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臺灣大學生持續使用生成式 AI 意願的決定因素

Determinants of Continuance Intention to Use ChatGPT in Higher Education: A Study in Taiwan

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摘要

本研究探討了生成式人工智慧（GenAI）對教育領域的影響，重點在於臺灣大學生對 ChatGPT 的看法和持續使用意願。 本研究採用定量方法，利用結構方程模式進行分析，探討績效預期和用後感知有用性對大學生對生成式 AI 的態度的影響，以及由此產生針對生成式 AI 的信任意願和持續使用意願。 結果表明，這些因素對學生的態度和持續使用生成式 AI 的意願有明顯的正面影響，並強調了教育機構有效整合 GenAI 的必要性。 本研究為教育領域人工智慧的廣泛討論做出了貢獻，為教育工作者、政策制定者和技術創新者在人工智慧驅動的教育進步背景下提供了有價值的見解。

關鍵字：生成式人工智慧（GenAI）、ChatGPT、教育科技、用後感知有用性、信任意願、結構方程模式

Abstract

This research examines the effects of Generative Artificial Intelligence (GenAI), with a special emphasis on ChatGPT, on the educational sector, highlighting the perceptions and ongoing usage intentions of university students in Taiwan. Adopting a quantitative approach, the study employs structural equation modeling to analyze survey data, exploring the influence of performance expectancy and post-usage usefulness on students' attitudes towards GenAI and their consequent trusting intention and continuance intention towards these technologies. The results reveal a significant positive impact of these factors on students' attitudes and their intention to persist with GenAI usage, emphasizing the necessity for educational institutions to integrate GenAI effectively. This study contributes to the broader conversation about AI in education, providing valuable insights for educators, policymakers, and technology innovators in the context of AI-driven educational advancements.

Keywords: Generative Artificial Intelligence (GenAI), ChatGPT, educational technology, post-usage usefulness, trusting intention, structural equation modeling

Acknowledgement

Completing my master's degree stands as a monumental achievement, and one that still astounds me as I reflect on reaching this significant milestone. I would like to raise a toast to everyone who has been an integral part of this remarkable journey.

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As I conclude my two-year master's journey, I can say the genuine pride that I am immensely satisfied with my accomplishments. This transformative journey has not only honed my skills as a researcher but also fostered personal growth, teaching me the invaluable lesson that perseverance indeed leads to rewarding outcomes.

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List of Symbols and Abbreviations

Statistical and Mathematical Symbols

Λ = indicator loading (also known as factor loading)

α = Cronbach's alpha

ρA = reliability coefficient (also known as *rhoA*)

R^2 = R-squared

f^2 = f-squared

k = number of folds in cross-validation

r = number of repetitions

β = path coefficients (also known as standard beta)

Key Terms in AI and Technology

AI = Artificial Intelligence

ChatGPT = Chat Generative Pre-trained Transformer

GenAI = Generative Artificial Intelligence

LLM = Large Language Model

Study Constructs and Variables

AA = affective attitude

CA = cognitive attitude

CI = continuance intention

PA = positive attitude

PE = performance expectancy

PU = post-usage usefulness

TI = trusting intention

Models and Theories

AIDUA = artificial intelligence device user acceptance

TAM = technology acceptance model

TPB = theory of planned behavior

TRA = theory of reasoned action

TTM = trust in technology model

UTAUT = unified theory of acceptance and use of technology

Scales and Indices

GAAIS = General Attitudes towards Artificial Intelligence Scale

TRI = Technological Readiness Index

Statistical Metrics

AVE = average variance extracted

CR = composite reliability

HTMT = heterotrait-monotrait ratio

MAE = mean absolute error

RMSE = root mean squared error

VIF = variance inflation factor

Modeling Techniques and Tools

LM = linear regression model

PLS = partial least squares. A structured equation modeling estimation technique which generates estimation of item loadings and path coefficients simultaneously.

PLSpredict = a holdout sample-based procedure that generates case-level predictions on an item or a construct level

PLS-SEM = partial least squares structural equation modeling

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Chapter 1

INTRODUCTION

1.1. Background

Recently, Generative Artificial Intelligence (GenAI), notably the enhanced conversational AI chatbot, Chat Generative Pre-trained Transformer (ChatGPT), has become a catalyst for profound transformations in various fields, especially education. The outputs of GenAI models are remarkably similar to what humans create as they were trained with a vast amount of data from the internet. For instance, ChatGPT used about 45 terabytes of text in its data training. These GenAI models have the ability to perform particular tasks, such as creating specific slide styles, writing targeted marketing campaigns, or generating high-resolution images (Chui et al., 2022).

Since its November 22 launch, ChatGPT, based on GPT-3.5, has gained mixed reactions from the academic community. It rapidly gained popularity, reaching 100 million users in just two months and averaging 25 million daily visitors by January 2023, a record-breaking growth rate for a consumer application (Similarweb, 2023). In comparison **Figure 1-1**, TikTok took nine months to hit the same number of users after its global release, and Instagram took over two years to reach that milestone (Badri et al., 2023; Milmo, 2023).

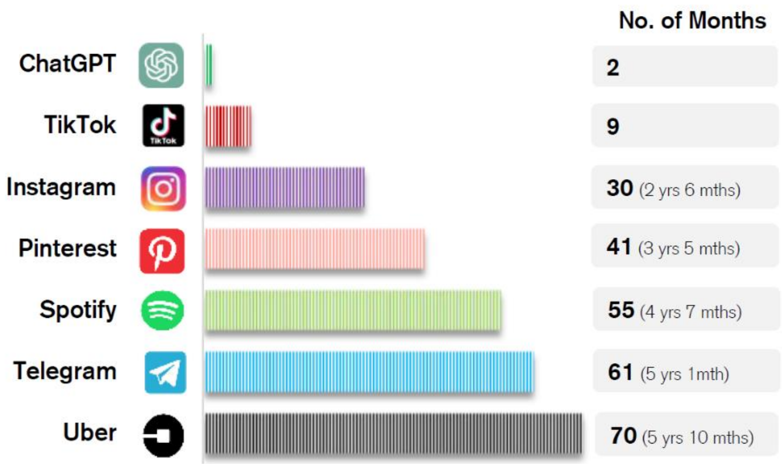

Figure 1-1 Comparison of Time to Reach 100M Users
Source: Badri et al. (2023)

This rapid technological advancement has necessitated a swift adaptation process. One perspective is that this rapid adoption aligns with forecasts from Gartner's 2023 Hype Cycle for emerging technology (Gartner, 2023), which anticipated that such foundational technologies would take 5 to 10 years before becoming widely used (**Figure 1-2**). In this evolving landscape, Baskerville and Myers (2009) remind us that scholarly writing and research, being complex skills developed over time, cannot be readily substituted by emergent technological trends, even as advancements such as GenAI make strides. As with any technological innovation, understanding the user perception is paramount to ensuring its successful acceptance and sustained use. This becomes even more critical when the technology in question has the potential to generate content that mimics human-like responses, as is the case with GenAI.

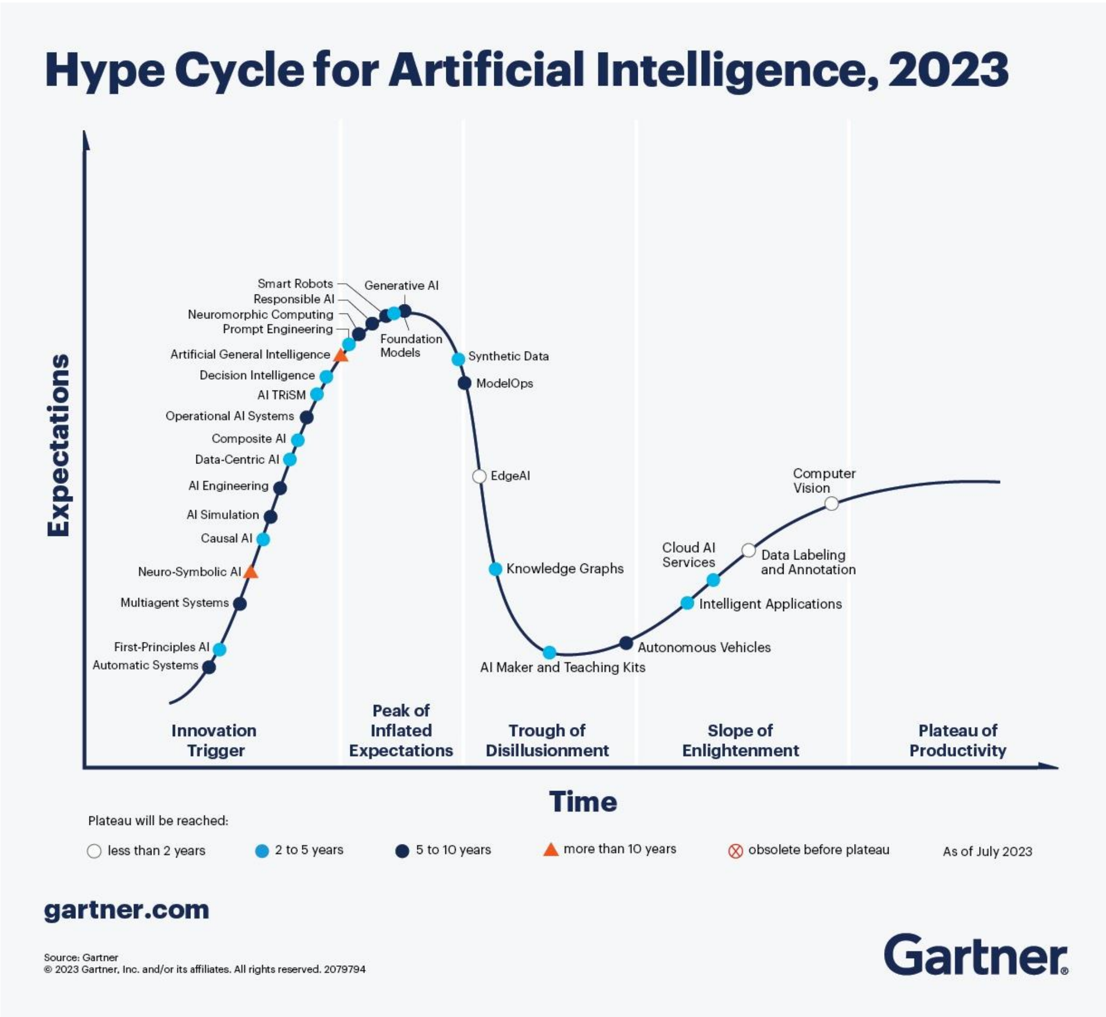

Figure 1-2 GenAI at the Peak of Heightened Expectations
Source: Gartner (2023)

A study by Sun et al. (2022) delved into the challenges faced by AI personal assistants, highlighting the effects of service failures on users' intentions to continue using these tools. The research underscored the importance of understanding potential pitfalls and user dissatisfaction that can arise from AI service failures. Such insights are crucial, especially when considering the integration of GenAI in educational settings, where the stakes are high, and user trust is paramount.

Further emphasizing the importance of user experience, a study by Li et al. (2023) explored the perceptions of User Experience Design (UXD) professionals regarding GenAI. The findings revealed that while experienced designers view GenAI as an assistive tool, valuing human factors such as “enjoyment” and “agency,” concerns arise, especially among junior designers, about skill degradation, job replacement, and creativity exhaustion. Such insights provide a nuanced understanding of the challenges and opportunities of integrating GenAI into UXD practices.

While the aforementioned studies provide insights specific to AI and GenAI, understanding user attitudes and continuance intention in the broader technological context can also offer valuable perspectives. For instance, research by Alhassan et al. (2020) in the domain of mobile payment services in Ghana highlighted how gratifications such as ease of use and perceived usefulness significantly influence user attitude, which in turn impacts continuance use intention. Similarly, a study on gamified task manager apps by Foroughi et al. (2023) emphasized the importance of meeting customer expectations and enhancing perceived experience and usefulness to ensure continued use.

In light of these findings, this research titled “Determinants of Continuance Intention to Use ChatGPT in Higher Education: A Study in Taiwan” seeks to bridge the existing knowledge gaps. By drawing insights from diverse technological domains, the study aims to provide a comprehensive understanding of the factors influencing the sustained use of GenAI in educational settings.

1.2. Research Question

The main focus of this research is understanding what leads university students to keep using GenAI in their studies. It's guided by the question: “What factors affect students' intention to continue using GenAI for their studies?” This central inquiry shapes the study's examination into different aspects that influence students' intentions regarding GenAI. To explore this, the research addresses several sub-questions that look at specific factors contributing to students' continuance intentions, ranging from *performance expectancy*, *post-usage usefulness*, *attitudes*, and *trusting intention* toward GenAI (Biever, 2023).

1.3. Research Scope

This study focuses on university students from Taiwan across different academic levels, encompassing both undergraduate and graduate programs, who have prior experience in using GenAI. The rationale for this specific focus is multifaceted. Primarily, there's a noticeable gap in the existing literature regarding Taiwanese students' experiences and attitudes towards GenAI, which this study aims to address. My interest in the education industry and the evolving role of GenAI in educational settings plays a significant role in this choice.

Furthermore, Taiwan, with its robust educational system and a strong emphasis on technological integration, serves as an ideal context to explore these dynamics. University students in Taiwan are often at the forefront of experiencing and interacting with new educational technologies, making their perceptions and attitudes toward GenAI both relevant and timely for investigation. For instance, National Taiwan University and National Tsing Hua University have established guidelines for use of GenAI in education on their websites (*Guidance for Use of Generative AI Tools for Teaching and Learning*, 2023; *NTHU Establishes Guidelines for AI in Education*, 2023).

Apart from perceptions of GenAI performance in study, the study assesses the student's attitudes toward GenAI, *trusting intention* and *continuance intention* toward GenAI. It is important to note that the study is not restricted to a specific field of study or discipline but rather seeks to understand the continuance intentions of students in various educational domains. The scope of the research is defined by its attention to the technology's integration within educational contexts, seeking to uncover the determinants of students' continuance intention of GenAI.

1.4. Research Purpose

The main goal of this research is to explore the factors of university students' continuance intention toward GenAI for educational tasks. The study seeks to understand the different aspects that influence students' views, feelings, and reliance on this technology, affecting their ongoing use of GenAI. By investigating these elements, the research aims to contribute to the field of technology in education, providing insights that can shape teaching methods, and academic regulations.

Chapter 2
LITERATURE REVIEW

The literature review was carried out for this study using online database such as Web of Science and Google Scholar, as well as leading publishers including Elsevier, Emerald, Springer, Taylor & Francis, and John Wiley & Sons. The search utilized key terms related to the field of study, such as GenAI, ChatGPT, large language model (LLM), artificial intelligence, chatbot, and search engine. To conduct an in-depth examination of research on user behavior, this study expanded its keyword selection. It included terms such as “behavioral intention”, “continuance intention”, “determinant factor”, and “influencing factor.”

2.1. Importance of GenAI in Higher Education

Since its debut, ChatGPT has captured the interest of researchers and the media, highlighting the potential and challenges of GenAI. Originating the development of Generative Adversarial Networks (GANS) in 2014, GenAI has evolved to provide realistic and complex outputs, such as noise maps and facial images (Creswell et al., 2018). Now, with Open AI’s interface, the leading GenAI, ChatGPT, responds in multiple languages, often mirroring expert human answers. According to McKinsey Global Survey on AI (Chui et al., 2023), around 79% of the respondents reported some level of exposure to GenAI, whether in a professional setting or personally; 22% indicated they frequently utilize GenAI tools in their work. This indicates that GenAI is becoming a new trend and a new skill to be competitive in job searching. Therefore, it is necessary for tertiary level students to equip themselves with relevant skills.

In addition, GenAI represents the latest in a series of technologies that have interfered the classroom experience for higher education students. Examples of previous disruptive technologies are calculators, Google search, and various statistical packages (Dwivedi et al., 2023). The feature of GenAI to produce highly original output is one of the main reasons it utilized in higher education as it enhance the students’ learning experience (Chan & Hu, 2023). Text-to-text AI tools helps students, particularly non-native English speakers (Chan & Lee, 2023), with providing comment on their writing and idea brainstorming (Atlas, 2023); while AI image generator tools such as Midjourney aid in teaching design and arts (Dehouche & Dehouche, 2023). GenAI also plays a role in data synthetizing and summarizing, contributing to data analysis in research (Berg, 2023; Chan & Zhou, 2023), and learning assessment (Crompton & Burke, 2023).

2.2. Students' Views on GenAI in Learning

The successful uptake of technological innovations relies heavily on user acceptance (Davis, 1989). In the 3P model (Presage-Process-Product) of teaching and learning by Biggs et al. (2022), the focus is on the crucial role of how students perceive their learning experiences. Biggs et al. (2022) highlight that students' learning approaches and outcomes are influenced by their perceptions of the learning environment, teaching strategies, and their abilities. Positive views lead to a deeper learning approach, focusing on understanding and connections between concepts, whereas negative perceptions result in a surface approach, centered on memorization (Biggs et al., 2022). In technological contexts like GenAI, students' perceptions and experiences significantly impact their usage and the technology's integration in learning. Research on student perceptions of AI, not necessarily powered by GenAI, often explores attitudes and influencing factors, but specific insights into GenAI remain less explored.

2.3. Students' Attitudes and Experiences with AI

Studies on AI in language education reveal its effectiveness. Tools like chatbots enhance language skills by assisting with grammar and idea generation (Bailey et al., 2021). AI KAKU, based on GPT-2, helped Japanese students in English classes, being user-friendly and aiding in expression (Gayed et al., 2022). AI chatbots in learning have improved student motivation and achievement (Essel et al., 2022; Lee et al., 2022). In business education, chatbots received positive feedback for their interactivity and responsiveness (Chen et al., 2023). Many students believe AI impacts their fields profoundly, showing a willingness to use AI in their studies and careers, and supporting its integration into university curricula (Gong et al., 2019; Sit et al., 2020; Yüzbaşıoğlu, 2021; Abdelwahab et al., 2023; Lee et al., 2023).

2.4. Acceptance of AI

Studies on chatbot acceptance have focused on user attitudes and intention from the perspective of technical and social factors. Technical acceptance studies, guided by technology acceptance model (TAM) and unified theory of acceptance and use of technology (UTAUT), found that attitudes are shaped by factors such as perceived usefulness and perceived ease of use. Kasilingam (2020) and Rese et al. (2020) noted the importance of utility and enjoyment in acceptance. In specific areas like pet health, accuracy and user-friendliness are crucial (Huang & Chueh, 2021). For banking chatbots, Eren (2021) highlighted the role of performance, trust, and reputation in banking chatbots, while Balakrishnan et al. (2022) emphasized the significance of perceived intelligence and anthropomorphism. Mogaji et al. (2021) found expertise, responsiveness, and security to be highly valued by users.

Other theories such as consumer acceptance of technology model (Zarouali et al., 2018), use and gratifications theory (Rese et al., 2020), expectation confirmation theory (Ashfaq et al., 2020; Eren, 2021), diffusion of innovation theory (Kasilingam, 2020; Hari et al., 2022; Kwangsawad & Jattamart, 2022), and perceived risk theory (Zhang et al., 2023) have also been applied to study how users feel about chatbots and their readiness to use them.

Chaves and Gerosa (2021) identify three social features key to chatbot-human interaction: conversational intelligence, social intelligence, and anthropomorphism. Chatbots' casual talking style creates a sense of connection, boosting usage and positive views of the brand (Li & Wang, 2023). Theories like computer-mediated communication (Lei et al., 2021), social exchange theory (Jiang et al., 2022), and social response theory (Huang & Lee, 2022) help understand chatbots' social traits.

2.5. Key Theories in AI Acceptance

In higher education, research on AI acceptance often uses models of TAM, theory of planned behavior (TPB, an extension of TRA, theory of reasoned action), UTAUT and UTAUT2, and the information system success model (Gambo & Shakir, 2023; Maheshwari, 2023; Strzelecki, 2023). These models, originally designed for non-AI technology, partly explain student’s intentions with AI tools (Im & Hancer, 2017; Lee & Cranage, 2018; Gursoy et al., 2019).

With AI's growing importance, new models like artificial intelligence device user acceptance (AIDUA) have emerged, focusing on AI acceptance in services. Originally introduced by Gursoy et al. (2019), it's been applied to AI in hospitality robots (Lin et al., 2020; Chi et al., 2023) and autonomous vehicles (Ribeiro et al., 2022). The model considers factors such as *performance expectancy* and user emotions. Later adaptations, for example, by Chi et al. (2023), included trust in human-robot interactions, specifically for AI social robots in hospitality. Meanwhile, Ma and Huo (2023) modified the model for acceptance of chatbot such as ChatGPT, replacing emotion with *cognitive attitude* and *affective attitude*.

2.6. Theoretical Foundations

GenAI marks a significant advancement in AI-generated content, integrating AI more into everyday life. It is vital to understand how students view and use GenAI in their studies. Yet, current research mainly covers specific areas, leaving gaps in understanding students' ongoing use intention of GenAI. Earlier studies, focusing on chatbot acceptance using models such as TAM, did not fully explore AI's unique features. This paper, therefore, aims to investigate students' perception and intent to use GenAI.

This study adapts AIDUA model introduced by Ma and Huo (2023) and particularly focusing on GenAI's acceptance among Taiwanese students. By integrating 3 other constructs, this study explores how factors like *performance expectancy (PE)* and *post-usage usefulness* (PU) affect students' various attitudes (*positive attitude* or PA, *affective attitude* or AA, *cognitive attitude* or CA), and how these attitudes influence their *trusting intention* (TI) and *continuance intention* (CI) in using GenAI in their studies.

2.6.1. Post-usage Usefulness

Perceived usefulness in the TAM refers to the belief that a system can enhance job performance (Davis, 1989; Pérez Pérez et al., 2004). *Post-usage usefulness* extends this concept, focusing on long-term utility based on sustained use (Bhattacherjee et al., 2008). This longer-term view has been shown to be key in continued IT product and service use, affecting attitudes and behavioral intentions toward technology, similar to TRA and TPB. This approach has been applied in various IT areas, including self-service technologies (Chen et al., 2009), open source software (Lee et al., 2009), business simulation games (Tao et al., 2009), e-learning (Lin & Wang, 2012), Web 2.0 (Chen et al., 2012), and app stores (Rezaei et al., 2016).

2.6.2. Positive Attitude

Attitude, as defined by Park and Joon Kim (2013), is about user preferences when interacting with technologies and devices. Dabholkar (1996) observed that a positive general attitude toward technology improves *perceived quality* in technology-based services. Parasuraman (2000) demonstrated that the Technology Readiness Index (TRI), which is an aggregated measure of four technology readiness constructs (*optimism*, *innovativeness*, *discomfort*, and *insecurity*), is linked to greater acceptance of various technology products and services, including cellular phones, computers, and self-service machines.

2.6.3. Trusting Intention

The study of *trust* in technology is a key research focus in the human-computer interaction field (Lankton et al., 2015). *Trust* is characterized by the perception of the reliability and trustworthiness of the AI agents' recommendations and responses (Shin, 2021). In studies of *initial trust*, *trusting intention* often represents the willingness to depend (McKnight et al., 2002). Mostafa and Kasamani (2022) found that when users trust AI chatbots, it positively affects their willingness to use them and increases their engagement. Furthermore, there is substantial evidence showing that higher trust levels in AI technology links to greater usage intention (Choung et al., 2023).

While it is known that *trust* is crucial for AI acceptance, the specific impact of *trusting intention* toward GenAI (readiness to rely on it) on the *continuance intention* (intention to keep using it long-term) is not well understood. Understanding this relationship is vital, as it influences the sustained use of GenAI, a key technology.

2.7. Challenges and Limitations of GenAI

ChatGPT's integration into education brings several challenges that require careful consideration. Firstly, the reliance on GenAI for assignments is feared to compromise students' critical thinking and writing skills (Chan, 2023; Warschauer et al., 2023), potentially diminish educational quality and students' learning outcomes (Chan, 2023; Horton, 2023; Korn & Kelly, 2023). Furthermore, over-dependence on

AI is cited as a cause for diminished human cognitive abilities and decision-making skills, potentially fostering a culture of laziness among students and teachers (Posner & Li, 2020; Mantello et al., 2021; Ahmad et al., 2023; Baron, 2023).

According to Májovský et al. (2023), the potential for GenAI to contribute to scientific fraud and misconduct is a growing concern, especially in the wake of several high-profile cases in recent years. This challenge poses significant ethical and integrity issues in academic research. Additionally, the role of AI in authorship is being debated, with major publishers like Springer-Nature clarifying that AIs such as ChatGPT cannot be credited as authors due to their inability to take responsibility for the content and integrity of scientific papers. ChatGPT was listed as one of the authors on a preprint article of medical education field in December 2022 (Stokel-Walker, 2023).

The opinion paper by Dwivedi et al. (2023) also addressed some concerns for ChatGPT usage in education. The attributes of GenAI that depends on data training and algorithm presents notable challenges such as data quality and bias, which can skew the AI's responses, and the lack of transparency in its decision-making process. Security concerns around sensitive student data, potential misuse for plagiarism, and limited understanding of context by GenAI also pose significant risks. Moreover, while ChatGPT can mimic human conversation, its limited understanding and inability to grasp context or nuances can hinder effective problem-solving and support.

Chapter 3

RESEARCH MODEL AND METHODS

3.1. Hypothesis Development and Research Model

This study developed a model to examine factors affecting students' intention to continue using GenAI, focusing on attitudes and trust. The model (**Figure 3-1**) suggests that *positive attitude*, *affective attitude*, and *cognitive attitude*, along with *trusting intention*, predict students' *continuance intention*. It considers *performance expectancy* and *post-usage usefulness* as antecedents of attitudes towards GenAI. Rather than age, the study emphasizes respondents' education levels, recognizing GenAI's strengths in offering personalized, useful, and immediate responses. This approach helps identify what drives students to persistently engage with GenAI.

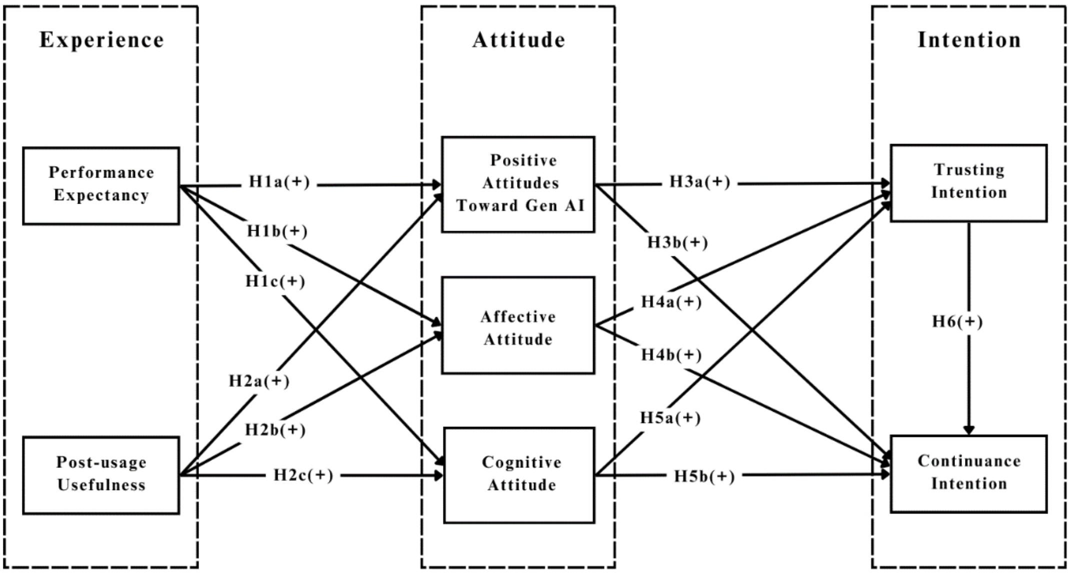

Figure 3-1 Proposed Conceptual Model

3.1.1. Performance Expectancy

Performance expectancy is “the extent to which users believe that using the system will assist them in achieving gains in job performance” (Venkatesh et al., 2003). For GenAI, it indicates the users’ views on how GenAI will assist them in various tasks, such as content generation and question answering. In literature of human-computer interaction field, users tend to adopt technology if it boosts their productivity (Venkatesh et al., 2012). This aligns with rational choice theory, where choices are made based on cost-benefit analysis for maximum benefit (Green Atkins & Kim, 2012). Essentially, people choose what offers them the most advantage (Aw et al., 2022). Users' performance expectations of GenAI involve its reliability and consistent service (Gursoy et al., 2019; Lv et al., 2022).

The influence of *performance expectancy* on *positive attitude* toward GenAI is a complex and multifaceted issue. Schepman and Rodway (2020, 2023) found that comfortableness with specific AI applications and perceived capability were strong predictors of general attitudes toward AI. Terblanche et al. (2023) further emphasized the role of performance expectations, with students perceiving AI coaching as accessible, easy to use, and intelligent. Therefore, the following hypothesis is proposed.

H1a. Performance expectancy positively affects positive attitude.

Studies by Chan and Zhou (2023) show a strong link between how valuable GenAI is perceived and the intention to use it. This is further supported by the findings by Terblanche et al. (2023) that students' positive attitudes and performance expectations significantly influence their interaction with an AI chatbot coach. This leads to the following hypothesis:

H1b. Performance expectancy positively affects affective attitude.

Research has consistently shown that *performance expectancy*, a key component of the expectancy-value theory, significantly influences *cognitive attitudes* toward GenAI (Chan & Zhou, 2023; Terblanche et al., 2023). This is further supported by Schepman and Rodway (2020), who found that comfortableness with specific AI applications, a factor influenced by *performance expectancy*, strongly predicts general attitudes toward AI. However, Szajna (1993) cautions that unrealistic expectations can lead to cognitive dissonance, which may impact perceptions of AI performance. Therefore, while *performance expectancy* is a crucial factor in shaping attitudes toward GenAI, it is important to manage and align these expectations to avoid potential negative consequences. Based on these findings, the following hypothesis is proposed:

H1c. Performance expectancy positively affects cognitive attitude.

3.1.2. Post-usage Usefulness

Existing research reveals several key findings on the influence of *perceived usefulness* on attitudes toward GenAI. Miyazaki et al. (2023) found that exposure to AI is positively correlated with positive sentiments, with casual usage of ChatGPT particularly associated with *positive attitude*. Kim et al. (2021) indicate that how useful AI is perceived to be plays a key mediator in linking the type of AI and users' attitude, which means, AI with practical functions leads to a stronger sense of its usefulness and, consequently, a more *positive attitude* toward it. However, according to Bhattacherjee et al. (2008), "*perceived usefulness*" construct is commonly associated with TAM and used for pre-usage perception. Hence, the construct is renamed as "*post-usage usefulness*" to reflect a long-term and more stable perception that associated with the preceding usage experience (Bhattacherjee et al., 2008). Chan and Hu (2023) and Russo (2023) both highlight the potential benefits of GenAI, such as personalized learning support and compatibility with existing workflows, but also note concerns about accuracy, privacy, and ethical issues. These studies collectively suggest that *post-usage usefulness* can indeed influence *positive attitude* toward GenAI, particularly when it aligns with individual needs and existing workflows. Based on this, the study proposes the following hypotheses:

H2a. Post-usage usefulness positively affects positive attitude.

The study by Svenningsson et al. (2022) emphasized on interest as a key affective component influencing attitudes toward technology. Meanwhile, Gado et al. (2022) discovered that how useful psychology students find AI greatly affects their attitudes toward AI. This finding can be extrapolated to suggest that university students' affective attitudes toward GenAI are likely influenced by the perceived post-usage usefulness of GenAI tools. If students recognize the practical benefits of GenAI in their academic tasks, their emotional response toward these tools is expected to be more positive. As a result, this study proposes a specific hypothesis to be explored:

H2b. Post-usage usefulness positively affects affective attitude.

Based on the study's findings by Alhababha et al. (2012), it can be hypothesized that the perceived *post-usage usefulness* of E-learning system significantly influences the *cognitive attitude* of students. The study suggested that when learners perceive a technology as useful, their *cognitive attitude*s, encompassing their belief and evaluations about the technology, are positively impacted. Similarly, the findings by Gado et al. (2022) suggest that *perceived usefulness* impacts students' *cognitive attitudes* (beliefs and evaluations) toward AI. Hence, the following hypothesis is made:

H2c. Post-usage usefulness significantly affects cognitive attitude.

3.1.3. Positive Attitude

Positive attitudes toward technology lead to higher usage intentions and behavioral changes (Davis, 1989; Davis et al., 1989). Meanwhile, the intent to trust plays a vital role in the continuance usage intention of technology (Dimitriadis & Kyrezis, 2010; Lankton et al., 2014; Ambalov, 2021). Conversely, negative attitudes can result in low trust, as seen with AI such as driverless taxis (Tussyadiah et al., 2017). Therefore, a new hypothesis is proposed based on these insights:

H3a. Positive attitude positively affects trusting intention.

In terms of the TRA, Fishbein and Ajzen (1975) stated that a person's intention to act is shaped by their attitude toward the behavior and perceived social pressure (subjective norm). A positive attitude and a sense of obligation increase the behavior intention. Past studies have shown a strong connection between attitude and the intention to continue a behavior (Hamari & Koivisto, 2015; Manser Payne et al., 2018). Individuals' ongoing behavior toward technology is influenced by their initial attitude (Wu & Chen, 2017). This applies to chatbot services as well, leading to the formulation of a new hypothesis:

H3b. Positive attitude positively affects continuance intention.

3.1.4. Affective Attitude

Davis et al. (1989, p. 984) define attitude as "the degree of a person's positive or negative feelings about performing a target behavior". Few studies have looked into how emotions and personality traits impact trust in AI. Hancock et al. (2011) noted this gap. For instance, conscientious individuals showed a preference for text interfaces over physical ones in social robots (Looije et al., 2010). People with high extraversion viewed robot interactions more positively, including trust (Sarkar et al., 2017). Mou and Xu (2017) found that people were less open, agreeable, extroverted, conscientious, and less likely to share personal information with AI compared to human interactions. These lower levels might contribute to reduced trust in AI.

Similar research on trust in AI found that positive emotions are linked to increased trust in AI (Hughes et al., 2009). On the other hand, negative past experiences can lead to less trust in AI, similar to how trust in automation works (Hengstler et al., 2016; Dikmen & Burns, 2017). This is consistent with the idea that users' enjoyment from interacting with ChatGPT can affect their trust (Ma & Huo, 2023). Based on these findings, a hypothesis is proposed.

H4a. Affective attitude positively affects trusting intention.

A user's emotional response to a computer application, such as GenAI, is linked to their satisfaction (Doll et al., 1998). This satisfaction can lead to loyalty, meaning they continue using GenAI (Niu & Mvondo, 2024). Attitudes, as emotional reactions, anticipate ongoing use (Dai et al., 2020). Studies show users' acceptance and behavioral intentions of AI devices is largely based on emotional judgments (Lin et al., 2020; Jin & Youn, 2022) and affects their actions (Le et al., 2020). This suggests students who feel positively about GenAI are likely to continue using it. Hence, a hypothesis is formed based on these insights:

H4b. Affective attitude positively affects continuance intention.

3.1.5. Cognitive Attitude

Fishbein and Ajzen (1975) identify three aspects that form attitudes: emotional (affective), thought-based (cognitive), and action-related (behavioral) components. Previous research has defined the cognitive component as relating to the content of an individual's thoughts, including their beliefs about what is considered a fact (M Fishbein & Ajzen, 1972; Bagozzi, 1978). Metsärinne and Kallio (2016) indicated that "Utility" as a cognitive attitude factor involves a learner's understanding, views, and beliefs about the potential outcomes of future learning experiences. It serves as a predictor for accomplishing personal learning goals. In the context of Self-Regulated Learning, this knowledge helps individuals think about their responsibilities, including their values and potential risks.

Lankton et al. (2014) found that when a system functions well and performs better tasks, it can lead to more positive user experiences and increase the likelihood of users relying on that technology. Frost-Arnold (2014) further supports this by highlighting the role of trust in practical reasoning, which can be influenced by *cognitive attitude*s. Therefore, the following hypothesis is formulated:

H5a. Cognitive attitude positively affects trusting intention.

Cognitive appraisals correspond to the utilitarian side of attitude (Lee et al., 2012; Jin & Youn, 2023). Therefore, cognitive appraisals may be connected to how users perceive GenAI's effectiveness in assisting with tasks or providing information. Essentially, *cognitive attitude*s play an important role in shaping how users intend to behave towards AI (Lee et al., 2011; Suseno et al., 2022; Huo et al., 2023). Chan and Zhou (2023) found that perceived value and cost are significant factors influencing intention to use GenAI, suggesting a potential link between attitude (cognitive perspective) and intention to use GenAI. This is also supported in the AIDUA model (Ma & Huo, 2023). Therefore, the hypothesis is proposed as follows:

H5b. Cognitive attitude positively affects continuance intention.

3.1.6. Trusting Intention

According to the trust in technology model (TTM), *trusting intention* represent the trustor's willingness to depend on technology, and thereby engage in trust-related behavior (McKnight et al., 2011). In another word, *trusting intention* is an object-oriented attitude because it reflects an evaluative response to these technology attributes (Benamati et al., 2010). In this study, *trusting intention* represents the users' willingness to depend on GenAI, and *continuance intention* indicates the behavioral intent to continue using GenAI over a longer-term usage period. Prior research has shown that *technology trusting intention* has significant impact on the *usage continuance intention* (Dimitriadis & Kyrezis, 2010; Lankton et al., 2014; Ambalov, 2021). Therefore, the following hypothesis is proposed:

H6. Trusting intention positively affects continuance intention.

3.2. Research Method

3.2.1. Measurement Instrument

The survey for this study had two parts: first on demographic details including gender, education level, and GenAI usage frequency, and the second on the questions based on all constructs' items, which adapted from prior research and tailored for the GenAI context. All questions in the second part were collected using a 5-point Likert scale, from "strongly disagree" (1) to "strongly agree" (5). The study defined each concept clearly, as shown in **Table 3-1**, and **Table 3-2** lists the measurement items used.

Table 3-1 Operational Definition

Construct	Operational Definition	Reference
Performance Expectancy	The degree to which students believe that using the GenAI would help them achieve their educational performance goals.	Venkatesh et al. (2003); Patil and Undale (2023)
Post-usage Usefulness	The extent of your belief that GenAI can continue to be useful after you've used it for studies purposes.	Bhattacherjee et al. (2008); Rezaei and Valaei (2017); Yeo et al. (2017)
Positive Attitude toward GenAI	The overall positive attitude toward GenAI, ranging from practical benefits to emotional reactions.	Schepman and Rodway (2023)
Affective Attitude	Affective attitude refers to the emotional and sentimental reactions or feelings a user has toward generative AI. It encompasses the positive or negative emotions, such as joy, frustration, satisfaction, or anxiety, that a user might associate with the use or thought of generative AI.	Lai and Tong (2022); Suh and Ahn (2022)
Cognitive Attitude	Cognitive attitude refers to the beliefs and perceptions a user holds about the attributes, functionalities, and capabilities of generative AI.	Przymuszała et al. (2021); Suh and Ahn (2022)
Trusting Intention	Trusting intentions toward GenAI refer to your willingness to rely on and have confidence in the GenAI's capabilities, believing that it will act in your best interest. In other words, it means how much you trust and rely on it. It's about believing in its ability to help you and make your life easier. If you trust it, you use it with confidence; if not, you might not use it much.	McKnight et al. (2002); Li et al. (2008); Dimitriadis and Kyrezis (2010); Lankton et al. (2014); Whang and Im (2018)
Continuance Intention	User's overall willingness to continue using Generative AI	Bhattacherjee (2001); Ashfaq et al. (2020); Al-Maroof and Salloum (2021); Jo (2022)

Table 3-2 Measurement Items for Each Construct

Construct	Item	Question	Reference
Performance Expectancy	PE1	I find generative AI useful for my studies.	Venkatesh et al. (2003); Patil and Undale (2023)
	PE2	Generative AI help me to improve my academic performance.	
	PE3	I believe Generative AI is very valuable for my studies.	
	PE4	Generative AI is highly beneficial for my studies.	
Post-usage Usefulness	PU1	Generative AI can make my studies more effective.	Bhattacherjee et al. (2008); Rezaei and Valaei (2017); Yeo et al. (2017)
	PU2	Generative AI can help me study more efficiently.	
	PU3	Generative AI can enhance my study experience.	
	PU4	Totally, I find the Generative AI useful in my studies.	
Positive Attitude toward GenAI	PA1	I am impressed by what Generative AI can do.	Schepman and Rodway (2023)
	PA2	I am interested in using Generative AI in my daily life.	
	PA3	There are many beneficial applications of Generative AI.	
	PA4	Generative AI can perform better than humans.	
	PA5	I would like to use Generative AI in my studies.	
Affective Attitude	AA1	Generative AI is very important for developing society.	Lai and Tong (2022); Suh and Ahn (2022)
	AA2	Generative AI helps me solve problems in real life.	
	AA3	Generative AI is necessary for everyone.	
	AA4	I think that most jobs in the future will require knowledge related to Generative AI.	
Cognitive Attitude	CA1	I think it is important to use Generative AI in studies.	Przymuszała et al. (2021); Suh and Ahn (2022)
	CA2	Generative AI is important.	
	CA3	I think that Generative AI should be used in studies.	
	CA4	I think every student should use Generative AI in studies.	
Trusting Intention	TI1	I would feel comfortable depending on Generative AI.	McKnight et al. (2002); Li et al. (2008); Dimitriadis and Kyrezis (2010); Lankton et al. (2014); Whang and Im (2018)
	TI2	I would feel comfortable using the Generative AI.	
	TI3	In order to have immediate suggestions for my assignment, I feel that I could rely on the Generative AI.	
	TI4	In order to have personalized feedback for my assignment, I feel that I could trust the Generative AI.	
	TI5	When I have an important class assignment, I feel I can depend on Generative AI.	
Continuance Intention	CI1	I intend to continue my use of Generative AI in the future.	Bhattacherjee (2001); Ashfaq et al. (2020); Al-Maroof and Salloum (2021); Jo (2022)
	CI2	I intend to increase my use of Generative AI in the future.	
	CI3	I will keep using the Generative AI as regularly as I do now.	
	CI4	If I could, I would like to continue my use of Generative AI.	
	CI5	I would recommend Generative AI to my classmates.	

3.2.2. Subject and Data Collection

To determine the required sample size for studying the constructs' relationships using structural equation modeling (SEM), an A-priori sample size calculator was used (Soper, 2020), following Cohen's (1992) recommendations on analysis power and sample size. With an expected effect size of 0.10, a statistical power level of 80%, seven latent variables, 31 observed variables, and a 0.05 probability level, the calculated minimum sample size is 88.

This study collected data using convenience and snowball sampling, which are cost-effective and facilitate easy data collection (Battaglia, 2008). Convenience sampling aligns with research objective, despite its haphazard nature (Saunders et al., 2019), while snowball sampling involves selecting subjects through networks or chains (Sekaran & Bougie, 2016). In snowball sampling, chosen subjects refer others from the same population, continuing until the sample size is met (Malhotra & Das, 2020).

Data was gathered from university students using an online platform. Before full distribution, the survey was piloted with 5 respondents, and 371 responses were collected over 16 days in November 2023. Respondents accessed the survey via an online link. To ensure relevant data, the questionnaire initially asked about the frequency of GenAI use. Responses from those who never used GenAI were excluded from analysis. Participants had to answer all questions on one page before proceeding. This process led to the elimination of 25 responses that didn't meet the criteria.

To ensure accurate data, the survey included a question about GenAI usage categories based on article by Meilleur (2023), with options like Text to Text and Image to Video. Respondents were asked to choose the frequency that best matched their experience. After removing unreliable responses, 228 valid data points were used for further analysis. This exceeds the necessary minimum of 88, meeting the sample size requirement for SEM.

Since the survey was conducted in Taiwan, the questionnaire was initially translated into Traditional Chinese. Any changes made for readability were re-translated into English to keep both versions consistent. The final English version of the measurement items is presented in **Appendix A**, and the Chinese version is in **Appendix B**.

3.2.3. Analytical Methods and Software

The analyses were conducted in two stages. The first stage focused on descriptive analysis of the responses to reveal respondents' use frequency of GenAI in general and use frequency of each GenAI category. SPSS Statistics 26 was used for demographic data analysis, which is the descriptive analysis.

The second stage involved the deeper structural analysis conducted by partial least squares structural equation modeling (PLS-SEM) method. According to Hair et al. (2019a), the PLS-SEM method is highly favored by many researchers due to its capability to handle complex models with many constructs, indicator variables, and structural paths. A key advantage is that it does not require strict assumptions about data distribution, making it more flexible in various research scenarios. Furthermore, PLS-SEM, chosen for its emphasis on prediction and causal explanations (Wold, 1982; Sarstedt et al., 2022), bridges the gap between academic research (explanation) and practical application (prediction) (Hair et al., 2019b). User-friendly tools like PLS-Graph (Chin, 2003) and SmartPLS (Ringle et al., 2005; Ringle et al., 2015) simplify using this method. In this stage, SmartPLS 4.0 is used to validated the measurement and structural models.

Chapter 4

DATA ANALYSIS AND FINDINGS

4.1. Demographic Characteristics

Descriptive statistics analysis shows that most of the respondents are male (53%). Most are currently pursuing bachelor's degree (75%), and they usually use GenAI several times a week (37%). **Table 4-1** presents the demographic information of the respondents.

Table 4-1 Respondent Profiles

Demographic Attribute	Subjects (N = 228)	
	Frequency	Percentage
Gender		
Male	122	53%
Female	106	47%
Highest Level of Educational Attainment		
Undergraduate	171	75.0
Graduate	57	25.0
How often do you use Generative AI on average		
Rarely (once in a long while)	47	21%
Sometimes (once in a week)	57	25%
Often (several times a week)	84	37%
Always (daily)	40	17%

Table 4-2 Percentage of Use Frequency by GenAI Category

Category of Gen AI	Never	Rarely (once in a long while)	Sometimes (once a week)	Often (several times a week)	Always (daily)
Text to Text (TTT)	0.0%	17.5%	28.5%	37.3%	16.7%
Text to Speech (TTS)	71.5%	18.4%	5.7%	3.1%	1.3%
Text to Image (TTI)	52.2%	28.5%	12.3%	6.1%	0.9%
Text to Video (TTV)	78.5%	17.1%	3.1%	0.0%	1.3%
Speech to Text (STT)	67.5%	16.7%	10.1%	3.5%	2.2%
Speech to Speech (STS)	76.3%	16.2%	4.8%	1.8%	0.9%
Image to Text (ITT)	73.7%	13.6%	7.0%	3.9%	1.8%
Image to Image (ITI)	67.5%	17.5%	10.1%	3.5%	1.3%
Image to Video (ITV)	83.3%	12.3%	2.6%	0.9%	0.9%
Video to Video (VTV)	85.5%	10.5%	1.8%	1.3%	0.9%

As shown in **Table 4-2**, all respondents have the experience in using Text to Text (100%), the second most used GenAI category is Text to Image (47.8%). **Figure 4-1** shows the data visualization of the percentage of GenAI categories by use frequency.

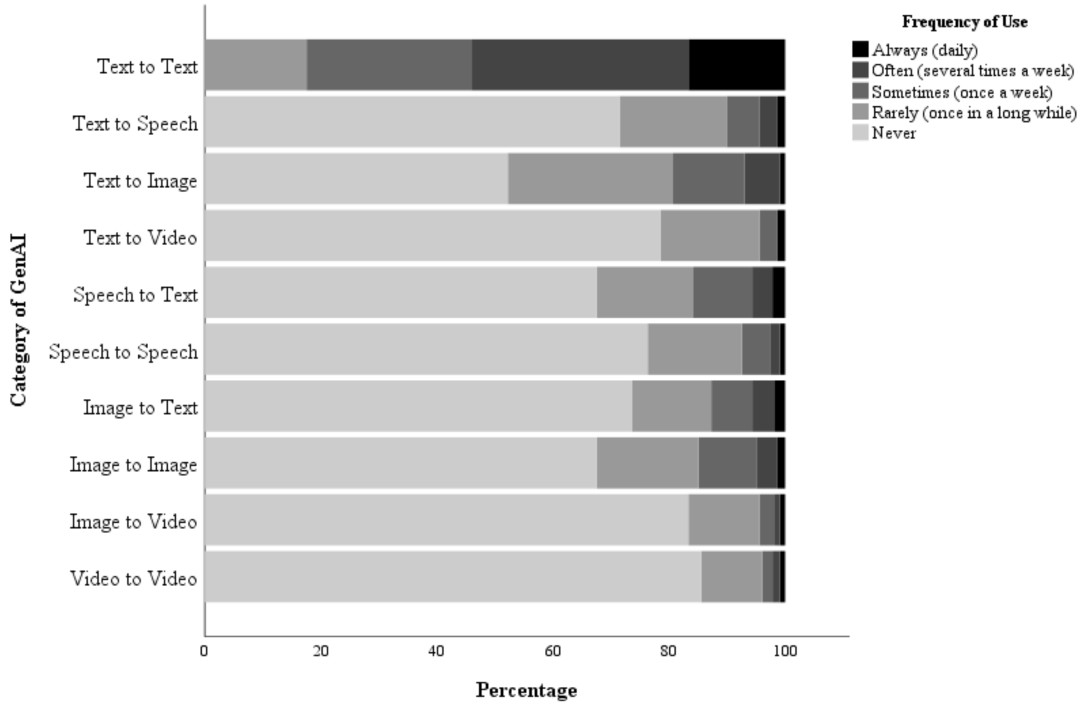

Figure 4-1 Stacked Bar Percentage of GenAI Category by Use Frequency

4.2. Measurement Model Assessment

Based on the hypotheses and collected data, **Figure 4-2** illustrates the initial results from SmartPLS 4.0. This figure visually displays two key components: the outer model, which includes the manifest variables that form the latent constructs, and inner model, which is the connection between these constructs. The figure also provides important details such as the strength of each variable (outer loadings), the strength and direction of relationships (path coefficients, also known as standard beta or β), and the R^2 values, which represent the coefficients of determination for the constructs being predicted.

In this study, the quality of the constructs is evaluated through the measurement model. This evaluation starts with the examination of indicator reliability, represented by factor loadings (Λ), and is followed by assessing the reliability and validity of the constructs. The results are displayed in **Table 4-3**.

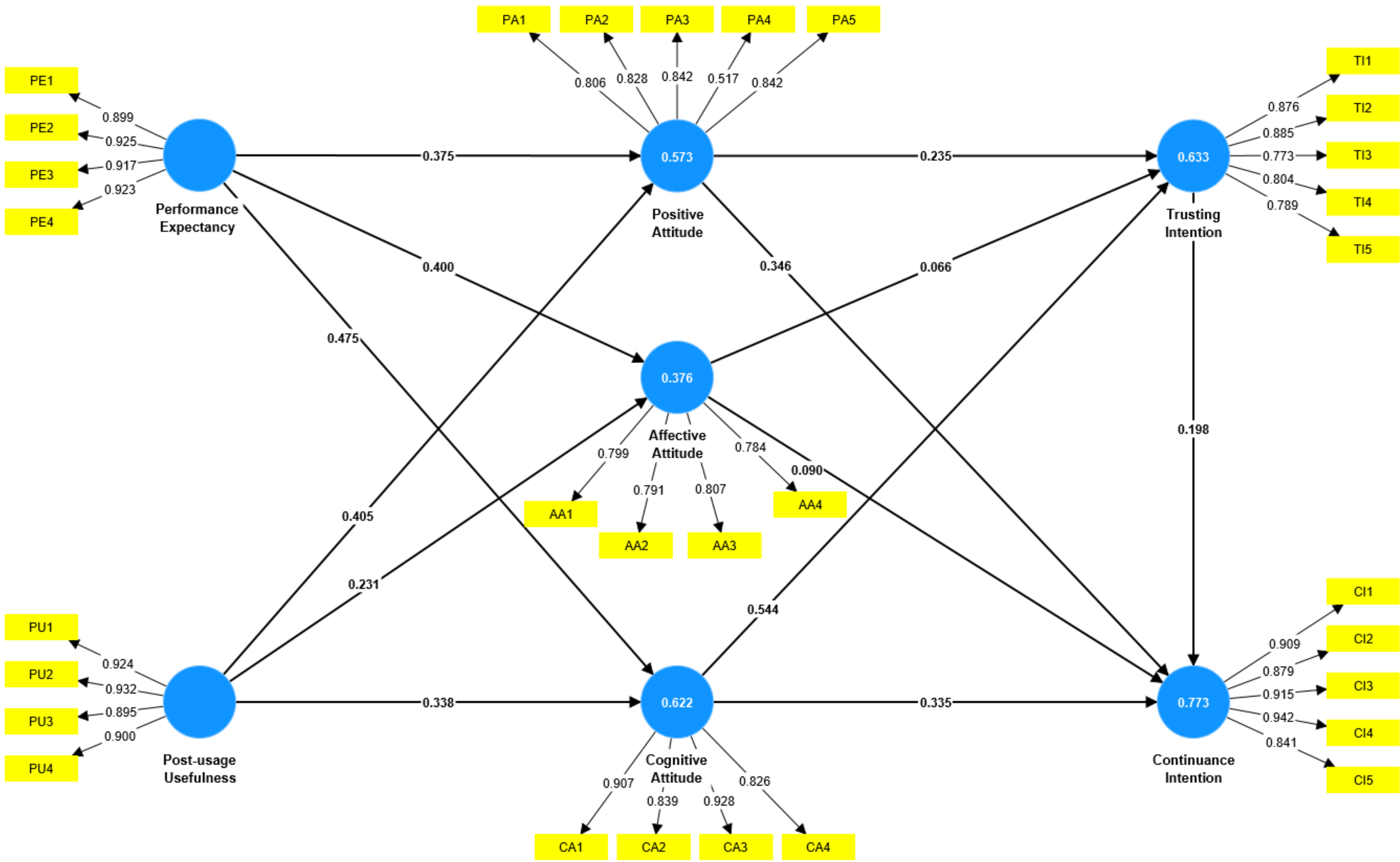

Figure 4-2 Initial Run of SmartPLS 4.0

Table 4-3 Loadings, Reliability, and Convergent Validity

Construct	Item	Λ	α	ρA	CR	AVE
Performance Expectancy	PE1	0.899	0.936	0.937	0.954	0.839
	PE2	0.925				
	PE3	0.917				
	PE4	0.923				
Post-usage Usefulness	PU1	0.924	0.933	0.935	0.952	0.833
	PU2	0.932				
	PU3	0.895				
	PU4	0.900				
Positive Attitude	PA1	0.806	0.828	0.861	0.881	0.604
	PA2	0.828				
	PA3	0.842				
	PA4	0.517				
	PA5	0.842				
Affective Attitude	AA1	0.799	0.807	0.808	0.873	0.633
	AA2	0.791				
	AA3	0.807				
	AA4	0.784				
Cognitive Attitude	CA1	0.907	0.898	0.904	0.929	0.767
	CA2	0.839				
	CA3	0.928				
	CA4	0.826				
Trusting Intention	TI1	0.876	0.884	0.893	0.915	0.683
	TI2	0.885				
	TI3	0.773				
	TI4	0.804				
	TI5	0.789				
Continuance Intention	CI1	0.909	0.940	0.941	0.954	0.806
	CI2	0.879				
	CI3	0.915				
	CI4	0.942				
	CI5	0.841				

4.2.1. Indicator Reliability

In evaluating the reflective measurement model, the first task is to assess the reliability of indicators. Indicator reliability measures the consistency of a variable, or a set of variables, represents what it is supposed to be measure (Urbach & Ahlemann, 2010). This reliability is checked by examining the loadings of reflective indicators. Loadings should ideally be 0.70 or higher, indicating that the construct explains a substantial portion (over 70%) of the variance of its indicators, thus confirming their reliability (Hair et al., 2019a). However, some indicators did not load significantly on their respective latent variables and were subsequently removed from the model (Gefen & Straub, 2005). For instance, the loading for the PA4 indicator was only 0.517, below the acceptable threshold, leading to its exclusion before rerunning the model. The rest of the indicators met the necessary threshold, indicating they effectively measure the latent variables. The revised model, including these indicator loadings, is shown in **Figure 4-3**.

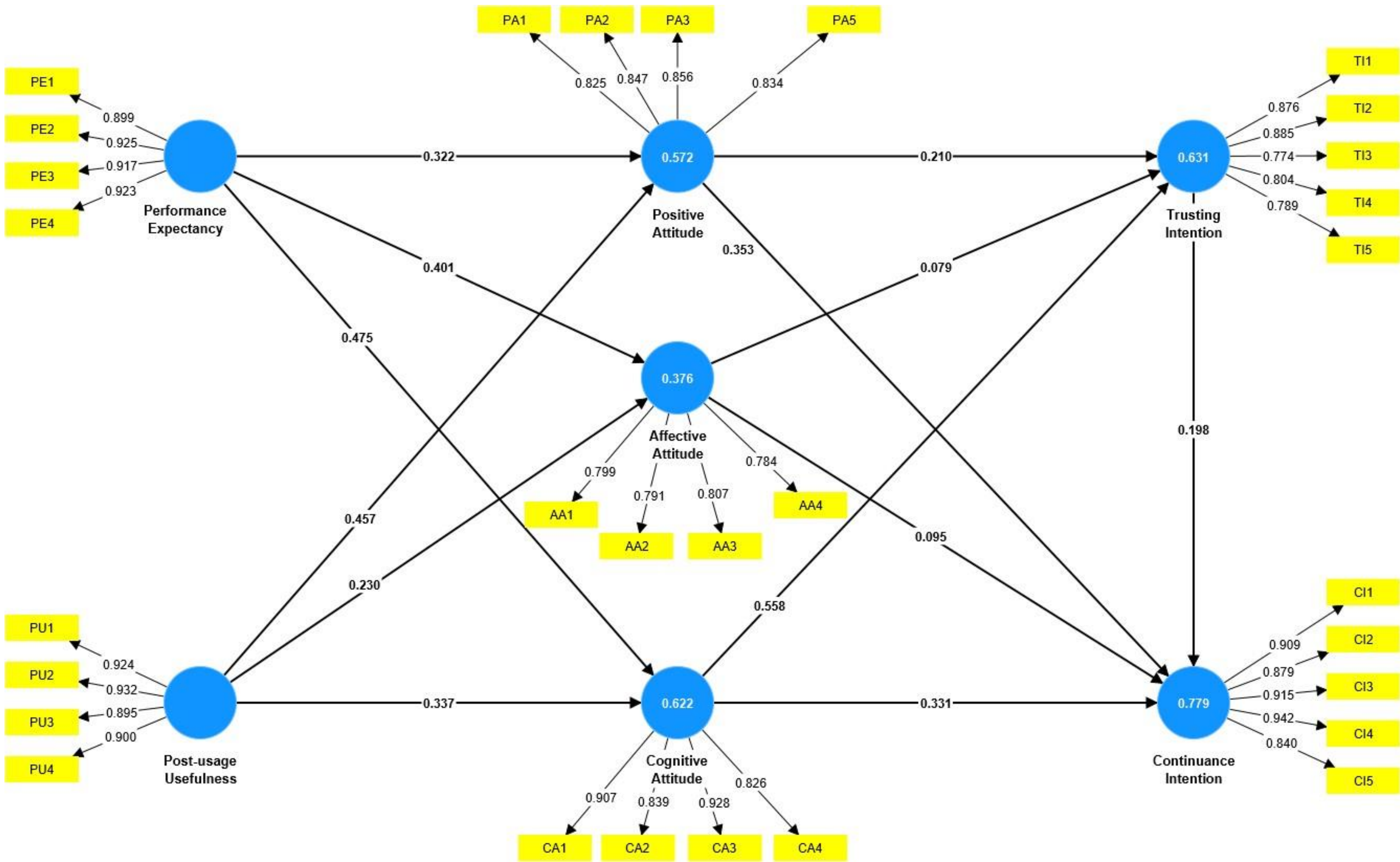

Figure 4-3 Indicator Loading After Factor Analysis

4.2.2. Construct Reliability

The second step in the assessment process is to check the internal consistency reliability, often using composite reliability (CR) as suggested by Jöreskog (1971). Higher CR values usually mean better reliability. For instance, values from 0.60 to 0.70 are acceptable for preliminary research, while 0.70 to 0.90 indicates satisfactory to good reliability. However, values above 0.95 can be problematic as they might suggest item redundancy, affecting the validity (Drolet & Morrison, 2001; Diamantopoulos et al., 2012). High values can also hint at response biases, leading to artificially high correlations. Another measure, Cronbach's alpha (α), also gauges internal consistency but tends to give lower values than CR because it treats all items equally without weighting. CR, on the other hand, weights items based on their individual loadings, resulting in higher values. While Cronbach's alpha might be more conservative and CR more liberal, the true reliability usually falls between these two. As a middle ground, Dijkstra and Henseler (2015) suggested *rhoA* (ρA), an approximate measure of reliability that lies between Cronbach's alpha and CR, offering a balanced option assuming the factor model is accurate.

4.2.3. Construct Validity

In the statistical method of PLS-SEM, construct validity is confirmed by demonstrating the presence of both convergent validity and divergent validity.

4.2.3.1. Convergent Validity

According to Hair et al. (2019a, p. 9), "Convergent validity is the extent to which the construct converges to explain the variance of its items." In another word, "Convergent validity is the degree to which multiple attempts to measure the same concept are in agreement. The idea is that two or more measures of the same thing should covary highly if they are valid measures of the concept" (Bagozzi et al., 1991, p. 425).

In term of the measurement, according to Hair et al. (2019a, p. 9), "The metric used for evaluating a construct's convergent validity is the average variance extracted (AVE) for all items on each construct. To calculate the AVE, one has to square the loading of each indicator on a construct and compute the mean value. An acceptable AVE is 0.50 or higher indicating that the construct explains at least 50 per cent of the variance of its items." If the AVE value is .50 or higher, as suggested by Fornell and

Larcker (1981), it indicates that the items effectively represent the construct they are intended to measure, thereby establishing convergent validity.

The convergent validity in this study, as indicated by the AVE statistics, shows that all constructs have values above .50. This means that convergent validity is confirmed, aligning with the criterion set by Hair et al. (2019a) that AVE of constructs should be at least 0.50. **Table 4-3** presents the AVE values for each construct.

4.2.3.2. Divergent (Discriminant) Validity

"Discriminant validity is the extent to which a construct is empirically distinct from other constructs in the structural model (Hair et al., 2019a, p. 9)." Fornell and Larcker (1981) introduced a standard method where the AVE for each construct is compared with its squared correlation with other constructs in the model, representing shared variance. For proper discriminant validity, the shared variance should not exceed the AVEs. **Table 4-4** displays both the discriminant validity and the correlation coefficients for each variable. The square roots of the AVEs, shown on the diagonal of the table, are greater than the correlation coefficients between the constructs.

Table 4-4 Discriminant Validity (Fornell and Larcker criterion)

	Affective Attitude	Cognitive Attitude	Continuance Intention	Performance Expectancy	Positive Attitude	Post-usage Usefulness	Trusting Intention
Affective Attitude	***0.795***						
Cognitive Attitude	0.740	***0.876***					
Continuance Intention	0.714	0.827	***0.898***				
Performance Expectancy	0.603	0.772	0.744	***0.916***			
Positive Attitude	0.699	0.770	0.812	0.725	***0.841***		
Post-usage Usefulness	0.583	0.756	0.746	0.881	0.741	***0.913***	
Trusting Intention	0.639	0.778	0.761	0.684	0.695	0.649	***0.827***

Recent studies suggest that the traditional metric for assessing discriminant validity, the Fornell-Larcker criterion, might not be the most effective. Henseler et al. (2015) pointed out that it falls short, especially when construct indicators have similar loadings (e.g. between 0.65 and 0.85). Instead, they introduced the heterotrait-monotrait (HTMT) ratio of correlations as an alternative (Voorhees et al., 2016).

HTMT is calculated by comparing the average correlations between items across different constructs to the mean correlations of items within the same construct. If the HTMT values are high, it indicates issues with discriminant validity. Henseler et al. (2015) suggest a threshold of 0.90 in cases where the constructs are very similar, such as *cognitive satisfaction* and *loyalty*. An HTMT value over 0.90 in these situations would imply a lack of discriminant validity.

When we first tested the HTMT, the results show that HTMT between *performance expectancy* and *post-usage usefulness* is higher than 0.90, cross loadings between these two constructs' items were checked. Two items (PE1 and PU4) were eliminated due to their strong correlation with other items in the opposing construct (Hair et al., 2019a). After these eliminations, as indicated in **Table 4-5**, we achieved discriminant validity.

Table 4-5 Discriminant Validity (Adjusted HTMT Correlation Matrix)

	AA	CA	CI	PE	PA	PU	TI
Affective Attitude							
Cognitive Attitude	0.870						
Continuance Intention	0.818	0.897					
Performance Expectancy	0.671	0.824	0.774				
Positive Attitude	0.832	0.856	0.893	0.767			
Post-usage Usefulness	0.622	0.789	0.753	0.895	0.788		
Trusting Intention	0.748	0.869	0.828	0.738	0.777	0.678	

Note: Affective Attitude (AA), Cognitive Attitude (CA), Continuance Intention (CI), Performance Expectancy (PE), Positive Attitude (PA), Post-usage Usefulness (PU), Trusting Intention (TI)

4.2.4. Cross Loadings

Cross loading checks whether an item from a specific construct aligns more strongly with its own construct rather than with others in the study. These results can be found in **Table 4-6**. The bold numbers are the item loadings, and they exceed the suggested threshold of 0.5. If an item's loading is higher for its own variable than for any other variable, it suggests that the constructs are distinct from each other, indicating discriminant validity. Therefore, the evaluation of cross-loadings confirms that discriminant validity has been achieved.

Table 4-6 Discriminant Validity (Cross Loading)

	Affective Attitude	Cognitive Attitude	Continuance Intention	Positive Attitude	Performance Expectancy	Post-usage Usefulness	Trusting Intention
AA1	**0.800**	0.604	0.618	0.590	0.499	0.477	0.549
AA2	**0.791**	0.528	0.580	0.581	0.472	0.445	0.462
AA3	**0.807**	0.615	0.522	0.514	0.452	0.395	0.544
AA4	**0.784**	0.608	0.544	0.535	0.427	0.391	0.472
CA1	0.622	**0.907**	0.736	0.710	0.737	0.729	0.674
CA2	0.734	**0.839**	0.767	0.713	0.632	0.588	0.667
CA3	0.644	**0.928**	0.766	0.717	0.698	0.674	0.727
CA4	0.595	**0.826**	0.620	0.540	0.567	0.527	0.657
CI1	0.632	0.764	**0.909**	0.778	0.713	0.672	0.722
CI2	0.651	0.783	**0.879**	0.717	0.639	0.595	0.706
CI3	0.625	0.731	**0.915**	0.696	0.641	0.660	0.671
CI4	0.669	0.751	**0.942**	0.775	0.664	0.670	0.688
CI5	0.626	0.678	**0.840**	0.671	0.588	0.552	0.626
PA1	0.539	0.537	0.634	**0.825**	0.542	0.597	0.504
PA2	0.577	0.591	0.640	**0.847**	0.557	0.560	0.537
PA3	0.605	0.601	0.660	**0.857**	0.520	0.564	0.553
PA5	0.620	0.817	0.772	**0.834**	0.690	0.646	0.710
PE2	0.583	0.731	0.697	0.645	**0.916**	0.755	0.650
PE3	0.544	0.695	0.685	0.668	**0.945**	0.776	0.634
PE4	0.505	0.688	0.645	0.633	**0.942**	0.791	0.608
PU1	0.516	0.678	0.659	0.656	0.780	**0.945**	0.583
PU2	0.485	0.673	0.667	0.661	0.780	**0.947**	0.577
PU3	0.505	0.668	0.637	0.660	0.754	**0.901**	0.583
TI1	0.612	0.691	0.677	0.594	0.590	0.572	**0.876**
TI2	0.597	0.732	0.724	0.692	0.686	0.670	**0.885**
TI3	0.491	0.600	0.633	0.552	0.529	0.493	**0.774**
TI4	0.461	0.607	0.535	0.513	0.468	0.445	**0.804**
TI5	0.454	0.566	0.552	0.493	0.490	0.352	**0.789**

4.3. Structural Model Assessment

After confirming that the measurement model is adequate, the next stage in examining PLS-SEM results involves evaluating the structural model. Key criteria to look in this assessment include the coefficient of determination (R^2), as well as the statistical significance and relevance of the path coefficients in the model.

4.3.1. Indicator Multicollinearity

Before conducting path analysis, it is important to check the structural model for collinearity, which is done by calculating the variance inflation factor (VIF). This factor, introduced by Fornell and Bookstein (1982), helps measure how much multicollinearity is in the model. The VIF is calculated by dividing the variance of the complete model, which includes several terms, by the variance of models with just one term at a time. As per Hair et al. (2019a), a VIF value under 5 indicates that multicollinearity isn't a major concern. The VIF values for the indicators in this study are shown in **Table 4-7**, and all are below the recommended threshold. This suggests that collinearity isn’t an issue, allowing the analysis to proceed.

Table 4-7 Multicollinearity Statistics (Inner VIF)

	VIF
Affective Attitude -> Continuance Intention	2.451
Affective Attitude -> Trusting Intention	2.434
Cognitive Attitude -> Continuance Intention	3.893
Cognitive Attitude -> Trusting Intention	3.049
Performance Expectancy -> Affective Attitude	3.184
Performance Expectancy -> Cognitive Attitude	3.184
Performance Expectancy -> Positive Attitude	3.184
Positive Attitude -> Continuance Intention	2.813
Positive Attitude -> Trusting Intention	2.694
Post-usage Usefulness -> Affective Attitude	3.184
Post-usage Usefulness -> Cognitive Attitude	3.184
Post-usage Usefulness -> Positive Attitude	3.184
Trusting Intention -> Continuance Intention	2.707

4.3.2. Explanatory Power

The ability of a model to explain the data it uses is measured by how well it fits that data, as shown by the PLS path model (Shmueli, 2010; Shmueli & Koppius, 2011; Shmueli et al., 2016). The coefficient of determination, or R^2 value, is a common way to assess this explanatory power (Hair et al., 2019a). This value shows how much the independent variables affect the dependent variable. R^2 values can range from 0 to 1, with higher values indicating better explanatory power (Hair Jr et al., 2022). Generally, R^2 values of 0.25, 0.50, and 0.75 are considered weak, moderate, and substantial, respectively (Henseler et al., 2009). **Table 4-8** presents the R^2 values for this model, showing they are within an acceptable range.

Table 4-8 Explanatory Power (R-squared)

	R-square	R-square adjusted	Explanatory Power
Positive Attitude	0.538	0.534	Moderate
Affective Attitude	0.350	0.344	Weak
Cognitive Attitude	0.600	0.597	Moderate
Trusting Intention	0.631	0.626	Moderate
Continuance Intention	0.779	0.775	Substantial

4.3.3. Structural Effect Size

Once the explanatory power of the structural model was evaluated, the impact of each path in the SEM was measured using Cohen's f^2. As per Cohen (1988), this effect size determines the significance of the influence that an independent construct exerts on a dependent construct. It gauges how much the dependent construct is affected by the independent one (Urbach & Ahlemann, 2010). In SmartPLS, f^2 values are calculated during the PLS algorithm run. Values of f^2 ranging from 0.020 to 0.150, 0.150 to 0.350, and above 0.350 indicate that the independent construct has a small, medium, or large effect, respectively, on the dependent construct (Chin, 1998; Gefen et al., 2000).

From **Table 4-9**, most of the items have small effect on the outcome. *Post-usage usefulness* has no effect on *affective attitude*, while *affective attitude* has no impact on both *trusting intention* and *continuance intention*. Three independent constructs have medium impact on their dependent constructs, those are *performance expectancy* to *cognitive attitude*, *positive attitude* to *continuance intention*, and *cognitive attitude* to *trusting intention*.

Table 4-9 Structural Effect Size (f-squared)

	f-square	Effect Size
Performance Expectancy -> Positive Attitude	0.081	Small
Performance Expectancy -> Affective Attitude	0.092	Small
Performance Expectancy -> Cognitive Attitude	0.195	Medium
Post-usage Usefulness -> Positive Attitude	0.121	Small
Post-usage Usefulness -> Affective Attitude	0.015	No effect
Post-usage Usefulness -> Cognitive Attitude	0.075	Small
Positive Attitude -> Trusting Intention	0.044	Small
Positive Attitude -> Continuance Intention	0.201	Medium
Affective Attitude -> Trusting Intention	0.007	No effect
Affective Attitude -> Continuance Intention	0.017	No effect
Cognitive Attitude -> Trusting Intention	0.277	Medium
Cognitive Attitude -> Continuance Intention	0.127	Small
Trusting Intention -> Continuance Intention	0.065	Small

4.3.4. Predictive Power

This study's predictive analysis uses Shmueli et al. (2019)'s PLSpredict method. According to Shmueli et al. (2019), PLSpredict involves using separate parts of the dataset — a training sample to estimate model parameters such as path coefficients, and a holdout sample for testing predictions. It predicts dependent variables in the holdout sample using estimates from the training sample. Predictions made for the training sample are called in-sample, while those for the holdout sample are out-of-sample. Close matches between actual and predicted values in the out-of-sample suggest high predictive power, whereas large differences indicate potential overfitting and low predictive power.

Shmueli et al. (2016) also propose an alternative benchmark considering the PLS path model's input layer, using a linear regression model (LM) to generate predictions, ignoring the model's structure. This analysis does not consider the measurement and structural theory. PLS-SEM-based predictions, which include the entire model structure, should outperform the LM benchmark, with greater improvements indicating better predictive power (Danks & Ray, 2018).

For predictive relevance in this study, both number of folds *k* and number of repetitions *r* and were set to 10 (i.e., ten folds and ten repetitions) as recommended by Shmueli et al. (2019). The $Q^2_{predict}$ values being over zero established predictive relevance, and RMSE (or MAE) values were compared with the LM benchmark. **Table 4-10** shows that RMSE and MAE values for PLS-SEM are lower than LM for most indicators, indicating that PLS-SEM has a medium predictive power for most indicators.

Table 4-10 Predictive Performance of the PLS Model Versus Benchmark LM

		PLS Predict			LM Predict		(LM-PLS)/PLS (%)	
Construct	Indicator	Q^2predict	RMSE	MAE	RMSE	MAE	RMSE	MAE
Positive Attitude	PA1	0.341	0.687	0.524	0.682	0.518	-0.73	-1.15
	PA2	0.328	0.803	0.600	0.819	0.611	1.99	1.83
	PA3	0.304	0.666	0.483	0.683	0.502	2.55	3.93
	PA5	0.464	0.768	0.562	0.775	0.534	0.91	-4.98
Affective Attitude	AA1	0.246	0.802	0.649	0.818	0.653	2.00	0.62
	AA2	0.218	0.884	0.699	0.900	0.708	1.81	1.29
	AA3	0.191	1.114	0.905	1.098	0.879	-1.44	-2.87
	AA4	0.170	0.962	0.765	0.987	0.786	2.60	2.75
Cognitive Attitude	CA1	0.573	0.728	0.566	0.719	0.539	-1.24	-4.77
	CA2	0.398	0.763	0.571	0.784	0.586	2.75	2.63
	CA3	0.503	0.709	0.548	0.727	0.551	2.54	0.55
	CA4	0.318	0.983	0.800	0.993	0.816	1.02	2.00
Continuance Intention	CI1	0.507	0.677	0.500	0.690	0.486	1.92	-2.80
	CI2	0.406	0.835	0.668	0.849	0.673	1.68	0.75
	CI3	0.447	0.805	0.596	0.803	0.579	-0.25	-2.85
	CI4	0.471	0.702	0.504	0.710	0.492	1.14	-2.38
	CI5	0.346	0.864	0.643	0.873	0.636	1.04	-1.09
Positive Attitude	PA1	0.341	0.687	0.524	0.682	0.518	-0.73	-1.15
	PA2	0.328	0.803	0.600	0.819	0.611	1.99	1.83
	PA3	0.304	0.666	0.483	0.683	0.502	2.55	3.93
	PA5	0.464	0.768	0.562	0.775	0.534	0.91	-4.98
Trusting Intention	TI1	0.360	0.907	0.739	0.907	0.728	0.00	-1.49
	TI2	0.475	0.778	0.645	0.778	0.625	0.00	-3.10
	TI3	0.276	0.970	0.782	0.997	0.795	2.78	1.66
	TI4	0.221	1.079	0.885	1.083	0.887	0.37	0.23
	TI5	0.193	1.100	0.879	1.083	0.873	-1.55	-0.68

Note: Gray-shaded values demonstrate indicators for which there is no improvement in predictive power of the PLS model over the LM benchmark.

4.4. Hypothesis Results (Direct Relationships)

After examining the explanatory and predictive power of the model, it was essential to assess the significance of the path coefficients linking the latent variables in the model (Urbach & Ahlemann, 2010). A bootstrapping algorithm was executed in SmartPLS, utilizing 5000 subsamples with a significance level of 0.05 (95%) for a one-tailed distribution. The bias-corrected and accelerated (BCa) bootstrap method was employed to determine the confidence intervals.

Table 4-11 Direct Relationship for Hypotheses Testing

Hypothesis	Relationship	Std beta	Std Error	|t-value|	p-value	Inference	5% CI LL	95% CI UL
H1a	PE -> PA	0.345	0.095	3.615	0.000	Accepted	0.192	0.502
H1b	PE -> AA	0.436	0.103	4.238	0.000	Accepted	0.269	0.606
H1c	PE -> CA	0.499	0.101	4.954	0.000	Accepted	0.324	0.655
H2a	PU -> PA	0.422	0.106	3.991	0.000	Accepted	0.231	0.581
H2b	PU -> AA	0.178	0.123	1.449	0.074	Rejected	-0.037	0.370
H2c	PU -> CA	0.310	0.103	3.018	0.001	Accepted	0.140	0.478
H3a	PA -> TI	0.210	0.066	3.180	0.001	Accepted	0.101	0.316
H3b	PA -> CI	0.353	0.057	6.251	0.000	Accepted	0.260	0.450
H4a	AA -> TI	0.079	0.061	1.296	0.098	Rejected	-0.021	0.177
H4b	AA -> CI	0.095	0.050	1.888	0.030	Accepted	0.016	0.179
H5a	CA -> TI	0.559	0.074	7.535	0.000	Accepted	0.433	0.676
H5b	CA -> CI	0.331	0.069	4.810	0.000	Accepted	0.217	0.443
H6	TI -> CI	0.198	0.058	3.429	0.000	Accepted	0.103	0.294

Note: Gray-shaded values demonstrate paths for which there is no improvement in predictive; Performance Expectancy (PE), Post-usage Usefulness (PU), Positive Attitude (PA), Affective Attitude (AA), Cognitive Attitude (CA), Trusting Intention (TI), Continuance Intention (CI)

Table 4-11 shows the hypothesis testing results. *Performance expectancy* positively impacts *positive attitude* (β = 0.345, p = 0.000), *affective attitude* (β = 0.436, p = 0.000), and *cognitive attitude* (β = 0.499, p = 0.000), therefore H1a, H1b, and H1c are verified. *Post-usage usefulness* positively influences *positive attitude* (β = 0.422, p = 0.000), and *cognitive attitude* (β = 0.310, p = 0.001), but does not significantly affect *affective attitude* (β = 0.178, p = 0.074). Consequently, H2a and H2c are supported, and H2b is rejected.

The results demonstrate that *positive attitude* positively impacts on *trusting intention* (β = 0.210, p = 0.001) and *continuance intention* (β = 0.353, p = 0.000), H3a and H3b are supported. Conversely, the effect of *affective attitude* on *trusting intention* is minimal (β = 0.079, p = 0.098), and H4a is rejected. Meanwhile, *affective attitude* positively affects *continuance intention* (β = 0.095, p = 0.030), and H4b is supported. *Cognitive attitude* was the most influential factor in increasing the *trusting intention* (β = 0.559, p = 0.000) and significantly positive affects *continuance intention* (β = 0.331, p = 0.000), confirming H5a and H5b. Lastly, *trusting intention* increased the *continuance intention* positively (β = 0.198, p = 0.000), verifying H6.

Chapter 5
DISCUSSION AND CONCLUSION

5.1. Findings

The hypothesis testing results reveal insightful patterns about students' attitudes toward GenAI. Notably, *performance expectancy* has a significant positive impact on all forms of attitude, i.e. *positive attitude*, *affective attitude*, and *cognitive attitude*. This indicates that the more students expect GenAI to perform well, the more positive, emotionally connected, and cognitively convinced they are about its usage. Concurrently, *post-usage usefulness* significantly influences *positive attitude* and *cognitive attitude*, suggesting that the stronger the belief that GenAI continue to be useful in studies purposes strengthen their overall positive attitudes and perceptions.

The positive impact of the *positive attitude* on both *trusting intention* and *continuance intention* aligns with the findings of prior studies (Davis, 1989; Hamari & Koivisto, 2015; Tussyadiah et al., 2017; Wu & Chen, 2017). The study also reveals that students' *cognitive attitude* positively influences the intention to trust and intention to continue using it, supports the studies by Lankton et al. (2014), Frost-Arnold (2014), and (Ma & Huo, 2023).

However, the *affective attitude*, which deals with emotional responses towards GenAI, may not be significantly influenced by *post-usage usefulness* as indicated in the hypothesis results. This could be due to the notion that emotional responses towards technology are less impacted by its utilitarian aspects, as suggested by Svenningsson et al. (2022) and Gado et al. (2022). Furthermore, the relationship between *affective attitude* and *trusting intention* was not supported, indicating a disconnect between students' emotional responses to GenAI and their trust in it.

The *affective attitude* does influence *continuance intention*, suggesting that emotions play a role in deciding to continue using GenAI. *Cognitive attitude* strongly impacts both *trusting intention* and *continuance intention*, underscoring the importance of cognitive processes in trust and continuance decisions. Lastly, *trusting intention* significantly influences *continuance intention*, suggesting that *trusting intention* is a key factor in students' intention to continue using GenAI.

In summary, the analysis of hypotheses has revealed that majority of the relationships suggested in the structural model are statistically significant and thus accepted. Two relationships, H2b and H4a, were not supported by the data and are rejected based on the p-values and confidence intervals. This suggests that while *performance expectancy* and *post-usage usefulness* significantly impact attitudes, the connections between *post-usage usefulness* and *affective attitude*, as well as between *affective attitude* and *trusting intention*, are less clear and require further investigation or theoretical consideration. Overall, these findings highlight the complex interplay of *performance expectancy*, *post-usage usefulness*, and various attitudes in shaping students' trust and continued intention to use GenAI.

5.2. Alternative Model and Interpretations

The most notable finding in the above analysis is the insignificant relationship between *affective attitude* and the other constructs. Given the findings, the model was updated by removing the H2b and H4a due to their insignificant path coefficient. H4b was also removed as the f-squared analysis showed that *affective attitude* has no effect on *continuance intention*.

Meanwhile, a new connection is added in the alternative model between *affective attitude* and *cognitive attitude*. According to Lindgaard et al. (2006), we often feel first and think later, especially when using technology. This idea is supported by other researchers in human-computer interaction, like Hassenzahl (2001) and Desmet and Hekkert (2007), who believe that our emotions about a technology come from how we think about it and its role in our lives. This is particularly relevant to our study, as it implies that Taiwanese students' first feelings about GenAI might influence how they think about its usefulness and relevance to their studies.

With this new focus, the alternative model now explores a direct link between students' emotions (*affective attitude*) and their thoughts (*cognitive attitude*) about GenAI. We want to see how their first impressions and feelings about GenAI might shape their later thoughts on its practicality and value for their education. This approach allows us to better understand the complex relationship between what students feel and think about using GenAI in their academic work. To test this possibility, the model of **Figure 5-1** was used to run on SmartPLS 4.0.

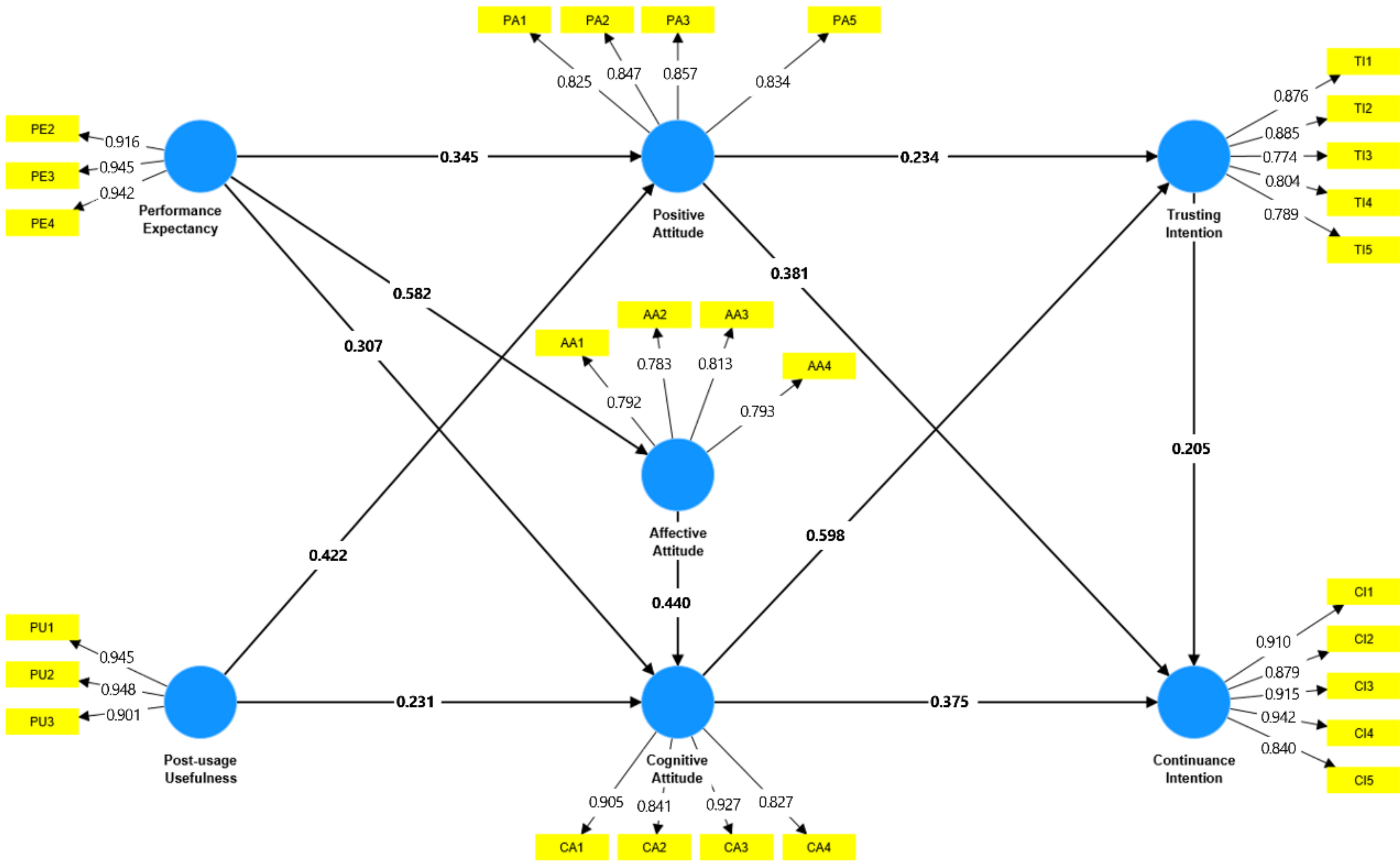

Figure 5-1 Alternative Model Run on SmartPLS 4.0

The indicator reliability is confirmed as the Cronbach's alpha (α), rhoA, and CR for all items are above 0.7. The AVE values exceed 0.5, while the model meets the Fornell-Larcker criterion, and the HTMT values are below 0.90. This means both convergent and discriminant validity are satisfactory. There are no collinearity issues, as all VIF measures are under 5. The coefficients of determination (R^2) and structural effect sizes (f^2) are within an acceptable range, and predictive relevance is established. In brief, based on these criteria, the model is valid as all constructs positively influence their subsequent constructs. Path coefficients are above 0.10 and significant, indicating that all relationships and paths, including the newly added hypothesis H7 (Affective Attitude -> Cognitive Attitude), are influential and significant. Therefore, the model can be accepted. **Table 5-1** represents the results of hypothetical assumptions for direct relationships.

Table 5-1 Hypotheses Testing for Alternative Model

Hypothesis	Relationship	Std beta	Std Error	|t-value|	P value	Inference	5% CI LL	95% CI UL
H1a	PE -> PA	0.345	0.095	3.615	0.000	Accepted	0.192	0.502
H1b	PE -> AA	0.582	0.052	11.173	0.000	Accepted	0.488	0.660
H1c	PE -> CA	0.307	0.086	3.581	0.000	Accepted	0.164	0.444
H2a	PU -> PA	0.422	0.106	3.989	0.000	Accepted	0.231	0.581
H2b	PU -> CA	0.231	0.080	2.880	0.002	Accepted	0.105	0.367
H3a	PA -> TI	0.234	0.063	3.693	0.000	Accepted	0.129	0.337
H3b	PA -> CI	0.381	0.056	6.856	0.000	Accepted	0.289	0.473
H5a	CA -> TI	0.598	0.064	9.344	0.000	Accepted	0.490	0.701
H5b	CA -> CI	0.375	0.067	5.577	0.000	Accepted	0.263	0.483
H6	TI -> CI	0.205	0.057	3.574	0.000	Accepted	0.108	0.299
H7	AA -> CA	0.440	0.053	8.305	0.000	Accepted	0.353	0.527

Note: Performance Expectancy (PE), Post-usage Usefulness (PU), Positive Attitude (PA), Affective Attitude (AA), Cognitive Attitude (CA), Trusting Intention (TI), Continuance Intention (CI)

5.3. Research Contributions

This study significantly contributes to the understanding of user acceptance of GenAI in educational settings. It offers a unique perspective by adapting the AIDUA model to include constructs like *post-usage usefulness* and trust, specifically tailored to the context of GenAI in university education. The research bridges a gap in existing literature by providing empirical evidence on how *post-usage usefulness* shape students' attitudes and intentions towards GenAI. Furthermore, it enhances managerial understanding by highlighting factors that educators and technology developers should consider for effective integration of GenAI in higher education.

5.3.1. Theoretical Implications

These findings make several contributions to the current literature. This is the first study to identify the *continuance intention* of GenAI by integrating the *post-usage usefulness*, *positive attitude*, and *trusting intention* constructs from previous studies. The strengths of the study included the in-depth analysis of the model, and built an alternative model based on the previous studies.

This study not only applies but potentially refines established AIDUA to the context of GenAI (Ma & Huo, 2023). It examines how constructs like *post-usage usefulness*, *positive attitude*, and *trusting intention* uniquely manifest in the realm of GenAI, thus extending the applicability of these models.

In addition, this study showcases the utility of PLS-SEM in dissecting complex relationships between various constructs related to technology acceptance, particularly in a novel area like GenAI. It provides a methodological model that future researchers can replicate or adapt in similar studies.

5.3.2. Managerial Implications

The findings of this study provide valuable insights into the perceptions of Taiwan university students regarding GenAI. Overall, the students exhibited a positive attitude towards incorporating GenAI into their learning experiences. Quantitative results indicate a willingness among students to continue using GenAI. These findings suggest that GenAI could revolutionize conventional education by offering personalized support, catering to diverse learning needs, enhancing effectiveness, and promoting self-directed learning (Chan & Hu, 2023).

In light of these results, it is recommended that educational institutions should focus more on investing in the development and incorporation of GenAI tools. Providing adequate support and resources is essential for effectively utilizing these technologies to their full potential. This suggestion is in line with the wider call in academic research for more support and direction in this area (Eke, 2023).

The findings from this study offer valuable guide for educators, policymakers, and technology developers aiming to better understand how students perceive and continued use of GenAI in educational settings. It is also important for tertiary education institutions to update their policies, course content, and teaching methods to ready students for a future where GenAI is common. This could include promoting learning across different subjects, focusing on critical reflection and imaginative skills, and enhancing education in digital skills and ethical consideration in AI. Also, it is crucial for GenAI users to use these technologies ethically and avoid causing harm to society.

5.3.3. Implications and Challenges of GenAI

The rising utilization of GenAI in education, notably ChatGPT, has sparked important discussions about its implications and challenges. Key among these is the concern that reliance on AI for tasks like take-home exams may compromise critical thinking and creativity. It is suggested that educational assessments should evolve to require more in-depth reasoning, focusing on students' analytical and creative skills (*NTHU Establishes Guidelines for AI in Education*, 2023).

Moreover, over-dependence on AI in decision-making is feared to diminish human cognitive abilities, suggesting a need for balanced use and proper training for educators and students in AI technologies (Ahmad et al., 2023). Utilizing tools such as ChatGPT can be entertaining by altering our interaction with computers. This shift highlights the necessity for further research to understand how cognitive and emotional factors influence our interactions with increasingly sophisticated chatbots and genuinely interactive conversational agents (Dwivedi et al., 2023).

As AI tools continue to evolve rapidly, ethical guidelines for their use in academic contexts must also adapt. Major journals and academic institutions are beginning to provide guidance on the use of AI in research and teaching. For instance, Nature has set principles for the use and attribution of AI-generated content, clarifying that AI does not qualify for authorship but its role should be acknowledged in research (*Preparing your material*, 2023). This reflects a broader trend where academic standards and practices are adjusting to the realities of advanced AI tools (Dwivedi et al., 2023).

5.4. Limitations and Future Research

There are certain limitations in this study that need to be kept in mind while considering the findings. Firstly, the relatively small sample size may restrict how well the results can be applied to the wider student population in Taiwan. Secondly, the lack of back-translation for questionnaires could lead to translation errors. The use of self-reported data might introduce biases, as participants may not accurately recalled their interactions with GenAI. The cross-sectional nature of the research does not capture insights into students' views on GenAI evolve with increased familiarity and experienced over time.

As GenAI is not commonly utilized in structured educational environments yet, students' experience to it is limited. This research did not examine the ways students are introduced to AI or GenAI’s direct consequence on their educational achievements, which are key to fully understanding how these technologies affect education. Also, it is important to acknowledge that this study did not directly address the darker aspects or potential negative consequences of GenAI, such as ethical concerns, misuse, and the impact on cognitive and critical thinking skills. This limitation highlights a crucial area for future research.

For future studies, it would be beneficial to use larger and more varied samples and to adopt long-term study designs to observe how students' views on GenAI change over time. Future research could concentrate on distinct student groups, varying in background, age, or cultural context, especially in relation to their AI literacy. Investigating the darker aspects of GenAI usage in education, such as its potential for promoting academic dishonesty or diminishing critical thinking skills, would also be a valuable direction for research.

In conclusion, this study serves as a starting point for future research on GenAI in educational contexts, laying the foundation for further investigations into various aspects of AI technology in learning environments. As recommended by Van Dis et al. (2023), future research could explore issues related to conversational AIs, such as how LLMs should be integrated into researchers' education and training. By addressing these areas, we can ensure responsible and effective use of these technologies in teaching and learning settings.

5.5. Conclusion

The primary aim of this research was to uncover the factors that influence university students' intention to continue using GenAI, focusing specifically on students from public universities in Taiwan. Representing a diverse range of academic fields and disciplines, the respondents in this study demonstrate the wide applicability of GenAI across various areas of study. The findings show that students' intention to continue using GenAI is influenced by two key factors: how much they expect GenAI to perform well (*performance expectancy*) and how useful they find it after using it (*post-usage usefulness*). Both of these factors have a positive impact on students' overall attitude toward GenAI, leading to a greater intention to trust and continue using GenAI.

This study underscores the significance of embracing GenAI in education and engaging with its advancements for beneficial changes. As Dwivedi et al. (2023) advocate, rather than the outright ban or dismissal of such technologies, we should aim for sustainable engagement with them. The research highlights how students perceive GenAI and its impact on their learning, resonating with Biggs (1999, 2003) findings that students' views greatly affect their learning outcomes. Favorable views typically lead to deeper learning, while negative views often result in a more superficial approach to learning. Thus, grasping students' perceptions regarding GenAI technologies is vital.

By focusing on what students think about GenAI, educators and policymakers can more effectively adapt these tools based on students' requirements and address their concerns, which is key for effective learning outcomes (Chan & Hu, 2023). Recognizing students' readiness and apprehensions about GenAI could help teachers effectively incorporate these tools into their classroom experiences, ensuring they support and strengthen conventional educating methods(Chan & Hu, 2023). Academics and educational institutions must be proactive in adapting their teaching, assessment methods, and ethical guidelines to this rapidly changing landscape.

In summary, this study contributes to understanding how Taiwan university students respond to GenAI. It provides insights into students' perceptions, attitudes, and intentions, shedding light on how GenAI can be integrated effectively into education. It is crucial to remember the saying, "AI won't replace humans, but humans with AI will replace humans without AI." This adage underscores the importance of staying updated with GenAI technologies, highlighting the need for both students and educators to engage actively with these advancements. While embracing GenAI's potential for social good, educators can better prepare students for a Gen-AI-powered future. Meanwhile, its deployment requires careful consideration of its impact on learning processes and academic integrity.

References

Abdelwahab, H. R., Rauf, A., & Chen, D. (2023). Business students' perceptions of Dutch higher educational institutions in preparing them for artificial intelligence work environments. *Industry and Higher Education*, *37*(1), 22-34. https://doi.org/10.1177/09504222221087614

Ahmad, S. F., Han, H., Alam, M. M., Rehmat, M. K., Irshad, M., Arraño-Muñoz, M., & Ariza-Montes, A. (2023). Impact of artificial intelligence on human loss in decision making, laziness and safety in education. *Humanities and Social Sciences Communications*, *10*(1), 311. https://doi.org/10.1057/s41599-023-01787-8

Al-Maroof, R. S., & Salloum, S. A. (2021). An Integrated Model of Continuous Intention to Use of Google Classroom. In M. Al-Emran, K. Shaalan, & A. E. Hassanien (Eds.), *Recent Advances in Intelligent Systems and Smart Applications* (pp. 311-335). Springer International Publishing. https://doi.org/10.1007/978-3-030-47411-9_18

Alhababha, M., Abu Ziden, A., Albdour, A., & Alsayyed, B. (2012). The Horse Before the Cart! The English Language Learners Experience of Using E-learning System. *International Journal of Emerging Technologies in Learning (iJET)*, *7*(2), 4-12.

Alhassan, M. D., Kolog, E. A., & Boateng, R. (2020). Effect of gratification on user attitude and continuance use of mobile payment services: a developing country context. *Journal of Systems and Information Technology*, *22*(4), 351-378. https://doi.org/10.1108/JSIT-01-2020-0010

Ambalov, I. A. (2021). An investigation of technology trust and habit in IT use continuance: a study of a social network. *Journal of Systems and Information Technology*, *23*(1), 53-81. https://doi.org/10.1108/JSIT-05-2019-0096

Ashfaq, M., Yun, J., Yu, S., & Loureiro, S. M. C. (2020). I, Chatbot: Modeling the determinants of users' satisfaction and continuance intention of AI-powered service agents. *Telematics and Informatics*, *54*, 101473. https://doi.org/https://doi.org/10.1016/j.tele.2020.101473

Atlas, S. (2023). *ChatGPT for Higher Education and Professional Development: A Guide to Conversational AI*. College of Business Faculty Publications, University of Rhode Island. https://digitalcommons.uri.edu/cba_facpubs/548

Aw, E. C.-X., Tan, G. W.-H., Cham, T.-H., Raman, R., & Ooi, K.-B. (2022). Alexa, what's on my shopping list? Transforming customer experience with digital voice assistants. *Technological Forecasting and Social Change*, *180*, 121711.

https://doi.org/https://doi.org/10.1016/j.techfore.2022.121711
Badri, S., Abrams, R., Caso, C., Cross, S., Ju, S., Metuku, A., Kanemoto, A., Tseng, C., Cheung, C., Chan, D., Liu, E., Lee, F., Liu, H., Chou, H., Wang, J., Su, J., Fong, K., Han, K., Wong, K., . . . Shen, Y. (2023). *ChatGPT: Unlocking the Potential of Large Language Models*. https://www.credit-suisse.com/media/assets/microsite/docs/securities-research/chatgpt.pdf
Bagozzi, R. P. (1978). The Construct Validity Of The Affective, Behavioral, And Cognitive Components Of Attitude By Analysis Of Covariance Structures. *Multivariate Behavioral Research*, *13*(1), 9-31. https://doi.org/10.1207/s15327906mbr1301_2
Bagozzi, R. P., Yi, Y., & Phillips, L. W. (1991). Assessing Construct Validity in Organizational Research. *Administrative Science Quarterly*, *36*(3), 421-458. https://doi.org/10.2307/2393203
Bailey, D., Southam, A., & Costley, J. (2021). Digital storytelling with chatbots: mapping L2 participation and perception patterns. *Interactive Technology and Smart Education*, *18*(1), 85-103. https://doi.org/10.1108/ITSE-08-2020-0170
Balakrishnan, J., Abed, S. S., & Jones, P. (2022). The role of meta-UTAUT factors, perceived anthropomorphism, perceived intelligence, and social self-efficacy in chatbot-based services? *Technological Forecasting and Social Change*, *180*, 121692. https://doi.org/https://doi.org/10.1016/j.techfore.2022.121692
Baron, N. S. (2023). Even kids are worried ChatGPT will make them lazy plagiarists, says a linguist who studies tech's effect on reading, writing and thinking. Retrieved January 18, 2023, from https://fortune.com/2023/01/19/what-is-chatgpt-ai-effect-cheating-plagiarism-laziness-education-kids-students/
Baskerville, R. L., & Myers, M. D. (2009). Fashion Waves in Information Systems Research and Practice. *MIS Quarterly*, *33*(4), 647-662. https://doi.org/10.2307/20650319
Battaglia, M. P. (2008). *Nonprobability Sampling*. SAGE Publications.
Benamati, J., Fuller, M. A., Serva, M. A., & Baroudi, J. (2010). Clarifying the Integration of Trust and TAM in E-Commerce Environments: Implications for Systems Design and Management. *IEEE Transactions on Engineering Management*, *57*(3), 380-393. https://doi.org/10.1109/TEM.2009.2023111
Berg, C. (2023). The Case for Generative AI in Scholarly Practice. https://ssrn.com/abstract=4407587
Bhattacherjee, A. (2001). Understanding Information Systems Continuance: An Expectation-Confirmation Model. *MIS Quarterly*, *25*(3), 351-370. https://doi.org/10.2307/3250921
Bhattacherjee, A., Perols, J., & Sanford, C. (2008). Information Technology

Continuance: A Theoretic Extension and Empirical Test. *Journal of Computer Information Systems*, *49*(1), 17-26. https://doi.org/10.1080/08874417.2008.11645302

Biever, C. (2023). ChatGPT broke the Turing test-the race is on for new ways to assess AI. *Nature*, *619*(7971), 686-689. https://doi.org/10.1038/d41586-023-02361-7

Biggs, J. (1999). What the Student Does: teaching for enhanced learning. *Higher Education Research & Development*, *18*(1), 57-75. https://doi.org/10.1080/0729436990180105

Biggs, J. (2003). *Teaching for Quality Learning at University*.

Biggs, J., Tang, C., & Kennedy, G. (2022). *Teaching for Quality Learning at University* (5th ed.). McGraw-hill education (UK).

Chan, C. K. Y. (2023). A comprehensive AI policy education framework for university teaching and learning. *International Journal of Educational Technology in Higher Education*, *20*(1), 38. https://doi.org/10.1186/s41239-023-00408-3

Chan, C. K. Y., & Hu, W. (2023). Students' voices on generative AI: perceptions, benefits, and challenges in higher education. *International Journal of Educational Technology in Higher Education*, *20*(1), 43. https://doi.org/10.1186/s41239-023-00411-8

Chan, C. K. Y., & Lee, K. K. W. (2023). The AI generation gap: Are Gen Z students more interested in adopting generative AI such as ChatGPT in teaching and learning than their Gen X and Millennial Generation teachers? *arXiv preprint arXiv:2305.02878*. https://doi.org/10.48550/arXiv.2305.02878

Chan, C. K. Y., & Zhou, W. (2023). Deconstructing Student Perceptions of Generative AI (GenAI) through an Expectancy Value Theory (EVT)-based Instrument. *arXiv preprint arXiv:2305.01186*. https://arxiv.org/abs/2305.01186

Chaves, A. P., & Gerosa, M. A. (2021). How Should My Chatbot Interact? A Survey on Social Characteristics in Human–Chatbot Interaction Design. *International Journal of Human–Computer Interaction*, *37*(8), 729-758. https://doi.org/10.1080/10447318.2020.1841438

Chen, S.-C., Yen, D. C., & Hwang, M. I. (2012). Factors influencing the continuance intention to the usage of Web 2.0: An empirical study. *Computers in Human Behavior*, *28*(3), 933-941. https://doi.org/https://doi.org/10.1016/j.chb.2011.12.014

Chen, S. C., Chen, H. H., & Chen, M. F. (2009). Determinants of satisfaction and continuance intention towards self-service technologies. *Industrial Management & Data Systems*, *109*(9), 1248-1263. https://doi.org/10.1108/02635570911002306

Chen, Y., Jensen, S., Albert, L. J., Gupta, S., & Lee, T. (2023). Artificial Intelligence (AI) Student Assistants in the Classroom: Designing Chatbots to Support Student Success. *Information Systems Frontiers*, *25*(1), 161-182. https://doi.org/10.1007/s10796-022-10291-4

Chi, O. H., Chi, C. G., Gursoy, D., & Nunkoo, R. (2023). Customers' acceptance of artificially intelligent service robots: The influence of trust and culture. *International Journal of Information Management*, *70*, 102623. https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2023.102623

Chin, W. W. (1998). The partial least squares approach for structural equation modeling. In *Modern methods for business research.* (pp. 295-336). Lawrence Erlbaum Associates Publishers.

Chin, W. W. (2003). *PLS-Graph user's guide (version 3.0)*. Soft Modeling Inc., Houston.

Choung, H., David, P., & Ross, A. (2023). Trust in AI and Its Role in the Acceptance of AI Technologies. *International Journal of Human–Computer Interaction*, *39*(9), 1727-1739. https://doi.org/10.1080/10447318.2022.2050543

Chui, M., Roberts, R., & Yee, L. (2022). Generative AI is here: How tools like ChatGPT could change your business. https://www.mckinsey.com/capabilities/quantumblac/our-insights/generative-ai-is-here-how-tools-like-chatgpt-could-change-your-business

Chui, M., Yee, L., Hall, B., Singla, A., & Sukharevsky, A. (2023). The state of AI in 2023: Generative AI's breakout year. https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai-in-2023-generative-ais-breakout-year#/

Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences* (2nd ed.). Lawrence Erlbaum Associates.

Cohen, J. (1992). A Power Primer. *Tutorials in Quantitative Methods for Psychology*, *112*. https://doi.org/10.1037/0033-2909.112.1.155

Creswell, A., White, T., Dumoulin, V., Arulkumaran, K., Sengupta, B., & Bharath, A. A. (2018). Generative Adversarial Networks: An Overview. *IEEE Signal Processing Magazine*, *35*(1), 53-65. https://doi.org/10.1109/MSP.2017.2765202

Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: the state of the field. *International Journal of Educational Technology in Higher Education*, *20*(1), 22. https://doi.org/10.1186/s41239-023-00392-8

Dabholkar, P. A. (1996). Consumer evaluations of new technology-based self-service options: An investigation of alternative models of service quality. *International Journal of Research in Marketing*, *13*(1), 29-51.

https://doi.org/https://doi.org/10.1016/0167-8116(95)00027-5

Dai, H. M., Teo, T., Rappa, N. A., & Huang, F. (2020). Explaining Chinese university students' continuance learning intention in the MOOC setting: A modified expectation confirmation model perspective. *Computers & Education*, *150*, 103850. https://doi.org/https://doi.org/10.1016/j.compedu.2020.103850

Danks, N. P., & Ray, S. (2018). Predictions from Partial Least Squares Models. In F. Ali, S. M. Rasoolimanesh, & C. Cobanoglu (Eds.), *Applying Partial Least Squares in Tourism and Hospitality Research* (pp. 35-52). Emerald Publishing Limited. https://doi.org/10.1108/978-1-78756-699-620181003

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, *13*(3), 319-340. https://doi.org/10.2307/249008

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. *Management Science*, *35*(8), 982-1003. https://doi.org/10.1287/mnsc.35.8.982

Dehouche, N., & Dehouche, K. (2023). What's in a text-to-image prompt? The potential of stable diffusion in visual arts education. *Heliyon*, *9*(6). https://doi.org/10.1016/j.heliyon.2023.e16757

Desmet, P., & Hekkert, P. (2007). Framework of Product Experience. *International Journal of Design*, *1*, 57-66.

Diamantopoulos, A., Sarstedt, M., Fuchs, C., Wilczynski, P., & Kaiser, S. (2012). Guidelines for choosing between multi-item and single-item scales for construct measurement: a predictive validity perspective. *Journal of the Academy of Marketing Science*, *40*(3), 434-449. https://doi.org/10.1007/s11747-011-0300-3

Dijkstra, T. K., & Henseler, J. (2015). Consistent Partial Least Squares Path Modeling. *MIS Quarterly*, *39*(2), 297-316. https://www.jstor.org/stable/26628355

Dikmen, M., & Burns, C. (2017, 5-8 Oct. 2017). Trust in autonomous vehicles: The case of Tesla Autopilot and Summon. 2017 IEEE International Conference on Systems, Man, and Cybernetics (SMC),

Dimitriadis, S., & Kyrezis, N. (2010). Linking trust to use intention for technology-enabled bank channels: The role of trusting intentions. *Psychology & Marketing*, *27*(8), 799-820. https://doi.org/https://doi.org/10.1002/mar.20358

Doll, W. J., Hendrickson, A., & Deng, X. (1998). Using Davis's Perceived Usefulness and Ease-of-use Instruments for Decision Making: A Confirmatory and Multigroup Invariance Analysis. *Decision Sciences*, *29*(4), 839-869. https://doi.org/https://doi.org/10.1111/j.1540-5915.1998.tb00879.x

Drolet, A. L., & Morrison, D. G. (2001). Do We Really Need Multiple-Item Measures in Service Research? *Journal of Service Research*, *3*(3), 196-204. https://doi.org/10.1177/109467050133001

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M. A., Al-Busaidi, A. S., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., . . . Wright, R. (2023). Opinion Paper: “So what if ChatGPT wrote it?” Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management*, *71*, 102642. https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2023.102642

Eke, D. O. (2023). ChatGPT and the rise of generative AI: Threat to academic integrity? *Journal of Responsible Technology*, *13*, 100060. https://doi.org/https://doi.org/10.1016/j.jrt.2023.100060

Eren, B. A. (2021). Determinants of customer satisfaction in chatbot use: evidence from a banking application in Turkey. *International Journal of Bank Marketing*, *39*(2), 294-311. https://doi.org/10.1108/IJBM-02-2020-0056

Essel, H. B., Vlachopoulos, D., Tachie-Menson, A., Johnson, E. E., & Baah, P. K. (2022). The impact of a virtual teaching assistant (chatbot) on students' learning in Ghanaian higher education. *International Journal of Educational Technology in Higher Education*, *19*(1), 57. https://doi.org/10.1186/s41239-022-00362-6

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention and behaviour: An introduction to theory and research* (Vol. 27).

Fornell, C., & Bookstein, F. L. (1982). Two Structural Equation Models: LISREL and PLS Applied to Consumer Exit-Voice Theory. *Journal of Marketing Research*, *19*(4), 440-452. https://doi.org/10.1177/002224378201900406

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, *18*(1), 39-50. https://doi.org/10.2307/3151312

Foroughi, B., Iranmanesh, M., Kuppusamy, M., Ganesan, Y., Ghobakhloo, M., & Senali, M. G. (2023). Determinants of continuance intention to use gamification applications for task management: an extension of technology continuance theory. *The Electronic Library*, *41*(2/3), 286-307. https://doi.org/10.1108/EL-05-2022-0108

Frost-Arnold, K. (2014). The cognitive attitude of rational trust. *Synthese*, *191*(9), 1957-1974. https://doi.org/10.1007/s11229-012-0151-6

Gado, S., Kempen, R., Lingelbach, K., & Bipp, T. (2022). Artificial intelligence in psychology: How can we enable psychology students to accept and use artificial intelligence? *Psychology Learning & Teaching*, *21*(1), 37-56. https://doi.org/10.1177/14757257211037149

Gambo, Y., & Shakir, M. Z. (2023). Evaluating students' experiences in self-regulated smart learning environment. *Education and Information Technologies*, *28*(1), 547-580. https://doi.org/10.1007/s10639-022-11126-0

Gartner. (2023). *What's New in Artificial Intelligence from the 2023 Gartner Hype Cycle*. Retrieved November 29, 2023 from https://www.gartner.com/en/articles/what-s-new-in-artificial-intelligence-from-the-2023-gartner-hype-cycle

Gayed, J. M., Carlon, M. K. J., Oriola, A. M., & Cross, J. S. (2022). Exploring an AI-based writing Assistant's impact on English language learners. *Computers and Education: Artificial Intelligence*, *3*, 100055. https://doi.org/https://doi.org/10.1016/j.caeai.2022.100055

Gefen, D., & Straub, D. (2005). A Practical Guide to Factorial Validity Using PLS-Graph: Tutorial and Annotated Example. *Communications of the Association for Information Systems*, *16*, 91-109. https://doi.org/10.17705/1CAIS.01605

Gefen, D., Straub, D., & Boudreau, M.-c. (2000). Structural Equation Modeling And Regression: Guidelines For Research Practice. *Communications of the Association for Information Systems*, *4*. https://doi.org/10.17705/1CAIS.00407

Gong, B., Nugent, J. P., Guest, W., Parker, W., Chang, P. J., Khosa, F., & Nicolaou, S. (2019). Influence of Artificial Intelligence on Canadian Medical Students' Preference for Radiology Specialty: ANational Survey Study. *Academic Radiology*, *26*(4), 566-577. https://doi.org/10.1016/j.acra.2018.10.007

Green Atkins, K., & Kim, Y. K. (2012). Smart shopping: conceptualization and measurement. *International Journal of Retail & Distribution Management*, *40*(5), 360-375. https://doi.org/10.1108/09590551211222349

Guidance for Use of Generative AI Tools for Teaching and Learning. (2023). National Taiwan University. Retrieved November 29, 2023 from https://www.dlc.ntu.edu.tw/en/ai-tools-en/

Gursoy, D., Chi, O. H., Lu, L., & Nunkoo, R. (2019). Consumers acceptance of artificially intelligent (AI) device use in service delivery. *International Journal of Information Management*, *49*, 157-169. https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2019.03.008

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019a). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2-24. https://doi.org/10.1108/EBR-11-2018-0203

Hair, J. F., Sarstedt, M., & Ringle, C. M. (2019b). Rethinking some of the rethinking of partial least squares. *European Journal of Marketing*, *53*(4), 566-584. https://doi.org/10.1108/EJM-10-2018-0665

Hair Jr, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). Sage Publications.

Hamari, J., & Koivisto, J. (2015). Why do people use gamification services? *International Journal of Information Management*, *35*(4), 419-431. https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2015.04.006

Hancock, P. A., Billings, D. R., Schaefer, K. E., Chen, J. Y. C., de Visser, E. J., & Parasuraman, R. (2011). A Meta-Analysis of Factors Affecting Trust in Human-Robot Interaction. *Human Factors*, *53*(5), 517-527. https://doi.org/10.1177/0018720811417254

Hari, H., Iyer, R., & Sampat, B. (2022). Customer Brand Engagement through Chatbots on Bank Websites– Examining the Antecedents and Consequences. *International Journal of Human–Computer Interaction*, *38*(13), 1212-1227. https://doi.org/10.1080/10447318.2021.1988487

Hassenzahl, M. (2001). The Effect of Perceived Hedonic Quality on Product Appealingness. *International Journal of Human–Computer Interaction*, *13*(4), 481-499. https://doi.org/10.1207/S15327590IJHC1304_07

Hengstler, M., Enkel, E., & Duelli, S. (2016). Applied artificial intelligence and trust—The case of autonomous vehicles and medical assistance devices. *Technological Forecasting and Social Change*, *105*, 105-120. https://doi.org/https://doi.org/10.1016/j.techfore.2015.12.014

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115-135. https://doi.org/10.1007/s11747-014-0403-8

Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. In R. R. Sinkovics & P. N. Ghauri (Eds.), *New Challenges to International Marketing* (Vol. 20, pp. 277-319). Emerald Group Publishing Limited. https://doi.org/10.1108/S1474-7979(2009)0000020014

Horton, A. (2023). John Oliver on new AI programs: 'The potential and the peril here are huge'. Retrieved January 18, 2024, from https://www.theguardian.com/tv-and-radio/2023/feb/27/john-oliver-new-ai-programs-potential-peril

Huang, D.-H., & Chueh, H.-E. (2021). Chatbot usage intention analysis: Veterinary consultation. *Journal of Innovation & Knowledge*, *6*(3), 135-144. https://doi.org/https://doi.org/10.1016/j.jik.2020.09.002

Huang, S. Y. B., & Lee, C.-J. (2022). Predicting continuance intention to fintech chatbot. *Computers in Human Behavior*, *129*, 107027. https://doi.org/https://doi.org/10.1016/j.chb.2021.107027

Hughes, J. S., Rice, S., Trafimow, D., & Clayton, K. (2009). The automated cockpit: A comparison of attitudes towards human and automated pilots. *Transportation Research Part F: Traffic Psychology and Behaviour*, *12*(5), 428-439. https://doi.org/https://doi.org/10.1016/j.trf.2009.08.004

Huo, W., Yuan, X., Li, X., Luo, W., Xie, J., & Shi, B. (2023). Increasing acceptance of medical AI: The role of medical staff participation in AI development. *International Journal of Medical Informatics*, *175*, 105073. https://doi.org/https://doi.org/10.1016/j.ijmedinf.2023.105073

Im, J., & Hancer, M. (2017). What Fosters Favorable Attitudes Toward Using Travel Mobile Applications? *Journal of Hospitality Marketing & Management*, *26*(4), 361-377. https://doi.org/10.1080/19368623.2017.1248805

Jiang, H., Cheng, Y., Yang, J., & Gao, S. (2022). AI-powered chatbot communication with customers: Dialogic interactions, satisfaction, engagement, and customer behavior. *Computers in Human Behavior*, *134*, 107329. https://doi.org/https://doi.org/10.1016/j.chb.2022.107329

Jin, S. V., & Youn, S. (2022). “They bought it, therefore I will buy it”: The effects of peer users' conversion as sales performance and entrepreneurial sellers' number of followers as relationship performance in mobile social commerce. *Computers in Human Behavior*, *131*, 107212. https://doi.org/https://doi.org/10.1016/j.chb.2022.107212

Jin, S. V., & Youn, S. (2023). Social Presence and Imagery Processing as Predictors of Chatbot Continuance Intention in Human-AI-Interaction. *International Journal of Human–Computer Interaction*, *39*(9), 1874-1886. https://doi.org/10.1080/10447318.2022.2129277

Jo, H. (2022). Continuance intention to use artificial intelligence personal assistant: type, gender, and use experience [Article]. *Heliyon*, *8*(9), 13, Article e10662. https://doi.org/10.1016/j.heliyon.2022.e10662

Jöreskog, K. G. (1971). Simultaneous factor analysis in several populations. *Psychometrika*, *36*(4), 409-426. https://doi.org/10.1007/BF02291366

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

Kim, J., Merrill Jr, K., & Collins, C. (2021). AI as a friend or assistant: The mediating role of perceived usefulness in social AI vs. functional AI. *Telematics and Informatics*, *64*, 101694.

https://doi.org/https://doi.org/10.1016/j.tele.2021.101694
Korn, J., & Kelly, S. (2023). New York City public schools ban access to AI tool that could help students cheat. Retrieved January 18, 2024, from https://edition.cnn.com/2023/01/05/tech/chatgpt-nyc-school-ban/index.html
Kwangsawad, A., & Jattamart, A. (2022). Overcoming customer innovation resistance to the sustainable adoption of chatbot services: A community-enterprise perspective in Thailand. *Journal of Innovation & Knowledge*, *7*(3), 100211. https://doi.org/https://doi.org/10.1016/j.jik.2022.100211
Lai, P. C., & Tong, D. L. (2022). An Artificial Intelligence-Based Approach to Model User Behavior on the Adoption of E-Payment. In P. C. Lai (Ed.), *Handbook of Research on Social Impacts of E-Payment and Blockchain Technology* (pp. 1-15). IGI Global. https://doi.org/10.4018/978-1-7998-9035-5.ch001
Lankton, N., McKnight, D. H., & Thatcher, J. B. (2014). Incorporating trust-in-technology into Expectation Disconfirmation Theory. *The Journal of Strategic Information Systems*, *23*(2), 128-145. https://doi.org/https://doi.org/10.1016/j.jsis.2013.09.001
Lankton, N. K., McKnight, D. H., & Tripp, J. (2015). Technology, Humanness, and Trust: Rethinking Trust in Technology. *JOURNAL OF THE ASSOCIATION FOR INFORMATION SYSTEMS*, *16*(10), 880-918. https://doi.org/10.17705/1jais.00411
Le, D., Pratt, M., Wang, Y., Scott, N., & Lohmann, G. (2020). How to win the consumer's heart? Exploring appraisal determinants of consumer pre-consumption emotions. *International Journal of Hospitality Management*, *88*, 102542. https://doi.org/https://doi.org/10.1016/j.ijhm.2020.102542
Lee, B., & Cranage, D. A. (2018). Causal Attributions and Overall Blame of Self-Service Technology (SST) Failure: Different from Service Failures by Employee and Policy. *Journal of Hospitality Marketing & Management*, *27*(1), 61-84. https://doi.org/10.1080/19368623.2017.1337539
Lee, J.-C., Tang, Y., & Jiang, S. (2023). Understanding continuance intention of artificial intelligence (AI)-enabled mobile banking applications: an extension of AI characteristics to an expectation confirmation model. *Humanities and Social Sciences Communications*, *10*(1), 333. https://doi.org/10.1057/s41599-023-01845-1
Lee, S.-Y. T., Kim, H.-W., & Gupta, S. (2009). Measuring open source software success. *Omega*, *37*(2), 426-438. https://doi.org/https://doi.org/10.1016/j.omega.2007.05.005
Lee, S., Ha, S., & Widdows, R. (2011). Consumer responses to high-technology products: Product attributes, cognition, and emotions. *Journal of Business*

Research, *64*(11), 1195-1200. https://doi.org/https://doi.org/10.1016/j.jbusres.2011.06.022

Lee, Y.-F., Hwang, G.-J., & Chen, P.-Y. (2022). Impacts of an AI-based chabot on college students' after-class review, academic performance, self-efficacy, learning attitude, and motivation. *Educational technology research and development*, *70*(5), 1843-1865. https://doi.org/10.1007/s11423-022-10142-8

Lee, Y., Chen, A. N. K., & Ilie, V. (2012). Can Online Wait Be Managed? The Effect of Filler Interfaces and Presentation Modes on Perceived Waiting Time Online. *MIS Quarterly*, *36*(2), 365-394. https://doi.org/10.2307/41703460

Lei, S. I., Shen, H., & Ye, S. (2021). A comparison between chatbot and human service: customer perception and reuse intention. *International Journal of Contemporary Hospitality Management*, *33*(11), 3977-3995. https://doi.org/10.1108/IJCHM-12-2020-1399

Li, J., Cao, H., Lin, L., Hou, Y., Zhu, R., & Ali, A. E. (2023). User Experience Design Professionals' Perceptions of Generative Artificial Intelligence. *arXiv preprint arXiv:2309.15237*, *1*.

Li, M., & Wang, R. (2023). Chatbots in e-commerce: The effect of chatbot language style on customers' continuance usage intention and attitude toward brand. *Journal of Retailing and Consumer Services*, *71*, 103209. https://doi.org/https://doi.org/10.1016/j.jretconser.2022.103209

Li, X., Hess, T. J., & Valacich, J. S. (2008). Why do we trust new technology? A study of initial trust formation with organizational information systems. *The Journal of Strategic Information Systems*, *17*(1), 39-71. https://doi.org/https://doi.org/10.1016/j.jsis.2008.01.001

Lin, H., Chi, O. H., & Gursoy, D. (2020). Antecedents of customers' acceptance of artificially intelligent robotic device use in hospitality services. *Journal of Hospitality Marketing & Management*, *29*(5), 530-549. https://doi.org/10.1080/19368623.2020.1685053

Lin, W.-S., & Wang, C.-H. (2012). Antecedences to continued intentions of adopting e-learning system in blended learning instruction: A contingency framework based on models of information system success and task-technology fit. *Computers & Education*, *58*(1), 88-99. https://doi.org/https://doi.org/10.1016/j.compedu.2011.07.008

Lindgaard, G., Fernandes, G., Dudek, C., & Brown, J. (2006). Attention web designers: You have 50 milliseconds to make a good first impression! *Behaviour & Information Technology*, *25*(2), 115-126. https://doi.org/10.1080/01449290500330448

Looije, R., Neerincx, M. A., & Cnossen, F. (2010). Persuasive robotic assistant for health self-management of older adults: Design and evaluation of social behaviors. *International Journal of Human-Computer Studies*, *68*(6), 386-397. https://doi.org/https://doi.org/10.1016/j.ijhcs.2009.08.007

Lv, X., Luo, J., Liang, Y., Liu, Y., & Li, C. (2022). Is cuteness irresistible? The impact of cuteness on customers' intentions to use AI applications. *Tourism Management*, *90*, 104472. https://doi.org/https://doi.org/10.1016/j.tourman.2021.104472

M Fishbein, a., & Ajzen, I. (1972). Attitudes and Opinions. *Annual Review of Psychology*, *23*(1), 487-544. https://doi.org/10.1146/annurev.ps.23.020172.002415

Ma, X., & Huo, Y. (2023). Are users willing to embrace ChatGPT? Exploring the factors on the acceptance of chatbots from the perspective of AIDUA framework. *Technology in Society*, *75*, 102362. https://doi.org/https://doi.org/10.1016/j.techsoc.2023.102362

Maheshwari, G. (2023). Factors influencing students' intention to adopt and use ChatGPT in higher education: A study in the Vietnamese context. *Education and Information Technologies*. https://doi.org/10.1007/s10639-023-12333-z

Májovský, M., Černý, M., Kasal, M., Komarc, M., & Netuka, D. (2023). Artificial Intelligence Can Generate Fraudulent but Authentic-Looking Scientific Medical Articles: Pandora's Box Has Been Opened. *J Med Internet Res*, *25*, e46924. https://doi.org/10.2196/46924

Malhotra, N. K., & Das, S. (2020). *Marketing Research: An Applied Orientation* (7th ed.). Pearson Education.

Manser Payne, E., Peltier, J. W., & Barger, V. A. (2018). Mobile banking and AI-enabled mobile banking. *Journal of Research in Interactive Marketing*, *12*(3), 328-346. https://doi.org/10.1108/JRIM-07-2018-0087

Mantello, P., Ho, M.-T., Nguyen, M.-H., & Vuong, Q.-H. (2021). Bosses without a heart: socio-demographic and cross-cultural determinants of attitude toward Emotional AI in the workplace. *AI & SOCIETY*, *38*(1), 97-119. https://doi.org/10.1007/s00146-021-01290-1

McKnight, D., Carter, M., Thatcher, J., & Clay, P. (2011). Trust in a specific technology: An Investigation of its Components and Measures. *ACM Transactions on Management Information Systems*, *2*, 12-32. https://doi.org/10.1145/1985347.1985353

McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). Developing and validating trust measures for e-commerce: An integrative typology [Review]. *Information Systems Research*, *13*(3), 334-359. https://doi.org/10.1287/isre.13.3.334.81

Meilleur, C. (2023, September 14, 2023). *10 categories of generative AI tools*. Retrieved November 18, 2023 from https://knowledgeone.ca/10-categories-of-generative-ai-tools/

Metsärinne, M., & Kallio, M. (2016). How are students' attitudes related to learning outcomes? *International Journal of Technology and Design Education*, *26*(3), 353-371. https://doi.org/10.1007/s10798-015-9317-0

Milmo, D. (2023). *ChatGPT reaches 100 million users two months after launch*. The Guardian. Retrieved December 2, 2023 from https://www.theguardian.com/technology/2023/feb/02/chatgpt-100-million-users-open-ai-fastest-growing-app

Miyazaki, K., Murayama, T., Uchiba, T., An, J., & Kwak, H. (2023). Public Perception of Generative AI on Twitter: An Empirical Study Based on Occupation and Usage. *arXiv preprint arXiv:2305.09537*. https://arxiv.org/abs/2305.09537

Mogaji, E., Balakrishnan, J., Nwoba, A. C., & Nguyen, N. P. (2021). Emerging-market consumers' interactions with banking chatbots. *Telematics and Informatics*, *65*, 101711. https://doi.org/https://doi.org/10.1016/j.tele.2021.101711

Mostafa, R. B., & Kasamani, T. (2022). Antecedents and consequences of chatbot initial trust. *European Journal of Marketing*, *56*(6), 1748-1771. https://doi.org/10.1108/EJM-02-2020-0084

Mou, Y., & Xu, K. (2017). The media inequality: Comparing the initial human-human and human-AI social interactions. *Computers in Human Behavior*, *72*, 432-440. https://doi.org/https://doi.org/10.1016/j.chb.2017.02.067

Niu, B., & Mvondo, G. F. N. (2024). I Am ChatGPT, the ultimate AI Chatbot! Investigating the determinants of users' loyalty and ethical usage concerns of ChatGPT. *Journal of Retailing and Consumer Services*, *76*, 103562. https://doi.org/https://doi.org/10.1016/j.jretconser.2023.103562

NTHU Establishes Guidelines for AI in Education. (2023). National Tsing Hua University. Retrieved November 29, 2023 from https://nthu-en.site.nthu.edu.tw/p/406-1003-249686,r4806.php

Parasuraman, A. (2000). Technology Readiness Index (Tri):A Multiple-Item Scale to Measure Readiness to Embrace New Technologies. *Journal of Service Research*, *2*(4), 307-320. https://doi.org/10.1177/109467050024001

Park, E., & Joon Kim, K. (2013). User acceptance of long-term evolution (LTE) services. *Program: electronic library and information systems*, *47*(2), 188-205. https://doi.org/10.1108/00330331311313762

Patil, H., & Undale, S. (2023). Willingness of university students to continue using e-

Learning platforms after compelled adoption of technology: Test of an extended UTAUT model. *Education and Information Technologies*. https://doi.org/10.1007/s10639-023-11778-6

Pérez Pérez, M., Martínez Sánchez, A., de Luis Carnicer, P., & José Vela Jiménez, M. (2004). A technology acceptance model of innovation adoption: the case of teleworking. *European Journal of Innovation Management*, *7*(4), 280-291. https://doi.org/10.1108/14601060410565038

Posner, T., & Li, F.-F. (2020). AI will change the world, so it's time to change AI. *Nature*, *588*. https://doi.org/10.1038/d41586-020-03412-z

Preparing your material. (2023). Nature. https://www.nature.com/nbt/submission-guidelines/preparing-your-submission

Przymuszała, P., Cerbin-Koczorowska, M., Marciniak-Stępak, P., Zielińska-Tomczak, Ł., Piszczek, M., Jasiński, J., & Marciniak, R. (2021). Affective and cognitive components of students' attitudes towards communication learning - validation of the Communication Skills Attitude Scale in a cohort of polish medical students. *BMC Medical Education*, *21*(1), 190. https://doi.org/10.1186/s12909-021-02626-7

Rese, A., Ganster, L., & Baier, D. (2020). Chatbots in retailers' customer communication: How to measure their acceptance? *Journal of Retailing and Consumer Services*, *56*, 102176. https://doi.org/https://doi.org/10.1016/j.jretconser.2020.102176

Rezaei, S., Kalantari Shahijan, M., Amin, M., & Wan Ismail, W. K. (2016). Determinants of App Stores Continuance Behavior: A PLS Path Modelling Approach. *Journal of Internet Commerce*, *15*, 408-440. https://doi.org/10.1080/15332861.2016.1256749

Rezaei, S., & Valaei, N. (2017). Crafting experiential value via smartphone apps channel [Article]. *Marketing Intelligence & Planning*, *35*(5), 688-702. https://doi.org/10.1108/mip-08-2016-0141

Ribeiro, M. A., Gursoy, D., & Chi, O. H. (2022). Customer Acceptance of Autonomous Vehicles in Travel and Tourism. *Journal of Travel Research*, *61*(3), 620-636. https://doi.org/10.1177/0047287521993578

Ringle, C. M., Wende, S., & Becker, J.-M. (2015). *SmartPLS 3*. SmartPLS, Bönningstedt.

Ringle, C. M., Wende, S., & Will. (2005). *SmartPLS 2*. SmartPLS, Hamburg.

Russo, D. (2023). Navigating the complexity of generative ai adoption in software engineering. *arXiv preprint arXiv:2307.06081*.

Sarkar, S., Araiza-Illan, D., & Eder, K. (2017). Effects of Faults, Experience, and Personality on Trust in a Robot Co-Worker.

Sarstedt, M., Ringle, C. M., & Hair, J. F. (2022). Partial Least Squares Structural Equation Modeling. In C. Homburg, M. Klarmann, & A. Vomberg (Eds.), *Handbook of Market Research* (pp. 587-632). Springer International Publishing. https://doi.org/10.1007/978-3-319-57413-4_15

Saunders, M., Lewis, P., & Thornhill, A. (2019). *Research Methods for Business Students* (8th ed.). Pearson Education Limited, Harlow, Essex, England.

Schepman, A., & Rodway, P. (2020). Initial validation of the general attitudes towards Artificial Intelligence Scale. *Computers in Human Behavior Reports*, *1*, 100014. https://doi.org/https://doi.org/10.1016/j.chbr.2020.100014

Schepman, A., & Rodway, P. (2023). The General Attitudes towards Artificial Intelligence Scale (GAAIS): Confirmatory Validation and Associations with Personality, Corporate Distrust, and General Trust. *International Journal of Human–Computer Interaction*, *39*(13), 2724-2741. https://doi.org/10.1080/10447318.2022.2085400

Sekaran, U., & Bougie, R. (2016). *Research Methods For Business: A Skill Building Approach* (7th ed.). John Wiley & Sons.

Shin, D. (2021). The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI. *International Journal of Human-Computer Studies*, *146*, 102551. https://doi.org/https://doi.org/10.1016/j.ijhcs.2020.102551

Shmueli, G. (2010). To Explain or to Predict? *Statistical Science*, *25*. https://doi.org/10.1214/10-STS330

Shmueli, G., & Koppius, O. R. (2011). Predictive Analytics in Information Systems Research. *MIS Quarterly*, *35*(3), 553-572. https://doi.org/10.2307/23042796

Shmueli, G., Ray, S., Velasquez Estrada, J. M., & Chatla, S. B. (2016). The elephant in the room: Predictive performance of PLS models. *Journal of Business Research*, *69*(10), 4552-4564. https://doi.org/https://doi.org/10.1016/j.jbusres.2016.03.049

Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J.-H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: guidelines for using PLSpredict. *European Journal of Marketing*, *53*(11), 2322-2347. https://doi.org/10.1108/EJM-02-2019-0189

Similarweb. (2023, June 21, 2023). *ChatGPT Tops 25 Million Daily Visits*. Retrieved December 2, 2023 from https://www.similarweb.com/blog/insights/ai-news/chatgpt-25-million/

Sit, C., Srinivasan, R., Amlani, A., Muthuswamy, K., Azam, A., Monzon, L., & Poon, D. S. (2020). Attitudes and perceptions of UK medical students towards artificial intelligence and radiology: a multicentre survey. *Insights into*

Imaging, *11*(1), 14. https://doi.org/10.1186/s13244-019-0830-7
Soper, D. S. (2020). *A-priori sample size calculator for structural equation models [Software]*. https://www.danielsoper.com/statcalc/
Stokel-Walker, C. (2023). ChatGPT listed as author on research papers: many scientists disapprove. *Nature*, *613*. Retrieved January 18, 2024, from
Strzelecki, A. (2023). To use or not to use ChatGPT in higher education? A study of students' acceptance and use of technology. *Interactive Learning Environments*, 1-14. https://doi.org/10.1080/10494820.2023.2209881
Suh, W., & Ahn, S. (2022). Development and Validation of a Scale Measuring Student Attitudes Toward Artificial Intelligence. *SAGE Open*, *12*(2), 21582440221100463. https://doi.org/10.1177/21582440221100463
Sun, Y., Li, S., & Yu, L. (2022). The dark sides of AI personal assistant: effects of service failure on user continuance intention. *Electronic Markets*, *32*(1), 17-39. https://doi.org/10.1007/s12525-021-00483-2
Suseno, Y., Chang, C., Hudik, M., & Fang, E. S. (2022). Beliefs, anxiety and change readiness for artificial intelligence adoption among human resource managers: the moderating role of high-performance work systems. *The International Journal of Human Resource Management*, *33*(6), 1209-1236. https://doi.org/10.1080/09585192.2021.1931408
Svenningsson, J., Höst, G., Hultén, M., & Hallström, J. (2022). Students' attitudes toward technology: exploring the relationship among affective, cognitive and behavioral components of the attitude construct. *International Journal of Technology and Design Education*, *32*(3), 1531-1551. https://doi.org/10.1007/s10798-021-09657-7
Tao, Y.-H., Cheng, C.-J., & Sun, S.-Y. (2009). What influences college students to continue using business simulation games? The Taiwan experience. *Computers & Education*, *53*(3), 929-939. https://doi.org/https://doi.org/10.1016/j.compedu.2009.05.009
Terblanche, N., Molyn, J., Williams, K., & Maritz, J. (2023). Performance matters: students' perceptions of Artificial Intelligence Coach adoption factors. *Coaching: An International Journal of Theory, Research and Practice*, *16*(1), 100-114. https://doi.org/10.1080/17521882.2022.2094278
Tussyadiah, I. P., Zach, F. J., & Wang, J. (2017). Attitudes Toward Autonomous on Demand Mobility System: The Case of Self-Driving Taxi. In R. Schegg & B. Stangl, *Information and Communication Technologies in Tourism 2017* Cham.
Urbach, N., & Ahlemann, F. (2010). Structural equation modeling in information systems research using Partial Least Squares. *Journal of Information Technology Theory and Application*, *11*.

Van Dis, E. A., Bollen, J., Zuidema, W., van Rooij, R., & Bockting, C. L. (2023). ChatGPT: five priorities for research. *Nature*, *614*(7947), 224-226.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, *27*(3), 425-478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. *MIS Quarterly*, *36*(1), 157-178. https://doi.org/10.2307/41410412

Voorhees, C. M., Brady, M. K., Calantone, R., & Ramirez, E. (2016). Discriminant validity testing in marketing: an analysis, causes for concern, and proposed remedies. *Journal of the Academy of Marketing Science*, *44*(1), 119-134. https://doi.org/10.1007/s11747-015-0455-4

Warschauer, M., Tseng, W., Yim, S., Webster, T., Jacob, S., Du, Q., & Tate, T. (2023). The Affordances and Contradictions of AI-Generated Text for Second Language Writers. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4404380

Whang, C., & Im, H. (2018). Does recommendation matter for trusting beliefs and trusting intentions? Focused on different types of recommender system and sponsored recommendation. *International Journal of Retail & Distribution Management*, *46*(10), 944-958. https://doi.org/10.1108/IJRDM-06-2017-0122

Wold, H. O. A. (1982). Soft modeling: the basic design and some extensions. In K. G. Jöreskog & H. O. A. Wold (Eds.), *Systems under indirect observation, Part II* (pp. 1-54). North-Holland, Amsterdam.

Wu, B., & Chen, X. (2017). Continuance intention to use MOOCs: Integrating the technology acceptance model (TAM) and task technology fit (TTF) model. *Computers in Human Behavior*, *67*, 221-232. https://doi.org/https://doi.org/10.1016/j.chb.2016.10.028

Yeo, V. C. S., Goh, S.-K., & Rezaei, S. (2017). Consumer experiences, attitude and behavioral intention toward online food delivery (OFD) services. *Journal of Retailing and Consumer Services*, *35*, 150-162. https://doi.org/https://doi.org/10.1016/j.jretconser.2016.12.013

Yüzbaşıoğlu, E. (2021). Attitudes and perceptions of dental students towards artificial intelligence. *Journal of Dental Education*, *85*(1), 60-68. https://doi.org/https://doi.org/10.1002/jdd.12385

Zarouali, B., Van den Broeck, E., Walrave, M., & Poels, K. (2018). Predicting Consumer Responses to a Chatbot on Facebook. *Cyberpsychology, Behavior, and Social Networking*, *21*(8), 491-497.

https://doi.org/10.1089/cyber.2017.0518

Zhang, B., Zhu, Y., Deng, J., Zheng, W., Liu, Y., Wang, C., & Zeng, R. (2023). "I Am Here to Assist Your Tourism": Predicting Continuance Intention to Use AI-based Chatbots for Tourism. Does Gender Really Matter? *International Journal of Human–Computer Interaction*, *39*(9), 1887-1903. https://doi.org/10.1080/10447318.2022.2124345

Appendix A. Measurement Items (English)

Performance Expectancy *(1: Strongly Disagree; 5: Strongly Agree)*

PE1. I find generative AI useful for my studies.

PE2. Generative AI help me to improve my academic performance.

PE3. I believe Generative AI is very valuable for my studies.

PE4. Generative AI is highly beneficial for my studies.

Post-usage Usefulness *(1: Strongly Disagree; 5: Strongly Agree)*

PU1. Generative AI can make my studies more effective.

PU2. Generative AI can help me study more efficiently.

PU3. Generative AI can enhance my study experience.

PU4. Totally, I find the Generative AI useful in my studies.

Positive Attitude *(1: Strongly Disagree; 5: Strongly Agree)*

PA1. I am impressed by what Generative AI can do.

PA2. I am interested in using Generative AI in my daily life.

PA3. There are many beneficial applications of Generative AI.

PA4. Generative AI can perform better than humans.

PA5. I would like to use Generative AI in my studies.

Affective Attitude *(1: Strongly Disagree; 5: Strongly Agree)*

AA1. Generative AI is very important for developing society.

AA2. Generative AI helps me solve problems in real life.

AA3. Generative AI is necessary for everyone.

AA4. I think that most jobs in the future will require knowledge related to Generative AI.

Cognitive Attitude *(1: Strongly Disagree; 5: Strongly Agree)*

CA1. I think it is important to use Generative AI in studies.

CA2. Generative AI is important.

CA3. I think that Generative AI should be used in studies.

CA4. I think every student should use Generative AI in studies.

Trusting Intention *(1: Strongly Disagree; 5: Strongly Agree)*

TI1. I would feel comfortable depending on Generative AI.

TI2. I would feel comfortable using the Generative AI.

TI3. In order to have immediate suggestions for my assignment, I feel that I could rely on the Generative AI.

TI4. In order to have personalized feedback for my assignment, I feel that I could trust the Generative AI.

TI5. When I have an important class assignment, I feel I can depend on Generative AI.

Continuance Intention *(1: Strongly Disagree; 5: Strongly Agree)*

CI1. I intend to continue my use of Generative AI in the future.

CI2. I intend to increase my use of Generative AI in the future.

CI3. I will keep using the Generative AI as regularly as I do now.

CI4. If I could, I would like to continue my use of Generative AI.

CI5. I would recommend Generative AI to my classmates.

Appendix B. Measurement Items (Chinese)

績效預期 *（1:非常反對；5:非常同意）*

PE1. 我發現生成式 AI 對我的學業很有幫助。

PE2. 生成式 AI 幫助我提升學業表現。

PE3. 我相信生成式 AI 對我的學習非常有價值。

PE4. 生成式 AI 對我的學習非常有益。

用後感知有用性 *（1:非常反對；5:非常同意）*

PU1. 生成式 AI 可以使我的學習更有效。

PU2. 生成式 AI 可以幫助我更有效地學習。

PU3. 生成式 AI 可以提升我的學習體驗。

PU4. 總的來說，我發現生成式 AI 在我的學習中很有用。

正面態度 *（1:非常反對；5:非常同意）*

PA1. 我對生成式 AI 的功能印象深刻。

PA2. 我對在日常生活中使用生成式 AI 感興趣。

PA3. 生成式 AI 有許多有益的應用。

PA4. 生成式 AI 的表現優於人類。

PA5. 我希望在學業中使用生成式 AI。

情感態度 *（1:非常反對；5:非常同意）*

AA1. 生成式 AI 對於社會的發展非常重要。

AA2. 生成式 AI 幫助我解決現實生活中的問題。

AA3. 生成式 AI 對每個人來說都是必要的。

AA4. 我認為未來大多數的工作都需要生成式 AI 相關的知識。

認知態度 *（1:非常反對；5:非常同意）*

CA1. 我認為在學業中使用生成式 AI 很重要。

CA2. 生成式 AI 很重要。

CA3. 我認為應該在學業中使用生成式 AI。

CA4. 我認為每位學生都應該在學業中使用生成式 AI。

信任意願 *（1:非常反對；5:非常同意）*

TI1. 我對依靠生成式 AI 感到自在。

TI2. 使用生成式 AI 讓我感覺很自在。

TI3. 為了獲得即時的作業反饋，我覺得我可以依靠生成式 AI。

TI4. 為了獲得客制化的作業反饋，我覺得我可以信任生成式 AI。

TI5. 當我有重要的課程作業時，我覺得我可以依靠生成式 AI。

持續使用意願 *（1:非常反對；5:非常同意）*

CI1. 我打算未來繼續使用生成式 AI。

CI2. 我打算未來更頻繁地使用生成式 AI。

CI3. 接下來我會像現在一樣持續經常使用生成式 AI。

CI4. 如果可以，我想繼續使用生成式 AI。

CI5. 我會向同學推薦生成式 AI。