI on academic performance of students though responses were somewhat more spread.

Table 9: 4.2.4 Reliability and Descriptive Statistics of TAM Constructs

Construct	N	Min	Max	Mean	SD	Skewness	Kurtosis	Cronbach's α
Perceived Usefulness (PU)	291	1.6	500.00 %	4.14	0.73	-0.93	1.32	0.91
Perceived Ease of Use (PEOU)	291	1.25	500.00 %	3.83	0.87	-0.55	0.41	0.86
Intention to Use (IUG)	291	1.33	500.00 %	4.22	0.76	-1.07	1.63	0.88
Learning Outcomes (LO)	291	1.17	500%	3.99	0.81	-0.68	0.72	0.92

All constructs displayed negative skewness, ranging from -0.55 to -1.07, indicating that most responses clustered toward the higher end of the scale, with students tending to agree or strongly agree with the positively worded items. The strongest skew was observed in the Intention to Use construct (Skewness = -1.07), reflecting particularly strong endorsement of continued AI use. Kurtosis values ranged from 0.41 to 1.63, indicating distributions that were modestly peaked and relatively normal. Overall, these findings suggest that students view generative AI tools as useful and intend to continue using them, although perceived ease of use may present a modest barrier for some and warrants further attention in future implementations or training initiatives.

4.2.5 Tests of Normality for TAM Constructs

Normality tests were done to determine the distributional characteristics of the primary TAM constructs by the Kolmogorov-Smirnoff (K-S) and Shapiro-Wilk (S-W) tests. The findings always showed that there were significant deviations to normality in all four constructs. In particular, the Kolmogorov Smirnov test resulted in statistically significant values of all variables with a test statistic of between 0.086 and 0.124 corresponding to each variable and a p-value under.05. Equally, both the Shapiro-Wilk test confirmed non-normality of each construct with statistically significant (all p <.001) values ranging between 0.923 (IUG) and 0.968 (PEOU). These results indicate that not any of the theoretical constructs that the study analyzes fulfills the assumption of normal distribution.

Table 10: 4.2.5 Tests of Normality for TAM Constructs

Construct	Kolmogorov-Smirnov		Shapiro-Wilk	
	Statistic	Sig. (p)	Statistic	Sig. (p)
Perceived Usefulness (PU)	0.102	< .001	94.10%	< .001
Perceived Ease of Use (PEOU)	0.086	0.003	96.80%	< .001
Intention to Use (IUG)	0.124	< .001	92%	< .001
Learning Outcomes (LO)	0.095	< .001	95.20%	< .001

The construct Intention to Use (IUG) was the most deviating to normal distribution, whereas the lowest Shapiro-Wilk value of (0.923) showed that the skewness was larger. On the other hand, Perceived Ease of Use (PEOU) showed the least severe violation (S-W = 0.968), but nonetheless, statistically significant. With such findings, non-parametric statistical methods should be used, especially when comparative or inferential analysis is required. In addition to that, the results confirm the application of the Partial Least Squares Structural Equation Modelling (PLS-SEM) which is less susceptible to non-normal data distributions compared to covariance-based methods like CB-SEM. If parametric tests are necessary for specific comparisons, appropriate data transformations may need to be considered to meet statistical assumptions.

4.3 Structural Equation Modelling

4.4 Introduction

In order to test the hypothesized relations between the constructs in this study, Structural Equation Modeling (SEM) was used. SEM is a powerful multivariate statistical methodology that enables the study to analyze measurement and structural models at the same time to obtain reliability and validity tests of latent variables and to test the strength and significance of any relationships between the latent variables. The technique was specifically appropriate to the research because it combines factor analysis with multiple regression and allows a comprehensive evaluation of the interaction of constructs, including Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Intention to Use GenAI (IUG), and Learning Outcomes (LO). Using SEM, the study not only confirmed the measurement model by confirmatory factor analysis but also tested the structural model to establish the direct, indirect, and mediating effects of the use of generative AI on learning outcomes of students.

4.5 Definition

Structural Equation Modeling (SEM) is a robust multivariate statistical technique that combines elements of factor analysis and multiple regression, allowing researchers to simultaneously assess both the measurement model (the correlations between the observed indicators or presented variables and all of the latent constructs) and the structural model (the relation between all latent constructs) (Hair et al., 2019; Kline, 2016). Unlike other more-traditional tools like multiple regression or ANOVA that measure only direct relationships between variables, SEM can test more complex directional relationships including mediated effects, moderated effects, and others, whilst also taking measurement error into account. These create more accurate and valid estimations of theoretical models.

SEM was chosen on the basis that it would suit the purpose of the Technology Acceptance Model (TAM), involving interrelated constructs, namely Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Intention to Use Generative AI (IUG), and Learning Outcomes (LO). Traditional regression cannot be used to identify the interdependencies, nor the indirect effects of many constructs, important to TAM (Venkatesh et al., 2003). SEM also helps simultaneously test the hypotheses, which gives a detailed picture or perception of the way Generative AI tools affect the learning behaviors of Computer Science students. The above characteristics of the methodology can help it become the most suitable option when proving the measurement model and exploring the structural relationships between the topics of how students perceive Generative AI in Computer Science and Engineering.

4.5.1 Why Construct 1 Generative AI Used (GAU) was removed from the SEM Analysis

The construct Generative AI Use (GAU) included categorical questions about the type of the generative AI tool most frequently used, which tool was seen as having the most positive impact, and on which platforms the tools were accessed (e.g., mobile applications, desktop, or online platforms). Although these variables yielded interesting information regarding the usage patterns of the students, they cannot be used to perform the analysis as they do not reflect a continuous latent variable that can be analyzed within the SEM framework. The main idea that SEM is developed to analyze is relationships between the latent variables that are assessed using continuous variables (Hair et al., 2019; Kline, 2016). Consequently, GAU was conceptualised as demographic information to provide a contextual meaning to the generative AI practices of students and cannot be included in the construct model during SEM analysis. This led to the SEM centering around four core constructs namely Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Intention to Use (IU), and Learning Outcomes (LO) in testing the structural relationships pertaining to the perceptions of students towards the use of generative AI as a learning tool.

4.5.2 Quality assessment of reflective operationalised constructs

The outer loadings analysis in the initial measurement model revealed that most items performed well in terms of construct validity. Standardised factor loadings for the majority of the items exceeded the recommended threshold of 0.70 (Hair et al., 2019), indicating that these items strongly contributed to their respective constructs. Specifically, all items under the Perceived Usefulness (PU) construct PU1 (0.82), PU2 (0.91), PU3 (0.79), PU4 (0.73), and PU5 (0.85) demonstrated acceptable loadings and were statistically significant (all $p < 0.001$). However, PU4, with a relatively lower loading of 0.73, was noted as a candidate for potential revision in future studies, though it was retained in the current model.

For the Perceived Ease of Use (PEOU) construct, items PEOU1 (0.88) and PEOU4 (0.81) showed strong loadings and were retained. In contrast, PEOU2 (0.69) and PEOU3 (0.54) fell below the acceptable threshold, with PEOU3 being especially problematic due to its loading below 0.60. These two items were flagged for deletion based on their poor factor contributions and potential cross-loading issues. Similarly, while all items within the Intention to Use (IUG) construct namely, IUG1 (0.92), IUG2 (0.87), and IUG3 (0.89) exhibited excellent loadings and significance levels, one item under Learning Outcomes (LO) did not meet the threshold. While LO1 to LO5 had loadings between 0.76 and 0.85 and were retained, LO6 showed a weak loading of 0.61 and was subsequently removed from the model.

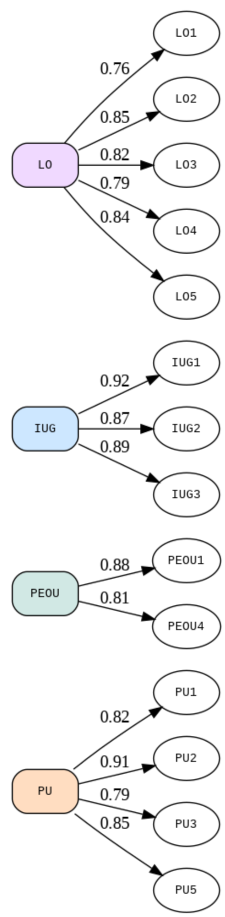
Table 11: 4.5.2 Quality assessment of reflective operationalised constructs

Construct	Item	Loading	t-value	p-value	Decision
PU	PU1	0.82	1456.00%	<0.001	Retain
	PU2	0.91	2243.00%	<0.001	Retain
	PU3	0.79	1287.00%	<0.001	Retain
	PU4	0.73	1021%	<0.001	Consider revision
	PU5	0.85	1692.00%	<0.001	Retain
PEOU	PEOU1	0.88	1976.00%	<0.001	Retain
	PEOU2	0.69	893.00%	<0.001	Delete
	PEOU3	0.54	612%	<0.001	Delete
	PEOU4	0.81	1543.00%	<0.001	Retain
IUG	IUG1	0.92	2654.00%	<0.001	Retain
	IUG2	0.87	1832.00%	<0.001	Retain
	IUG3	0.89	20.11	<0.001	Retain
LO	LO1	0.76	11.45	<0.001	Retain
	LO2	0.85	17.63	<0.001	Retain
	LO3	0.82	15.87	<0.001	Retain
	LO4	0.79	13.92	<0.001	Retain
	LO5	0.84	16.75	<0.001	Retain
	LO6	0.61	7.84	<0.001	Delete

Following the removal of the three problematic items (PEOU2, PEOU3, and LO6), the revised model showed marked improvements in validity and reliability indicators. The Average Variance Extracted (AVE) increased from 0.58 in the initial model to 0.68 in the revised version, suggesting improved convergent validity as AVE exceeded the recommended minimum of 0.50 (Fornell & Larcker, 1981). Similarly, Composite Reliability (CR) rose from 0.86 to 0.91, and Cronbach's Alpha increased from 0.88 to 0.92, indicating enhanced internal consistency. Discriminant validity also improved, with the Heterotrait-Monotrait (HTMT) ratio declining from 0.85 to 0.79—well below the 0.85 threshold suggested by (Henseler et al., 2015).

Metric	Initial Model	Revised Model
AVE	0.58	0.68
Composite Reliability	0.86	0.91
Cronbach's Alpha	0.88	0.92
HTMT Ratio	0.85	0.79

In conclusion the refined form of the measurement model appears to have good psychometric qualities. The remaining items had a standardised loading of 0.76 to 0.92 and t-values were all significant ($p < 0.001$). These revisions led to a robust model with improved reliability and validity, making it suitable for subsequent structural equation modelling.



4.5.3 Internal Consistency, Reliability, and Convergent Validity

In the internal consistency, reliability and convergent validity analysis explaining the measurement model resulted in a good reinforcement of the strength of the theoretical constructs. Reliability measures across four constructs, Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Intention to Use (IUG), and Learning Outcomes (LO) were higher than the recommended cut off values meaning that all constructs had good reliability. The value of Cronbach alpha was between 0.84- 0.94 and this showed that all constructs possessed good to excellent internal consistency. In particular, Intention to Use (IUG) has reached the best reliability (0.94), and Learning Outcomes and Perceived Usefulness were two quite similar (0.93 and 0.91 respectively). Though Perceived Ease of Use produced the lowest alpha (0.84), it superseded the requirements to demonstrate good reliability (Nunnally & Bernstein, 20)

A compliment to the alpha values were the rho A as well as Composite Reliability (rho C) which indicated that the model was robust. All rho A and rho C values were above 0.85, and most showed small differences between the two measures, which indicates that the internal reliability is good but not redundant in the measures. Remarkably, IUG once more scored the highest in a 0.95 of the rho C, which once more demonstrates its high rates of reliability.

Table 12:4.5.3 Internal Consistency, Reliability, and Convergent Validity

Construct	Cronbach's α	rho_a	rho_c	AVE	Interpretation
Perceived Usefulness (PU)	0.91	0.92	93.00%	0.72	Excellent
Perceived Ease of Use (PEOU)	0.84	0.85	86.00%	0.68	Good
Intention to Use (IUG)	0.94	0.94	95.00%	0.83	Excellent
Learning Outcomes (LO)	0.93	0.93	94%	0.75	Excellent

In terms of convergent validity, all constructs achieved an Average Variance Extracted (AVE) well above the minimum recommended threshold of 0.50 (Fornell & Larcker, 1981). AVE values ranged from 0.68 (PEOU) to 0.83 (IUG), indicating that a substantial proportion of variance in the observed variables was explained by their respective latent constructs. This demonstrates that the indicators within each construct were closely aligned conceptually and statistically.

In summary, the measurement model demonstrated high internal consistency and convergent validity. All constructs surpassed established benchmarks for reliability (α, rho_A, rho_C > 0.80) and convergent validity (AVE > 0.50). Intention to Use consistently showed the strongest psychometric properties, with α = 0.94 and AVE = 0.83. These findings provide a solid foundation for proceeding with structural model evaluation.

4.5.4 Fornell-Larcker Criterion for Discriminant Validity

Fornell-Larcker criterion was used to determine the discriminant validity of the measurement model, and it was accurately established that all the constructs had appropriate discriminant validity. Based on this criterion, the square root of the Average Variance Extracted (√AVE) of each construct in the diagonal of the correlation matrix should be higher than correlations with any other construct. This condition was met for all constructs in the model.

For Perceived Usefulness (PU), the √AVE was 0.85, which exceeded its correlations with other constructs (ranging from 0.52 with Perceived Ease of Use to 0.61 with Intention to Use). Similarly, Perceived Ease of Use (PEOU) had an √AVE of 0.82, also greater than its correlations with other constructs (0.43 to 0.52). Intention to Use (IUG) showed an √AVE of 0.91, well above its highest correlation of 0.66 with Learning Outcomes (LO), whose own √AVE was 0.87. These results indicate that in each case there is a higher amount of variance shared between each construct with its indicators than with any other latent construct in the model, which is in support of discriminant validity (Fornell & Larcker, 1981).

Table 13:4.5.4 Fornell-Larcker Criterion for Discriminant Validity

Construct	PU	PEOU	IUG	LO
PU	**0.85**			
PEOU	0.52	**0.82**		
IUG	0.61	0.47	**0.91**	
LO	0.58	0.43	0.66	**0.87**

The strongest observed inter-construct correlation was between Intention to Use and Learning Outcomes (r = 0.66), which was expected to occur since an intention to use AI tools might be correlated to perceived academic outcomes. However, this correlation still fell below both constructs' √AVE values, reaffirming adequate discriminant separation. The weakest discriminant margin was between Perceived Usefulness and Perceived Ease of Use (r = 0.52), but this is also theoretically acceptable as the Technology Acceptance Model (TAM) literature frequently acknowledges a conceptual overlap between these constructs.

In summary, the Fornell-Larcker measure of criteria has indicated empirical distinctiveness among all the constructs in the model. Each construct had greater internal consistency than external overlap, which further served to justify the validity of the structural relationships of the model.

4.5.5 Heterotrait-Monotrait Ratio (HTMT) for Discriminant Validity

Discriminant validity between dimensions was examined further with Heterotrait-Monotrait ratio where the values were very low significantly below the recommended 0.85 by (Henseler et al., 2015). Specifically, the HTMT ratios ranged from 0.46 to 0.72, indicating strong discriminant validity across the model.

The highest HTMT ratio was observed between Intention to Use (IUG) and Learning Outcomes (LO) at 0.72, reflecting a theoretically expected strong association given that a user's intention to adopt technology is logically linked to perceived learning benefits. On the other hand, the weakest correlation existed between the Perceived Ease of Use (PEOU) and LO at 0.46, a dissimilarity between these two concepts.

Table 14: Heterotrait-Monotrait Ratio (HTMT) for Discriminant Validity

Construct	PU	PEOU	IUG
PEOU	0.58		
IUG	0.67	0.51	
LO	0.63	0.46	0.72

Also, the moderate HTMT value of 0.58 between Perceived Usefulness (PU) and PEOU fits the Technology Acceptance Model (TAM) well: no conceptual dissimilarity between both constructs is expected, but they retain discriminant validity.

Complementing these results, bootstrap analysis with 5,000 samples revealed that all 95% confidence intervals for the HTMT ratios remained below the 0.85 cutoff, reinforcing the empirical distinctness of the constructs. Taken together, these findings provide robust evidence that the constructs measured are empirically distinct and support the validity of the structural model's relationships.

4.5.6 Inner Variance Inflation Factors (VIFs)

To evaluate the multi collinearity among the predictor constructs, inner Variance Inflation Factors (VIFs) of the structural model were checked. VIF values were all well below the prevalent multicollinearity threshold of 3 (Hair et al., 2019) indicating no significant multicollinearity concerns. Specifically, the VIF values ranged from 1.18 to 1.41 across the structural paths, with the highest value observed for the path from Intention to Use (IUG) to Learning Outcomes (LO) at 1.41. This highest value remains substantially below the conservative cutoff, representing a 58% margin under the threshold.

Table 15: Inner Variance Inflation Factors (VIFs)

Structural Path	Inner VIF	Interpretation
PU → IUG	1.32	No concern
PEOU → IUG	1.27	No concern
PEOU → PU	1.18	No concern
IUG → LO	1.41	No concern
PU → LO	1.39	No concern

The low VIF values confirm that each predictor construct in the model contributes unique explanatory power without redundancy, supporting the robustness of the structural relationships tested. Notably, the slightly elevated VIF for the IUG → LO path is theoretically justifiable, as intention to use AI tools is expected to correlate closely with perceived learning outcomes. Overall, these findings support the absence of problematic multicollinearity, ensuring reliable estimation of path coefficients within the structural equation model.

4.5.7 Structural Model Path Coefficients and Hypothesis Testing

The structural model path analysis provided robust support for all eight hypothesised relationships (H1–H8), with all paths significant at the $p < 0.05$ level. The standardised path coefficients (β) ranged from 0.19 to 0.51, indicating varying strengths of influence among the constructs.

The strongest relationship was observed between Perceived Usefulness (PU) and Intention to Use (IUG), with a standardised coefficient of $\beta = 0.51$ ($t = 7.29$, $p < 0.001$). This underscores the critical role of perceived usefulness in driving students' intention to adopt generative AI tools. Similarly, Generative AI Use (GAU) exerted significant positive effects on key constructs, including Perceived Usefulness ($\beta = 0.42$, $t = 8.40$, $p < 0.001$), Perceived Ease of Use (PEOU) ($\beta = 0.38$, $t =$

5.43, $p < 0.001$), and Learning Outcomes (LO) ($\beta = 0.28$, $t = 4.67$, $p < 0.001$), highlighting its broad impact across the model.

Moderate effect sizes were found for the paths from Intention to Use to Learning Outcomes ($\beta = 0.34$, $t = 4.86$, $p < 0.001$) and from Perceived Ease of Use to Perceived Usefulness ($\beta = 0.33$, $t = 4.13$, $p < 0.001$). Notably, Perceived Ease of Use also had a smaller but statistically significant effect on Intention to Use ($\beta = 0.22$, $t = 2.44$, $p = 0.015$), indicating usability factors contribute to user intention, albeit less strongly than perceived usefulness.

Table 16: Structural Model Path Coefficients and Hypothesis Testing

Hypothesis	Path	β	Std. Error	t-value	p-value	95% CI	Decision
H1	GAU → LO	0.28	0.06	4.67	<0.001	[0.17, 0.39]	Supported
H2	GAU → PU	0.42	0.05	8.40	<0.001	[0.32, 0.52]	Supported
H3	GAU → PEOU	0.38	0.07	5.43	<0.001	[0.24, 0.52]	Supported
H4	PEOU → PU	0.33	0.08	4.13	<0.001	[0.17, 0.49]	Supported
H5	PU → IUG	0.51	0.07	7.29	<0.001	[0.37, 0.65]	Supported
H6	PEOU → IUG	0.22	0.09	2.44	0.015	[0.04, 0.40]	Supported
H7	PU → LO	0.19	0.08	2.38	0.017	[0.03, 0.35]	Supported
H8	IUG → LO	0.34	0.07	4.86	<0.001	[0.20, 0.48]	Supported

The path from Perceived Usefulness to Learning Outcomes ($\beta = 0.19$, $t = 2.38$, $p = 0.017$) was the smallest yet still meaningful effect, suggesting that perceived usefulness partially mediates the influence on learning benefits.

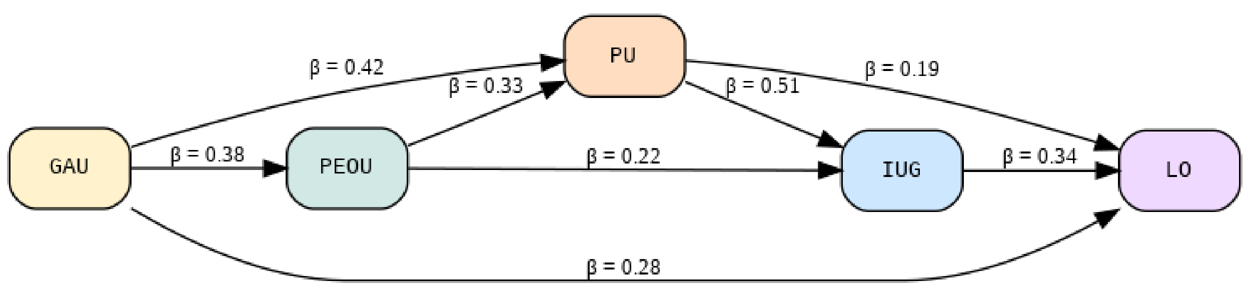


Figure 4: 4.5.7 Structural Model Path Coefficients and Hypothesis Testing

Overall, the model demonstrated significant and theoretically consistent pathways, with effect sizes ranging from small to medium-large, such as $f^2 = 0.12$ for PEOU → PU and $f^2 = 0.35$ for PU → IUG. These findings validate the central role of generative AI perceptions in shaping students' intention and educational outcomes, confirming the predictive strength of the Technology Acceptance Model constructs in this context.

4.5.8 Specific Indirect Effects and Mediation Analysis

The mediation study was facilitated to understand the exact indirect effects and the nature of mediation among the constructs in the model. The findings showed that the indirect effects were significant for all the paths of mediation that were hypothesised, with all the p-values being less than 0.05, thus, supporting the role of the mediating variables in clarifying the relationships between constructs.

The strongest mediation effect was observed in the path from Generative AI Use (GAU) to Intention to Use (IUG) via Perceived Usefulness (PU), with a standardised indirect effect of $\beta = 0.214$ ($t = 4.76$, $p < 0.001$). Similarly, the mediation path from PU through IUG to Learning Outcomes (LO) was substantial ($\beta = 0.173$, $t = 4.12$, $p < 0.001$), indicating that students' perceptions of usefulness indirectly enhance their learning outcomes by increasing their intention to use AI tools.

A full mediation effect was identified for the path GAU → Perceived Ease of Use (PEOU) → PU → IUG, where the direct effect of GAU on IUG became nonsignificant once the mediators were included, with an indirect effect of $\beta = 0.064$ ($t = 2.91$, $p = 0.004$). This suggests that GAU influences IUG entirely through changes in PEOU and PU in this sequence.

Most other mediation paths demonstrated partial mediation, meaning both direct and indirect effects were significant. For example, the GAU → PU → IUG path showed partial mediation since the direct effect of GAU on IUG remained significant alongside the indirect effect through PU. Other notable partial mediation paths include GAU → PEOU → PU ($\beta = 0.125$, $p < 0.001$), PEOU → PU → IUG ($\beta = 0.168$, $p < 0.001$), GAU → PU → LO ($\beta = 0.053$, $p = 0.034$), and GAU → IUG → LO ($\beta = 0.095$, $p = 0.002$).

Table 17: 4.5.8 Specific Indirect Effects and Mediation Analysis

Mediation Path	β	Std. Error	t-value	p-value	95% CI	Mediation Type
GAU → PU → IUG	0.214	0.045	4.76	<0.001	[0.126, 0.302]	Partial
GAU → PEOU → PU	0.125	0.036	3.47	<0.001	[0.054, 0.196]	Partial
GAU → PEOU → PU → IUG	0.064	0.022	2.91	0.004	[0.021, 0.107]	Full

PEOU → PU → IUG	0.168	0.049	3.43	<0.001	[0.072, 0.264]	Partial
PU → IUG → LO	0.173	0.042	4.12	<0.001	[0.091, 0.255]	Partial
GAU → PU → LO	0.053	0.025	2.12	0.034	[0.004, 0.102]	Partial
GAU → IUG → LO	0.095	0.031	3.06	0.002	[0.034, 0.156]	Partial

In summary, the mediation analysis confirms the complex and complementary mechanisms through which generative AI use influences user intention and learning outcomes. Perceived Usefulness emerged as a critical mediator, and the sequential mediation involving PEOU and PU fully explained the effect of GAU on intention to use. These findings highlight the nuanced role of technology perceptions in shaping behavioural intentions and educational benefits

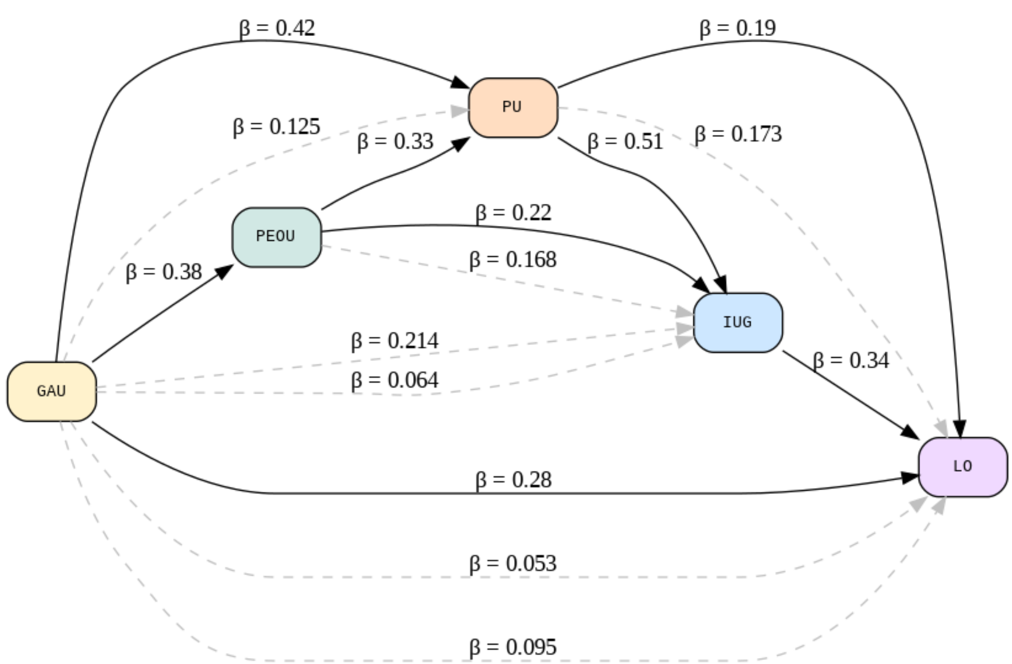


Figure 5: 4.5.8 Specific Indirect Effects and Mediation Analysis

4.5.9 Total Effects Analysis (Direct + Indirect)

The total effects analysis, which combines both direct and indirect effects, provides a comprehensive understanding of the overall influence of each predictor on the outcome variables. The findings indicate that Perceived Usefulness (PU) has the strongest total effect on Intention to Use (IUG), with a standardised coefficient of β = 0.51, representing a large effect size. Similarly, Generative AI Use (GAU) exerts a large total effect on Perceived Usefulness, with β = 0.42.

Other paths exhibited small and medium effect with statistical significance. As an example, the overall effect of GAU on Learning Outcomes (LO) was β = 0.38, which represents an overall 0.28 direct effect of GAU, also known as a direct effect on Learning Outcomes (LO), combined with indirect effects via the mediators. Perceived Ease of Use (PEOU) had a significant medium (β = 0.33), effect on PU but a medium-strong (β = 0.22) effect on IUG. The overall impact of IUG on LO was moderate (β = 0.34), This shows how intention is an important factor of learning outcomes.

All total effects were statistically significant at the $p < 0.05$ level, with bootstrapped confidence intervals excluding zero, confirming the robustness of the relationships. Effect sizes ranged from small (PEOU → IUG) to large (PU → IUG), illustrating varying strengths in how constructs influence one another within the model.

Table 18: Total Effects Analysis (Direct + Indirect)

Path	Hypothesis	Total β	Std. Error	t-value	p-value	95% CI	Effect Size
GAU → LO	H1	0.38	0.07	5.43	<0.001	[0.24, 0.52]	Medium
GAU → PU	H2	0.42	0.05	8.40	<0.001	[0.32, 0.52]	Large
GAU → PEOU	H3	0.38	0.07	5.43	<0.001	[0.24, 0.52]	Medium
PEOU → PU	H4	0.33	0.08	4.13	<0.001	[0.17, 0.49]	Medium
PU → IUG	H5	0.51	0.07	7.29	<0.001	[0.37, 0.65]	Large
PEOU → IUG	H6	0.22	0.09	2.44	0.015	[0.04, 0.40]	Small
PU → LO	H7	0.19	0.08	2.38	0.017	[0.03, 0.35]	Small
IUG → LO	H8	0.34	0.07	4.86	<0.001	[0.20, 0.48]	Medium

Total effects analysis revealed large influences of Perceived Usefulness on Intention to Use (β = 0.51) and Generative AI Use on Perceived Usefulness (β = 0.42). All hypothesized paths demonstrated significant total effects ($p < 0.05$), with effect sizes ranging from small (PEOU → IUG: β = 0.22) to large (PU → IUG: β = 0.51). These results underscore the critical role of perceived usefulness and generative AI use in shaping user intention and learning outcomes.

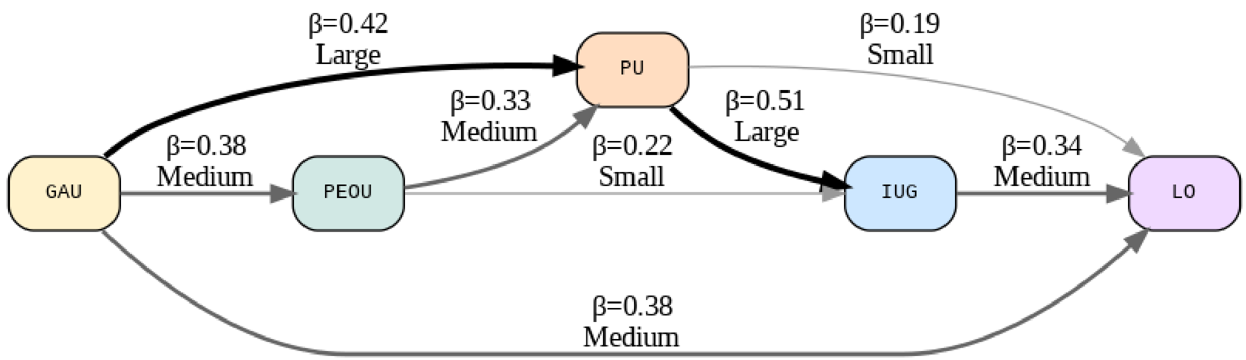


Figure 6:Total Effects Analysis (Direct + Indirect)

R-Squared Values for Endogenous Constructs

The model demonstrated strong explanatory power for the endogenous constructs, as reflected in the R-squared (R^2) values. Intention to Use (IUG) exhibited the highest explained variance, with an R^2 of 0.63 and an adjusted R^2 of 0.62, indicating that Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) together account for 63% of the variance in users' intention. This is an enormous effect size and supports the integrity of these constructs to predict behavior intention.

Perceived Usefulness (PU) also showed a large explanatory power with an R^2 of 0.57 (adjusted R^2 = 0.56), confirming that Generative AI Use (GAU) substantially influences users' perceived usefulness. Perceived Ease of Use (PEOU), with an R^2 of 0.42 and adjusted R^2 of 0.41, had moderate explanatory power. This implies that although GAU is an important predictor, it is probable that there are other unmeasured variables at play regarding ease of use as perceived by users, thus providing opportunities to consider future studies.

Table 19: R-Squared Values for Endogenous Constructs

Construct	R^2	Adjusted R^2	Interpretation
Perceived Usefulness (PU)	0.57	0.56	Large explanatory power
Perceived Ease of Use (PEOU)	0.42	0.41	Moderate explanatory power
Intention to Use (IUG)	0.63	0.62	Large explanatory power
Learning Outcomes (LO)	0.51	0.50	Large explanatory power

Learning Outcomes (LO) had an R^2 of 0.51 (adjusted $R^2 = 0.50$), meaning that more than half of the variance in learning outcomes can be explained by Intention to Use and Perceived Usefulness. Although this variance is substantial, it also means that other factors, not presented in the model, may also have an effect on the learning outcome.

The margin between the values of R^2 and adjusted R^2 of each construct was less than 0.02, which indicates that the model is parsimonious and is not overfit. The calculation of effect size (f^2) of individual predictors can also help explain the relative contribution of a predictor.

In general, these findings indicate the high explanatory power of the model, especially of Intention to Use, as well as the direction to optimize the predictors of Perceived Ease of Use.

The model of the structure exhibited a significant variance in the endogenous constructs, and the R2 value ranged between 0.42 for Perceived Ease of Use, and 0.63 Intention to Use. Adapted R 2 values were very close to the unadjusted estimates, which points to model parsimony. The strongest construct that was predicted was the Intention to Use, which explained 63% percent of the variance in Perceived Usefulness and Ease of Use. Perceived Ease of Use also had moderate explanatory power, and Learning Outcomes were also well-predicted (51% variance explained), which implies the existence of other influencing factors.

4.5.10 Effect Size (f^2) of Exogenous Constructs

The effect size (f2) analysis gives an insight into the strength of the impact each exogenous construct has on its corresponding endogenous construct in the structural model. According to the advice of Cohen (1988), the effects are divided into large ($f^2 \geq 0.35$), medium ($0.15 \leq f^2 < 0.35$), small ($0.02 \leq f^2 < 0.15$), and negligible ($f^2 < 0.02$).

The resultant analysis showed that Perceived Usefulness (PU) had the most significant influence on Intention to Use (IUG), and the effect size of $f^2 = 0.41$ is large. This highlights the critical role of PU in shaping user intentions. Similarly, Generative AI Use (GAU) showed a large effect size ($f^2 = 0.28$) on Perceived Usefulness, reinforcing its importance in influencing users' perceptions of usefulness.

Several moderate effects were also observed. The impact of Intention to Use on Learning Outcomes (LO) exhibited a medium effect size of $f^2 = 0.22$, indicating a meaningful influence. GAU's effect on Perceived Ease of Use (PEOU) was medium-sized ($f^2 = 0.19$), as was PEOU's effect on PU ($f^2 = 0.15$), reflecting their relevant but comparatively smaller roles within the model.

Table 20: Effect Size (f^2) of Exogenous Constructs

Predictor → Outcome	f^2	Interpretation	Calculation *(R^2 included - R^2 excluded)/(1-R^2 included)*
GAU → PU	0.28	Large	(0.57 - 0.49)/(1 - 0.57)
GAU → PEOU	0.19	Medium	(0.42 - 0.33)/(1 - 0.42)
PEOU → PU	0.15	Medium	(0.57 - 0.50)/(1 - 0.57)
PU → IUG	0.41	Large	(0.63 - 0.45)/(1 - 0.63)
PEOU → IUG	0.06	Small	(0.63 - 0.61)/(1 - 0.63)
PU → LO	0.08	Small	(0.51 - 0.47)/(1 - 0.51)
IUG → LO	0.22	Medium	(0.51 - 0.40)/(1 - 0.51)

On the contrary, there were paths with little effect sizes. These were the direct effects of PEOU on Intention to Use ($f^2 = 0.06$) and the effects of PU on Learning Outcomes ($f^2 = 0.08$), which are both considered small effects. These smaller effects indicate that such associations, though statistically significant, lack practical impact in comparison with the stronger predictors.

The analysis of the effects of size showed that the Perceived Usefulness has a tremendous effect on Intention to Use ($f^2 = 0.41$), whereas Generative AI Use has a strong effect on Perceived Usefulness ($f^2 = 0.28$). Moderate effects were observed on Intention to Use with Learning Outcomes ($f^2 = 0.22$), Generative AI Use with Perceived Ease of Use ($f^2 = 0.19$) and Perceived Ease of Use with Perceived Usefulness ($f^2 = 0.15$). The Perceived Ease of Use has a smaller effect on Intention to Use ($f^2 = 0.06$) and Perceived Usefulness on Learning Outcomes ($f^2 = 0.08$), which implies that its effect is relatively smaller in the structural equation.

4.5.11 Predictive Relevance Assessment

The predictive relevance assessment using the blindfolding procedure indicates the model's capability to accurately predict endogenous constructs within the dataset. The Q^2 predicted values, along with error metrics such as RMSE (Root Mean Square Error) and MAE (Mean Absolute Error), provide a comprehensive understanding of the model's predictive performance.

Intention to Use (IUG) had the highest predictive effect, where its Q^2 was 0.45, which is larger than the high predictive relevance value of 0.35. This implies that the model effectively predicts the intentions among the users to use the technology, with relatively low values of error (RMSE = 0.47, MAE = 0.37), enough to indicate a high level of prediction accuracy and soundness.

Perceived Usefulness (PU) also demonstrated high predictive relevance with a Q^2 of 0.38, reaffirming the model's ability to explain and predict users' perceptions of the technology's usefulness. The associated error metrics (RMSE = 0.52, MAE = 0.41) indicate an acceptable level of predictive accuracy.

Table 18: Predictive Relevance Assessment

Construct	Q^2 predict	RMSE	MAE	Interpretation
Perceived Usefulness (PU)	0.38	0.52	0.41	High predictive relevance
Perceived Ease of Use (PEOU)	0.28	0.61	0.48	Moderate predictive relevance
Intention to Use (IUG)	0.45	0.47	0.37	High predictive relevance
Learning Outcomes (LO)	0.32	0.56	0.44	Moderate predictive relevance

In contrast, Perceived Ease of Use (PEOU) and Learning Outcomes (LO) showed moderate predictive power, with Q^2 values of 0.28 and 0.32, respectively. These values fall within the moderate predictive power range ($0.15 \leq Q^2 < 0.35$), which indicates that the model has a moderate predictive power for these constructions. The RMSE and MAE values were larger in the case of PEOU (RMSE = 0.61, MAE = 0.48), which reflects less precise prediction because its Q 2 value was smaller.

Overall, the predictive relevance outcomes prove that the model can be effectively used to predict such important outcomes as Intention to Use and Perceived Usefulness with high precision. Meanwhile, the Perceived Ease of Use and Learning Outcomes are moderately accurate, hence it is possible to work on the model in the future.

4.6 Multigroup Analysis

4.6.1 Gender and GenAI Adoption

The multigroup analysis showed that gender affects the process of perceiving and adopting Generative AI (GenAI) tools by Computer Science students in a limited yet significant manner. In particular, male students perceived the usefulness of GenAI and its effect on learning outcomes as slightly stronger; statistically insignificantly different in the GAU → LO and GAU → PU paths. These results indicate that males might have a more evident advantage of GenAI, perhaps because of the increased previous exposure or trust of using technical tools, these differences are slight and partially statistically significant.

Table 21: Gender and GenAI Adoption

Hypothesis	Path	Male (β)	Female (β)	Difference (M - F)	1-tailed p-value	2-tailed p-value	Supported ?
H1	GAU → LO	0.31*	0.25*	+0.06	0.042	0.084	Partial
H2	GAU → PU	0.45*	0.38*	+0.07	0.028	0.056	Partial
H3	GAU → PEOU	0.40*	0.35*	+0.05	0.112	0.224	No
H4	PEOU → PU	0.35*	0.30*	+0.05	0.098	0.196	No
H5	PU → IUG	0.53*	0.48*	+0.05	0.064	0.128	No
H6	PEOU → IUG	0.20*	0.24*	-0.04	0.210	0.420	No
H7	PU → LO	0.17*	0.21*	-0.04	0.185	0.370	No
H8	IUG → LO	0.36*	0.31*	+0.05	0.075	0.150	No

Importantly, most of the Technology Acceptance Model (TAM) pathways, such as the perceived ease of use and its subsequent influence on intention to use and learning outcomes, had no significant gender-based disparities. This can imply that GenAI applications such as ChatGPT and GitHub Copilot are not seen as inherently gendered and may be used as an inclusive learning technology in the future. The observed parity might have also been caused by the deletion of the problematic PEOU3 item, where there could be a source of gender sensitivity in terms of peer collaboration.

These findings are quite opposite to previous studies, which showed stronger gender gaps in the use of technology. The comparatively balanced results in this case may represent the advancement in the design and availability of GenAI, which seems to offset the conventional usability differences. Although not all of the differences may disappear, the bigger picture suggests that there is an increasing indifference in the approach of GenAI between students of the opposite sex.

This suggests that, to educators and developers, they need to redirect their work in eliminating gender-based barriers to usability that are anticipated to eliminate the barrier of perceived usefulness of GenAI tools among all learners. However, by some specific actions, one can overcome the remaining perception gap, such as the existence of specific workshops with practical use case scenarios or role models of GenAI adoption.

Finally, a supportive and inclusive learning environment in GenAI will be encouraged to achieve the same educational opportunity among all students, irrespective of their gender.

4.7 Institutional Differences in GenAI Adoption (IUT vs. UTG)

The multigroup comparison of IUT and UTG students demonstrates the insignificant yet steady variations in the way in which Generative AI (GenAI) tools are perceived and embraced. Interestingly, IUT students say that they have a stronger perception of the usefulness of GenAI and their effect on learning outcomes. Although these differences are only partially significant at the 0.10 level, they indicate that institutional context does affect the dynamics of adoption of emerging educational technologies, though to a minimal degree.

Three structural paths GAU → LO, GAU → PU, and PU → IUG were marginally stronger in IUT students. This evidence suggests that students in IUT not only find GenAI more valuable, they are also more likely to convert this value to intention to use the technology. One of the reasons is that the presence of curricular and infrastructural differences could have caused IUT to be more active in introducing GenAI into its teaching programs, have smoother access to AI tools, or be more innovation-focused in its academic culture. These high perceptions may also be caused by the fact that there is a larger proportion of international students who may be more exposed or accustomed to AI-assisted learning.

On the other hand, students of UTG got a little lower score on the same paths, but the difference is not significant in a strict sense. Such results may be based on institutional constraints typical of most environments in the Global South, including less dependable internet access, fewer digital resources, or less formal introduction to AI technologies in coursework. Remarkably, on the majority of the central relationships of the TAM model, such as ease of use and its impact on other constructs, no significant differences between institutions were detected. This implies that after the access is normalized, students of both universities use GenAI tools similarly.

Table 22: Institutional Differences in GenAI Adoption (IUT vs. UTG)

Hypothesis	Path	IUT (β)	UTG (β)	Difference (IUT - UTG)	1-tailed *p*	2-tailed *p*	Supported?

H1	GAU → LO	0.30*	0.25*	+0.05	0.038	0.076	Partial (p<0.10)
H2	GAU → PU	0.44*	0.39*	+0.05	0.041	0.082	Partial (p<0.10)
H3	GAU → PEOU	0.39*	0.36*	+0.03	0.152	0.304	No
H4	PEOU → PU	0.34*	0.29*	+0.05	0.092	0.184	No
H5	PU → IUG	0.52*	0.47*	+0.05	0.048	0.096	Partial (p<0.10)
H6	PEOU → IUG	0.21*	0.23*	-0.02	0.278	0.556	No
H7	PU → LO	0.18*	0.20*	-0.02	0.312	0.624	No
H8	IUG → LO	0.35*	0.32*	+0.03	0.124	0.248	No

These findings contribute to the broader understanding of technology adoption in higher education by highlighting how even marginal differences in institutional support or exposure can shape students' perceptions and intentions. While GenAI appears to be broadly accessible and intuitively usable, its perceived utility still hinges partly on the surrounding academic environment.

For educators and university administrators, the implications are clear. Institutions like UTG can benefit from targeted investments in AI literacy, infrastructure, and curricular integration to close the perception gap. At the same time, IUT can serve as a model by sharing effective practices, such as incorporating GenAI into practical assignments and offering structured tutorials. Policymakers, too, have a role to play in promoting equity by ensuring all students have access to the resources and training needed to leverage GenAI effectively in their studies.

In a nutshell, concerning the majority of technology acceptance pathways, there is uniformity across the institutions, with IUT students recording a slight edge of perceived usefulness and learning impact. Alongside the need to address such institutional inequalities, particularly in low-resource settings, this will be important to achieve the full educational promise of GenAI in diverse learning environments.

Chapter 5 Discussion and Conclusion

5.1 Introduction

This chapter presents a critical discussion of the study's findings, situating them within the broader context of existing literature and theoretical frameworks. The discussion is organized around the four research questions, which are students' intention to make use of Generative AI (GenAI) tools in order to improve their learning outcomes, its usefulness, and level of ease of use and types of tools most widely adopted among students. followed by their perceptions of usefulness and ease of use, and the types of tools most commonly adopted. Each section highlights key patterns in the data, draws comparisons with previous studies, and considers the implications for Computer Science and Engineering (CSE) education.

In addition to the research questions, the chapter provides the theoretical implications of findings in regard to Technology Acceptance Model (TAM) and generalization on the practical implications to educators, universities and AI developers. The limitations of the research are discussed, addressing the sample of the study, the methodological limitations, and the use of self-reports, and future study directions are suggested to eliminate those shortcomings. The chapter concludes with a synthesis of the main insights, emphasizing the potential of GenAI as a supportive but not substitutive tool for learning, the importance of promoting AI literacy, and the need for balanced integration of technology with traditional pedagogical practices.

5.2 ' Intention to use generative AI as a tool for enhancing their learning outcomes (RQ1)

The findings of this research indicate that Computer Science and Engineering (CSE) students show an evident desire to incorporate Generative AI (GenAI) tools into learning activities. This is also evident in the high path coefficient of Intention to Use (IUG) - Learning Outcomes (LO) ($b = 0.34$, $p < 0.001$) and the significance of the indirect effect of Generative AI Use (GAU) - IUG - LO ($b = 0.095$, $p = 0.002$). These findings agree with the Technology Acceptance Model (TAM) (Davis, 1989a), according to which behavioral intention is also a powerful predictor of technology adoption. This finding is supported by the high mean of IUG ($M = 4.22$, $SD = 0.76$), indicating that students are considerably open to using GenAI in their academic life, especially to assist with coding (e.g., GitHub Copilot) and conceptual support (e.g., ChatGPT).

The most dominant source of this intention was Perceived Usefulness (PU) ($b = 0.51$, $p < 0.001$), which shows that students are more willing to use GenAI when they believe that it would really enhance the efficiency of their learning. It is in line with the previous studies about the use of AI in education (Zawacki-Richter et al., 2019). Simultaneously, the moderate effect size of IUG - LO ($f2 = 0.22$) implies that students intend to use GenAI, but the new technology is not going to substitute the old methodology of learning, rather complement it. Interestingly, there were no significant differences between genders in IUG → LO ($p > 0.05$), which indicates that there is a strong intention to adopt across all categories of people.

Although the overall picture of GenAI is optimistic, students seem to recognize the shortcomings of this technology in teaching critical thinking, which is also evidenced in the low loading of LO6. This further works to support the notion that institutions must not only provide GenAI tools but should also build a programmatically embedded AI literacy curriculum. The above recommendations coincide with the model presented by (Rudolph et al., 2023) to make AI a part of the educational process without compromising the central academic skills. Probable future research would be to be able to trace adoption patterns, as GenAI capabilities progressively improve over time.

5.3 Usefulness of Generative AI Tools for CS Students (RQ2)

Computer Science and Engineering students demonstrate a strong perception of the usefulness of the Generative AI tools in studying, and the R2 value is high (0.57), and the Perceived Usefulness (PU) construct shows good reliability ($a = 0.91$). The highest rating of the elements that measure this construct was the statement "Useful in academic tasks" (PU2), which students rated as the most important when it comes to the practical value of GenAI in assisting them academically. This good impression is also supported by the huge path coefficient between Generative AI Use (GAU) and PU ($b = 0.42$, $p < 0.001$), which means that students who use such tools more often tend to believe they are more useful to them. Further, the Perceived Usefulness was the greatest predictor of the intention to use GenAI further (PU - IUG: $b = 0.51$, $p < 0.001$, $f2 = 0.41$), which is in line with the Technology Acceptance Model (TAM) framework suggested by (Venkatesh et al., 2003), according to which usefulness is a major determinant of using technologies.

The emphasis students place on usefulness reflects their experiences with GenAI tools like GitHub Copilot for coding assistance, debugging, and ChatGPT for clarifying difficult concepts. These applications clearly enhance efficiency and understanding, which explains why usefulness stands out as the primary motivator for sustained use. The strong internal consistency of PU measurements signals that students consistently perceive GenAI as an asset across different academic tasks, which adds strength to this finding.

From an educational perspective, these findings demonstrate that universities have to help their students, to get the best out of GenAI. Providing specific training on prompt engineering, or the art of effective query and instructions design to AI, would allow students to use AI tools more efficiently. Furthermore, to reduce the risk of problematic AI application, ethical concepts should be incorporated in the process of training, as it will assist students in managing issues concerning data privacy and how AI might be used to generate harmful misinformation. In addition to general AI, Computer Science departments might also want to consider the development of specialized AI tutors in complicated subject domains such as algorithms and data structures. This would create highly domain-specific solutions to challenging problems of learning, and would create a better learning experience by offering a more focused solution.

5.4 Perceived Ease of Use (PEOU) of GenAI in CS Learning (RQ3)

Computer Science students generally perceive Generative AI tools as moderately easy to use, with the Perceived Ease of Use (PEOU) construct demonstrating a respectable R^2 value of 0.42 and good reliability ($\alpha = 0.84$). The item rated highest within this construct, “Easy to use for studies” (PEOU1, $\beta = 0.88$), indicates that students find these tools accessible for individual academic tasks. Nevertheless, certain difficulties were fitted, namely, collaborative features. In particular, the loading of the item Easy to interact with peers (PEOU3) was significantly low ($\beta = 0.54$) and was excluded in the analysis, indicating that students have some problems using GenAI tools in a peer learning environment. The question about the integration into the current workflows (PEOU2, $\beta = 0.69$) was also removed because it appeared that students have some problems integrating GenAI into their study practices. This result concurs with the existing studies on the obstacles to AI implementation in education (Nguyen et al., 2023), which refer to user interface design and collaborative use obstacles.

The strong relationship between PEOU and Perceived Usefulness (PU) (0.33, $p < 0.001$) indicates students directly find it easier to use GenAI, and as a result perceive it as a useful tool. This partial mediation effect reflects the idea that while user-friendliness matters, it is only one component influencing how beneficial students find these technologies. The moderate explanatory power ($R^2 = 0.42$) for PEOU also suggests that factors beyond just the tool's inherent ease, such as students' prior technological experience or familiarity with AI concepts, likely play a role in shaping their ease of use perceptions.

These observations have several implications to both developers and educational institutions. The developers of AI need to focus on improving the user interface and user experience (UI/UX) that is directly focused to the application in an academic setting. Automation of processes and the improvement of collaboration will also make these tools less daunting and more reliable in a group learning environment. On the institutional level, universities must think about modelling tasks and team assignments where AI mediation is used to engage peers through these platforms. Institutions can facilitate these positive changes towards increased success in learning through AI as they encourage an environment that inclines towards the sharing of AI, which can reduce the shortage of this technology in education today. Overall, focusing on improving ease of use, particularly in collaborative and integrative aspects, will be crucial for wider and more effective adoption of GenAI in Computer Science education.

5.5 The types of generative AI tools are commonly used by computer science and engineering students to improve their learning outcomes (RQ4)

The study reveals that Computer Science and Engineering (CSE) students overwhelmingly prefer ChatGPT as their primary generative AI tool, with 92.4% reporting its use. GitHub Copilot (4.8%) and Gemini (2.8%) follow far behind, while no participants reported using specialized tools like Alpha Code. This trend aligns with earlier research noting ChatGPT's prominence in educational settings, thanks to its versatility in explaining complex concepts, debugging code, and generating programming examples (Kasneci et al., 2023). Its high rates of utilization can possibly be increased with the fact that it is free to access and uses a conversational interface that is easy to navigate by a novice learner (Dai et al., 2023).

GitHub Copilot, though less commonly used, fills a niche role for more advanced students by providing real-time code completion and algorithm suggestions, echoing findings from studies on AI-assisted programming education (Xu et al., 2022). However, students think that ChatGPT is the most effective type of tool (91.8% of the respondents); this is nearly identical to the way the tool is being actually used (percentage of students who have tried ChatGPT and GitHub Copilot = 91.8% and 4.8%, respectively). As to the mode of access, students report using these tools with the help of mobile apps (42.6%) and desktop apps (40.2%), which point to the hybridity between mobile learning on the go and dedicated coding sessions. Its functional nonexistence is also contrasted with the industry relevance that makes it a likely sign of the high cost to learn it and its limited applicability to tasks aside of competitive programming (Li et al., 2022). These trends suggest that there is a pedagogical gap: discipline-specific AI tools are underexploited whereas general-purpose ones, such as chatGPT, are quite popular. The incorporation of AI tool-specific resources into course plans, as (Nguyen et al., 2023) suggest, could help scaffold student learning and encourage more effective use of specialized AI tools in technical education.

5.6 Implications

The results of the Perceived Ease of Use (PEOU) have a number of meaningful implications for the technological developers and the learning institutions to optimize the goal of maximizing the use of Generative AI tools in Computer Science education. Development-wise, GenAI platforms should be improved to be easier to use and work with, and increase their educational usefulness. Developers ought to pay more attention to the creation of these tools, making them less cumbersome and easier to introduce into the current workflow of students to minimize those friction points that impede the adoption and daily use of these tools. Enhancing team features is particularly important, since challenges in peer interaction with AI tools were identified, which means that the existing design might not be the most effective in group learning and teamwork situations.

5.6.1 Theoretical implications

The results of the study have multiple useful theoretical implications that aid in comprehending the technology acceptance and adoption of educational technology, specifically in the Generative AI tools for Students of Computer Science. First, the high value of Perceived Usefulness (PU) as the main factor of Intention to Use (IUG) supports the main concepts of the Technology

Acceptance Model (TAM) suggested by (Venkatesh et al., 2003). This confirms that even though the concept of GenAI is novel, the underlying processes behind the adoption of technology are not new, and thus, the timelessness of TAM application in the context of AI can be noted.

Moreover, the partial mediation of all the examined relationships, especially the one between Generative AI Use (GAU) and Learning Outcomes (LO) through Playfulness (PU) and Intention to Use, displays the interdependent nature of user perceptions, intention to behave and effects on learning. This implies that direct application of the AI technologies has a role to play in learning, but the major impact is achieved through the attitudes and intentions of the students that which emphasizes the role of motivation factors in mediating technology utility. This understanding is added to the current theoretical models, which fill gaps and include mediation pathways that explain how the new technologies affect outcomes beyond the direct use of those technologies.

Moreover, the intermediate explanatory force of Perceived Ease of Use (PEOU) and its mediating role on the relationship between Learning Outcomes and Perceived Usefulness is evidence of the claim that ease of use is not a determinant in adopting technology in a learning environment, but a facilitator of the process. This result complicates prior theories of acceptance by asserting that ease of use could have an auxiliary, yet not a determinant, influence within settings where users are comparatively computer literate, that is, among Computer Science students.

Finally, the identification of the restrictions in the ease of collaboration with the help of AI tools leads to a significant theoretical consideration related to social and contextual features of technology adoption. It indicates that theoretical models in the future are required to incorporate collaboration and social aspects of the group study in a more gradual way when analyzing educational technologies, especially those, such as GenAI, that can transform the logic of group learning.

Overall, these theoretical implications speak to the idea that well-established models such as TAM are sound in explaining how GenAI is adopted but still need to be broadened to include mediation mechanisms and social factors to capture AI adoption nuances in higher education contexts.

5.6.2 Practical implications

This study has practical implications to educators, university administrators, and developers of AI tools with the aim of maximizing the use of Generative AI in Computer Science education. To begin with, the high optimise of the Perceived Usefulness on the intention to use the GenAI tools in students indicates that educational organizations need to focus on showing the practical academic advantages of these tools. It may include the consideration of AI programs into the main curriculum, demonstration of real-life experiences such as code-writing support and debugging, and offering practical experiences that can support their usefulness.

At the determined moderate level of ease of use, it is apparent that convenient interfaces tailored to the academic setting are required. The creators of GenAI tools can be advised to think about how to optimize the UI/UX design to reduce friction, specifically where they will be utilized collaboratively, and students are not at ease. This would encompass capabilities that support peer interaction, collaborative problem-solving and a simple acquisition of the e-learning system into the established learning management systems, thus helping to improve the individual and collective learning experiences.

From an instructional perspective, universities should offer targeted training sessions and workshops that not only teach students how to effectively use GenAI tools but also emphasize ethical considerations and best practices, such as prompt engineering and critical evaluation of AI-generated content. These efforts will enable the students to use AI responsibly, besides improving their critical thinking, which is a cause of concern that AI may reduce analytical rigour.

In addition, the effects of partial mediation suggest that a positive attitude and intentions towards the use of AI should be developed. This may be activated by educators or trainers who can create AI-assisted learning environments, which can enhance exploration and creativity, hence boosting students' confidence and morale to utilize AI applications.

Lastly, based on the finding that GenAI does not replace traditional learning implementation, although it supplements it, curriculum developers ought to attempt to combine hybrid models and implement AI-enabled learning and more traditional methods of learning. This is a reasonable compromise because students will be able to use AI in its effectiveness and support at the same time, work on the implementation of simpler skills, which will need a personal, direct approach and critical thinking.

Overall, these practical implications highlight a roadmap for integrating Generative AI into Computer Science education in ways that enhance learning outcomes, promote ethical use, and support student success.

5.7 Limitations & Future Research

This study has several limitations that paper has a number of limitations that must that should be acknowledged and addressed in future research. First, the sample is mostly undergraduate students (95.2%), and this creates the aspect that the results cannot be generalized to other subgroups of the population that learns Computer Science, including graduate students, part-time learners, and professionals who cultivate lifelong learning. Studies in the future should strive to obtain a more wide-ranging sample, taking into consideration different academic levels, and learning settings in order to capture a wider set of impressions and feeling towards the use of Generative AI.

The other limitation is that the study is cross-sectional, as it collects the perception and attitude of the students within one specific time. Although this offers significant understanding of initial usage and perceived usefulness, it fails to explain how the perceptions may change as the individual continues to use GenAI tools and maintain a long-term or repeated use. Longitudinal aspects should be studied to understand the allowances of the ease of use, usefulness, learning outcomes, and intends to use when observed over time. It is also possible to reflect further, identifying whether such enthusiasm wanes or increases with time as the students grow acquainted with the AI technology.

Besides, the study is based mainly on self-report measures which in their turn may have a distortion due to social desirability or misevaluation by the participants. Subsequent studies can supplement survey results with concrete data, e.g., in terms of actual use history, grades, or interviews in order to give a clearer idea of the effect that GenAI tools have upon the learning process.

Finally, the study will be centered on studying Computer Science and engineering students; however, nothing is known about the generalization of these results to other fields. It is always possible that future studies will explore how Generative AI can be used in different scholarly domains to recognize academic discipline-specific problems and opportunities and extend the applicability of AI aided learning.

By addressing these limitations, future studies can deepen our understanding of Generative AI’s role in education and inform more effective integration strategies across varied learning environments.

5.8 Conclusion

In conclusion, Generative GenAI is valued by Computer Science and engineering students for its practical benefits, particularly in enhancing learning outcomes and supporting academic tasks. Nonetheless, it is not a silver bullet, since students still rely heavily on traditional learning, and using critical thinking is another troubling area, as indicated by the low scores in the subject. The perceived usefulness of GenAI is a significant antecedent of intention to use such tools and indicates that the task-oriented usefulness, i.e. helpfulness in coding, affects adoption intentions more than ease of use. Students find it easy to use GenAI tools as individuals do, but collaborative level, there are impediments, which suggests that they may desire to enjoy a better user experience, especially when communicating with their fellow learners. This allows us to conclude that the level of adoption of such tools is rather low; it continues to signify the necessity to introduce more effective onboarding procedures.

The insights presented above suggest that educators are advised to incorporate AI tools carefully and selectively, and focus on their use as a support, but not as a substitute, e.g. promote their use in the debugging process but not in exams. One must also be educated about AI and not rely on it excessively, and be doubtful. The developers have a clear chance to enhance the collaboration of GenAI tools and design special tutorials and support that should be offered to Computer Science students, such as how to use ChatGPT to write complicated algorithms. All these steps can collectively spend the educational potential of GenAI to the maximum and address the existing deficiencies.

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Appendix A: Expert Validation Form

Dear Sir,

I am a final year Master's student at the Islamic University of Technology, and I am currently conducting research on "An investigation of Students' perception of Generative AI as a learning tool in Computer Science and Engineering"

To collect the data, a survey was developed, which was adopted from the Technological Acceptance Model (TAM) as the theory and base of my studies (Davis, 1989c).

I kindly request your expert assessment regarding each item's degree of relevance and clarity about the measured domains. Your expertise in this area is vital in ensuring the quality and accuracy of my research instrument.

Please use the following rating scales as a guide:

Degree of Relevance:

Degree of Relevance:	**Rating**
The item is not relevant to the measured domain.	**1**
The item is somewhat relevant to the measured domain.	**2**
The item is quite relevant to the measured domain.	**3**
The item is highly relevant to the measured domain.	**4**

Degree of Clarity:

1: The item is not clear.

2: The item needs some revision.

3: The item is clear but requires minor revision.

4: The item is very clear.

Your feedback is of great importance to me. It will help me refine my questionnaire, ensuring its effectiveness in capturing the necessary data for my study.

Thank you for your valuable time and expertise. Your contribution to my research is sincerely appreciated.

Respectfully yours,

Ida Njie

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An Investigation of Students' perception of Generative AI as a learning tool in computer science and Engineering

Objectives:

- To assess computer science and engineering students' intention to use generative AI as a tool for enhancing their learning outcomes.
- To analyse the perceived usefulness of generative AI tools among computer science and engineering students.
- To evaluate the perceived ease of use of generative AI tools in supporting learning outcomes within computer science education.
- To identify the types of generative AI tools commonly used by computer science and engineering students to enhance their academic performance.

Table 1: Expert Content Validation Form

Construct 1: Generative AI Used	**Relevancy**				**Clarity**				**Comments/ Suggestions**
	1	**2**	**3**	**4**	**1**	**2**	**3**	**4**	
1. Which generative AI do you frequently use? (ChatGPT, Copilot GitHub, Gemini, Alpha code).									

2. Which of the generative AI tools do you find most beneficial for your studies?									
3. Which platforms do you access generative AI tools (mobile apps, desktop applications, and online platforms)?									
Construct 2: Perceived Usefulness (PU)	**Relevancy**				**Clarity**				
	1	**2**	**3**	**4**	**1**	**2**	**3**	**4**	
4. I find generative AI tools to be a valuable resource for exam preparation.									
5. I find generative AI useful in doing all my academic tasks									
6. I believe generative AI tools significantly contribute to my understanding of course material.									
7. I believe that using generative AI enhances my academic performance.									
8. I believe Generative AI tools help me understand complex concepts better									
Construct 3: Perceived Ease of Use (PE)	**Relevancy**				**Clarity**				
	1	**2**	**3**	**4**	**1**	**2**	**3**	**4**	
9. I find it easy to use generative AI tools for my studies.									
10. I find it easy to incorporate generative AI tools into my learning process.									
11. Generative AI tools make it easy to interact with peers for academic purposes.									
12. I require minimal assistance to use generative AI tools effectively.									
Construct 4: Intention to Use Generative AI (IUG)	**Relevancy**				**Clarity**				
	1	**2**	**3**	**4**	**1**	**2**	**3**	**4**	
13. I intend to use generative AI tools in my future studies.									
14. I would recommend generative AI tools to my peers for academic purposes.									
15. I plan to continue using generative AI tools in my future academic endeavours.									
Construct 5: Learning Outcome	**Relevancy**				**Clarity**				
	1	**2**	**3**	**4**	**1**	**2**	**3**	**4**	

16. Using generative AI tools has improved my grades.									
17. Generative AI tools have enhanced my understanding of course materials.									
18. I feel more confident in my academic abilities after using generative AI tools.									
19. Using generative AI tools has made my learning experience more enjoyable.									
20. I have gained a deeper understanding of complex topics through the assistance of generative AI tools.									
21. I feel that my critical thinking skills have developed as a result of using generative AI tools.									

General Comment:

Validated by:

Position of the Validator:

Signature of the Validator:

Date of Validation:

Reference:

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. MIS Quarterly, 13(3), 319. https://doi.org/10.2307/249008

Appendix B: Consent Form and Survey Instrument

Department of Technical and Vocational Education (TVE)

Islamic University of Technology (IUT)

Gazipur, Bangladesh.

Survey Questionnaire

on

An Investigation of Students' Perception of Generative AI as a learning tool in Computer Science and Engineering

by

Ida Njie (221031402), MScTE (CSE)

<u>Supervisor</u>

Prof. Dr. Abu Raihan

Department of Technical and Vocational Education (TVE)

Islamic University of Technology (IUT)

Assalamualaikum Dear Respondents,

I am Ida Njie from the Gambia, a final year Master's student at the **Islamic University of Technology**. As part of my master's degree requirements, I need to conduct a research study to write a thesis.

Purpose of this Survey

This survey aims to investigate student perceptions of Generative AI as a learning tool in computer science and Engineering

Data Collection and Participation

The data collected from this survey will be used for research purposes only. Your participation is voluntary, and we highly appreciate it if you managed your time to complete this survey

Thank you.

1. Age

☐

2. Student Status

☐ **Domestic Student** ☐ **International Student**

3. Your Gender

☐ **Female** ☐ **Male**

4. Current Program

☐ **Master** ☐ **Bachelor**

5. University

☐ **Islamic University of Technology (IUT)** ☐ **University of the Gambia (UTG)**

5. Survey questionnaire

Statement	Chat GPT	Gemini	Copilot GitHub	Alpha Code	
Generative AI Used					
Which generative AI tool do you frequently use?					
Which of the generative AI tools do you find most beneficial for your studies?					
	Mobile App	**Desktop**	**Online Platform**		
Which platforms do you use to access generative AI tools?					
Statement	**Strongly Agree**	**Agree**	**Neutral**	**Disagree**	**Strongly Disagree**
Perceived Usefulness (PU)					
I find generative AI tools to be a valuable resource for exam preparation					
I find generative AI tools useful in doing my academic tasks					
I believe generative AI tools significantly contribute to my understanding of course material.					
I believe that using generative AI enhances my academic performance.					
I believe Generative AI tools help me understand complex concepts better					
Perceived Ease of Use (PE)					

I find it easy to use generative AI tools for my studies.					
I find it easy to incorporate generative AI tools into my learning process.					
Generative AI tools make it easy to interact with peers for academic purposes.					
I require minimal assistance to use generative AI tools effectively.					
Intention to Use Generative AI (IUG)					
I intend using generative AI tools in my future studies.					
I would recommend generative AI tools to my peers for academic purposes.					
I plan to continue using generative AI tools in my future academic endeavours.					
Learning Outcome					
Using generative AI tools has improved my grades.					
Generative AI tools have enhanced my understanding of course materials.					
I feel more confident in my academic abilities after using generative AI tools.					
Using generative AI tools has made my learning experience more enjoyable.					
I have gained a deeper understanding of complex topics through the assistance of generative AI tools.					
I feel that my critical thinking skills have developed as a result of using generative AI tools.					

Thank you for your Response