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Generative AI – a transformative tool for Cambodian communication professionals?

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Master's thesis

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Abstract

Generative AI – A transformative tool for Cambodian communication professionals?

The emergence of Generative Artificial Intelligence (AI) promises a significant transformation of communication practices. Given the surging global interest in Generative AI among communication professionals, particularly considering its potential economic benefits for developing nations like Cambodia, this study investigated the key factors influencing Cambodian communication professionals' acceptance of Generative AI in their work. Derived from the Unified Theory of Acceptance and Use of Technology 2 (UTAUT 2) and previous studies, six factors emerged as determinants of Generative AI acceptance: performance expectancy, effort expectancy, social influence, facilitating condition, hedonic motivation, and price value. A quantitative online survey method was conducted with 150 Cambodian communication professionals to examine the six determined factors. The results indicated that hedonic motivation exerts the most influence on users' intention to use Generative AI, followed by performance expectation. On the contrary, Effort Expectancy, Social Influence, Facilitating Condition and Price Value did not significantly impact the behaviour intention. Importantly, the survey respondents expressed positive intention towards adopting Generative AI, highlighting their enjoyment in using the technology and their perception of its utility in improving productivity and task completion.

Keywords: Generative AI, Communication Professionals, Technology Acceptance, Unified Theory of Acceptance and Utilization of Technology, Cambodia

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Table of contents

1. Introduction

Artificial intelligence, or AI, encompasses a wide range of technologies designed to enable computers to simulate human intelligence, including learning, problem-solving, and even making decisions (What Is Artificial Intelligence (AI)? | IBM, n.d.). As technology keeps evolving, different forms of AI have emerged. Generative Artificial Intelligence (Generative AI), a subfield of artificial intelligence, uses machine learning algorithms to create AI-generated content – text, images, music, and even videos (Prasad, 2023). Generative AI was developed and trained on massive amounts of data that can not only summarise information or answer questions but also use its knowledge to generate fresh and unique outputs (Prasad, 2023). Moreover, Generative AI models are adaptable. They can be fine-tuned for specific tasks based on user prompts (input in the form of commands), making them versatile tools for creative work (Lim et al., 2023)

In recent years, Generative AI has witnessed significant advancements, and its potential applications have expanded across various industries, including communication and creative media. For instance, ChatGPT, developed by Open Artificial Intelligence (Open AI), took the Internet by storm since its first release in 2022 due to its chat function, where one can ask the tool to generate any response directly (Sheikh et al., 2023). Due to its responsive functionality and open accessibility, ChatGPT has become the fastest-growing user base internet application of all time, having around 100 million monthly users (Stieglitz et al., 2024). This Generative AI tool has been fostering the current transformation as one can witness a constant stream of similar AI tools emerging, and businesses are rapidly adopting them to streamline their processes (Haleem et al., 2022).

While Generative AI has surged in popularity and transformed content production and creation, its advantages are not uniformly accessible to everyone, particularly in developing nations where limited access to advanced technology and inadequate infrastructure pose challenges (Mannuru et al., 2023). Mannuru et al. (2023) emphasised that AI technology, particularly Generative AI, can be a powerful tool for developing countries in the Fourth Industrial Revolution. They argued that technological advancements are key to progress and equal opportunities in these nations, and Generative AI has the potential to be a significant driver (Mannuru et al., 2023).

For instance, Cambodia is one of the emerging developing countries in terms of the digital economy and technology transformation in Southeast Asia. The country's majority of businesses (99.7%) are micro, small, and medium-sized enterprises (MSMEs), according to the Cambodia Socio-Economic Survey 2021 (National Institute of Statistics, 2022). In 2020, Cambodia’s economy was struck by the COVID-19 pandemic, which led to a significant impact on the MSMEs. A report by the Asian Vision Institute (AVI) (2021) reveals a significant drop in revenue for over 84% of MSMEs. In response, nearly half (48%) of these businesses have adapted by transitioning to remote work and leveraging online platforms, especially social media, for communication, marketing and selling their products and services (AVI, 2021). The report also shows that a substantial majority of businesses plan to continue using social media and explore other technologies for their work in the future (AVI, 2021). These findings show that as the country has been experiencing rapid digital economy transformation, many professionals, including communication professionals, plan to enhance their skills and capabilities in utilising digital technologies for their work. Therefore, the attitudes of Cambodian communication professionals toward adopting Generative AI as one of the potential means of their professional work in the future make for an interesting subject to study.

1.1 Problem definition

Previous research suggests that AI, particularly Generative AI, has a significant advantage in producing original content that can be utilised within the creative industry (Haleem et al., 2022). As creative content creation and storytelling are part of the key competencies of communications professionals (Tench et al., 2013), Generative AI is expected to become a popular tool among practitioners (Mariani et al., 2023). There was evidence that communication practitioners around the world are increasingly adopting Generative AI technologies to enhance content creation, improve efficiency, and streamline communication processes (Mariani et al., 2023; Dwivedi et al., 2023).

Though communication professionals increasingly show interest in Generative AI's potential, widespread adoption remains elusive. Scepticism persists regarding the accuracy, reputational risks, ethical considerations, and legal concerns that have been raised among communication professionals (Dwivedi et al., 2023; Stieglitz et al., 2024). Furthermore, limited knowledge and a perceived lack of impact could also hinder wider acceptance of the technology among communication professionals in Europe (Zerfass et al., 2020). Zerfass et al. (2020) also pointed out that the uncertainty of the technology could also be due to many organisations having yet to recognise and integrate Generative AI into their operations. Another point to notice is that the acceptance of new technology can vary based on the country or region of the study, as social, cultural and economic factors may play a vital role, according to the diffusion of innovations theory by Rogers et al. (2009).

Given these contexts, it could be argued that the premise of how Generative AI is being perceived and accepted among communication professionals has been conflicted as the technology is still in its early stage of development. Users' acceptance of new technology cannot be generalised across the different countries and regions. Therefore, determining the factors that lead to a potential adoption in a specific industry and country is essential.

1.2 Purpose and research question

By localising the study to Cambodia, the researcher can explore a different lens on how new technology is accepted, as cultural and socio-economic factors may play a significant role in the acceptance of technologies. Since Generative AI is a global trend for communication practitioners (Mariani et al., 2023; Dwivedi et al., 2023), it is valuable to understand better what drives Cambodian communication professionals to adopt new technology for their competitive advantage in the current country’s digital economic transformation. Therefore, this study aims to determine which factors impacted the decision process of accepting Generative AI among Cambodian communication practitioners. By understanding these contributing factors, this study can provide insights into the decision-making processes, as well as challenges and opportunities in adopting this technology within the country's communication industry. In addition, this study could also benefit communication or organisation leaders in introducing new technology like Generative AI into their departments or organisations. This, therefore, contributes to understanding the current landscape and the future of the communication profession in Cambodia.

This study aims to answer the research question: *"Which factors drive the acceptance of Generative AI among Cambodian Communication Practitioners?"*

1.3 Relevance

This study contributed to the field of Strategic Communication by providing valuable insights into the contemporary landscape of the communication profession in Cambodia. As defined by Falkheimer and Heide (2018), Strategic Communication refers to the purposeful use of communication to achieve the organisation's strategic goals. In this sense, the study of adopting new communication tools could contribute to understanding the potential tools or technology for communication professionals to maximise efficiency and productivity in achieving their organisation's objectives. As technology keeps evolving, many applications have offered advanced solutions for communication professionals. As studies suggested, Generative AI, in particular, has been demonstrated as a new tool for people in the creative and communication industry to increase productivity and ease their workloads (Mariani et al., 2023; Dwivedi et al., 2023). Therefore, by investigating the perceived behavioural intention among Cambodian communication professionals toward adopting Generative AI for their work, this research can provide valuable insights into how the technology could potentially be a common communication tool that Cambodian communication professionals would leverage to streamline workflows and achieve organisational objectives.

1.4 Disposition

This Master's thesis is comprised of five chapters. Following this introductory chapter, which has outlined the research topic and study objectives, Chapter 2 delves into the literature review and theoretical framework, drawing on previous research to shape the research model. Chapter 3 details the methodological approach employed for the empirical analysis. Chapter 4 presents the findings from the analysis, and the concluding chapter, Chapter 5, discusses the implications of these findings in relation to the developed hypotheses.

2. Previous research and theoretical framework

This section provided an overview of the current research on communication professionals, Generative AI, and technology acceptance. By examining relevant concepts and associated theories, the researcher aimed to establish a foundation for research execution. Subsequently, the theoretical framework underpinning the analysis will be presented, followed by the introduction of the study's hypotheses.

2.1 Communication professional

The dynamic world of communication demands skilled professionals who can navigate its complexities. Communication professionals strategically use purposeful communication activities to advance the organisation's mission (Hallahan et al., 2007). They excel at crafting compelling messages, understanding diverse audiences, and ensuring clear information flow across various channels (Hallahan et al., 2007). From writing press releases and managing social media to crafting brand narratives and delivering persuasive presentations, communication professionals play a pivotal role in shaping an organisation's voice and its connection with the world. Their expertise encompasses the organisation's internal communication and societal research aspects, including strategic thinking and a deep understanding of human behaviour in the ever-evolving communication landscape (Falkheimer & Heide, 2018).

According to Hallahan (2004), cited in Hallahan et al. (2007), the researcher addressed six communication specialities commonly found within organisations. The first speciality is management communication; this speciality's purpose is to facilitate the organisation's operations. Second is the marketing communication speciality, which includes creating brand awareness and promoting sales of the products or services. Third is public relations. The purpose of this speciality is mainly to establish and maintain relationships with key stakeholders. Fourth is technical communication, which specialises in providing technical support to customers, employees and others to improve the organisation's efficiency. Fifth is political communication; the purpose of this speciality is to establish political consensus on important issues involving the exercise of political power. Finally, information/social marketing campaigns, the purpose of this speciality is to promote social causes for the community's betterment.

2.2 Communication professionals and AI technology

Communication professionals are increasingly demanding AI tools to enhance their work. In 2018, the Chartered Institute of Public Relations (CIPR) established the #AIinPR panel to explore the impact of technology, specifically AI, on PR skills and careers (Valin, 2018). According to the CIPR report, the panel defines AI as advanced technology that allows machines to perform tasks like learning, analysis, and problem-solving, similar to humans. The #AIinPR panel identified and categorised over 130 AI tools (Valin, 2018), which were later described and assigned a sophistication level based on their AI functionality on a five-point scale: Level 1: Simplification - Tools that automate basic PR tasks or offer routine services; Level 2: Listening and Monitoring - Tools for social media and media listening and monitoring; Level 3: Automation - Tools that automate specific tactical tasks; Level 4: AI for Structured Data - Machine learning applied to organised data sets; Level 5: AI for Unstructured Data - Machine learning applied to complex, unorganised data sets (Valin, 2018). This categorisation system highlights the increasing variety and sophistication of AI tools available to PR professionals.

Despite the hype that AI might change the communication profession enormously, Zerfass et al. (2020) argued that many communication professionals found the technology not so impactful for their tasks. Zerfass et al. (2020) conducted a study to investigate the perspective of communication practitioners in European countries on the impacts of AI on their profession. The study showed that there is a limited understanding of AI among communication professionals. Moreover, they did not expect the technology to affect many changes in their organisation and even less in their personal lives. The study suggested that communicators need to familiarise themselves with AI technology, and communication leaders should recognise their responsibility for implementing AI into their department or agency.

As technology keeps evolving and many types of AI have been introduced, recent studies have shown that communication professionals, traditionally tasked with crafting compelling messages, managing information flow, and building relationships, are increasingly exploring AI's potential to enhance their capabilities (Anderson & Rainie, 2023). According to a 2023 study by the Pew Research Center, 63% of communication professionals believe AI will become an essential tool in their field within the next five years (Anderson & Rainie, 2023). In the field of communication and creative media, Generative AI is used for content generation, copywriting, design, and personalisation (Mariani et al., 2023). Furthermore, studies showed that the use of Generative AI can help practitioners in the creative industry automate their routine tasks, create high-quality content, and improve user engagement (Dwivedi et al., 2023; Ritala et al., 2023). As highlighted by Ritala et al. (2023), ChatGPT, for instance, extends beyond simply being a chatbot. It functions as a versatile tool, capable of serving as a search engine for inspiration, fostering creativity, and providing comprehensive overviews on diverse topics. Its content production capabilities allow users to generate drafts for various documents, including academic articles, legal agreements, business pitches, social media content, blog posts, and even video content outlines (Ritala et al., 2023). Furthermore, software developers can leverage ChatGPT's abilities to write, review, and debug code (Eloundou et al., 2023; Ritala et al., 2023). To summarise, even though there were arguments that communication professionals have not widely accepted AI and Generative AI technologies, the technology's potential in the communication and creative work industry has been demonstrated.

2.3 Acceptance of Technology Theories

Throughout the years, various models have been extensively developed to assess technology acceptance among individuals. Davis et al. (1989), for instance, developed the Technology Acceptance Model (TAM) initially to predict the adoption of new technologies in the workplace. TAM suggested two key factors influencing technology adoption: perceived usefulness and perceived ease of use. Perceived usefulness reflects a user's belief that the technology improves their job performance. Perceived ease of use focuses on how effortless it is to learn and operate the technology. In summary, the theory suggests users are primarily driven to adopt applications that enhance their work, with user-friendliness playing a secondary but still important role (Davis et al., 1989).

Rogers' Innovation Diffusion Theory (IDT) (2003), on the other hand, explored how the intention to adopt new technology could be influenced by the social system. The theory focuses on the decision-making process individuals go through before adopting or rejecting a new technology. This process consists of five key stages: knowledge, persuasion, decision, implementation, and confirmation (Roger, 2003). In the initial knowledge stage, individuals gain three types of understanding: awareness of the innovation, how to use it (how-to knowledge), and the underlying principles. During the persuasion stage, people develop an opinion about the innovation (positive or negative). This opinion is shaped by five key factors: relative advantage, compatibility, complexity, trialability, and observability (how easy it is to see others using it) (Rogers, 2003). The decision stage is when users decide to embrace or reject the innovation. Rogers (2003) suggests that trying a new technology often leads to adoption, and offering free samples can accelerate the adoption rate. The implementation stage is where the new idea is put into practice or experiment. Finally, the confirmation stage involves ongoing information seeking and analysis to solidify the decision to keep using the technology (Rogers, 2003).

2.4 Unified Theory of Acceptance and Use of Technology (UTAUT)

With many models available, researchers found it challenging to either cobble together constructs from various models or prioritise a single model, potentially overlooking valuable insights from others. Venkatesh et al. (2003) addressed the need for a comprehensive review and synthesis of existing models, paving the way for a unified understanding of user technology acceptance.

Venkatesh et al. (2003) developed one of the most prominent technology acceptance theories, namely the Unified Theory of Acceptance and Use of Technology (UTAUT), by reviewing and integrating eight user acceptance models (1) The Theory of Reasoned Action (TRA); (2) The Technology Acceptance Model

(TAM) ; (3) The Motivational Model (MM); (4) The Theory of Planned Behavior (TPB) ; (5) A Model Combining TAM and TPB (C-TAM-TPB); (6) The Model of PC Utilization (MPCU) ; (7) The Innovation Diffusion Theory (IDT); and (8) The Social Cognitive Theory (SCT) (Venkatesh et al., 2003, p. 425).

The model suggests that the perceived likelihood of adopting new technology hinges on the effect of four key constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions. The impact of the four constructs is moderated by age, gender, experience, and voluntariness of use (Venkatesh et al., 2003).

Table 1: The core construct of UTAUT

Constructs	Variables	Model contributing to construct
Performance expectancy	Perceived usefulness	Technology Acceptance Model (TAM) 1-3; Combined TAM-TPB (Theory of Planned Behavior)
	Extrinsic motivation	Motivation Model (MM)
	Job-fit	Model of PC Utilization (MPCU)
	Relative advantage	Innovation Diffusion Theory (IDT)
	Outcome expectations	Social Cognition Theory (SCT)
Effort expectancy	Perceived ease of use	TAM 1-3
	Complexity	MPCU
Social influence	Subjective norms	TRA, TAM2, TPB/DTPB, and combined TAM-TPB
	Social factors	MPCU
Facilitating conditions	Perceived behavior control	TPB/DTPB and combined TAM-TPB
	Facilitating conditions	MPCU

(Venkatesh et al., 2003)

2.5 UTAUT 2

Given that UTAUT was initially developed to examine technology acceptance and use in an organisational setting, the model needs a systematic exploration and formulation of the significant factors applicable to the context of consumer technology acceptance (Venkatesh et al., 2012). To address this limitation, Venkatesh et al. (2012) extend the UTAUT to be applicable to a broader context (such as consumer context) and to improve its predictive power by adding three new constructs, such as hedonic motivation, price value, and habit; while altering some relationships from the previous model such as removing the voluntariness from the moderate variables (Venkatesh et al., 2012). Compared to the previous model, the UTAUT 2 holds high promise due to its very high explanatory power in Behavioural Intention and Use Behaviour, which can be applied to various technologies within the consumer market (Venkatesh et al., 2012).

The UTAUT 2 model, designed for a holistic understanding of consumer technology adoption, has become widely adopted across various research contexts. Since its introduction, the model has been applied in numerous studies spanning organisational and non-organizational settings, investigating the acceptance of new technologies by diverse user groups and cultural contexts.

2.5.1 Key constructs of UTAUT 2

The seven UTAUT 2 principal constructs that can predict or determine users' behavioural intention on the acceptance of the technology include performance expectancy, effort expectancy, facilitating conditions, social influence, hedonic motivation, price value and habit.

The first construct is Performance Expectancy (PE). It is defined as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (Venkatesh et al., 2003, p. 447). This construct measures an individual's perceived usefulness of technology for their professional role. It measures the extent to which they believe the technology can enhance their work performance or contribute to positive outcomes. The second construct is Effort Expectancy (EE), which is defined as "the degree of ease associated with the use of the system" (Venkatesh et al., 2003, p. 450). In other words, it measures an individual's perceived ease of use of the technology for their job. The third construct is Social Influence (SI), which is defined as "the degree to which an individual perceives that important others believe he or she should use the new system" (Venkatesh et al., 2003, p. 451). In simpler terms, it refers to the degree to which an individual perceives that important people in their social sphere can influence whether they should use technology in their job. The fourth construct is Facilitating Conditions (FC), which is defined as “the degree to which an individual believes that an organisational and technical infrastructure exists to support the use of the system” (Venkatesh et al., 2003, p. 453). Besides resource and technology facilitating conditions, the users’ knowledge to use the system was also considered as the FC factor (Venkatesh et al., 2003). The fifth conduct is Hedonic Motivation (HM), which is defined as “the fun or pleasure derived from using technology, and it has been shown to play an important role in determining technology acceptance and use" (Venkatesh et al., 2012, p. 161). In other words, users are likely to adopt new technology if they perceive it as fun and interesting to use. The sixth construct is Price Value (PV), which is defined as “consumers’ trade-off between the perceived benefits of the applications and the monetary cost for using them” (Venkatesh et al., 2012, p. 161). It reflects that the users also consider the monetary cost of the technology before deciding to use it. Lastly, the eighth construct is Habit (HA), which is defined as “the extent to which people tend to perform behaviours automatically because of learning” (Venkatesh et al., 2012, p. 161).

Venkatesh et al. (2012) convinced that the seven independent constructs have a direct influence on Behavioural Intention (BI), which refers to a measure of the strength of one’s intention to perform a specific behaviour (Fishbein & Ajzen, 1977). According to Ajzen (1991, p. 181), “intentions are assumed to capture the motivational factors that influence a behaviour; they are indications of how hard people are willing to try, of how much of an effort they are planning to exert, in order to perform the behaviour.” In other words, BI reflects users’ willingness and readiness to engage in a particular action. Finally, Use Behavior (UB) refers to the actual frequency of technology use, not just the intention (Venkatesh et al., 2003). To summarise, the UTAUT 2 model reflects that an individual’s intention to use and the actual use behaviour of the technology can be directly determined by the seven factors.

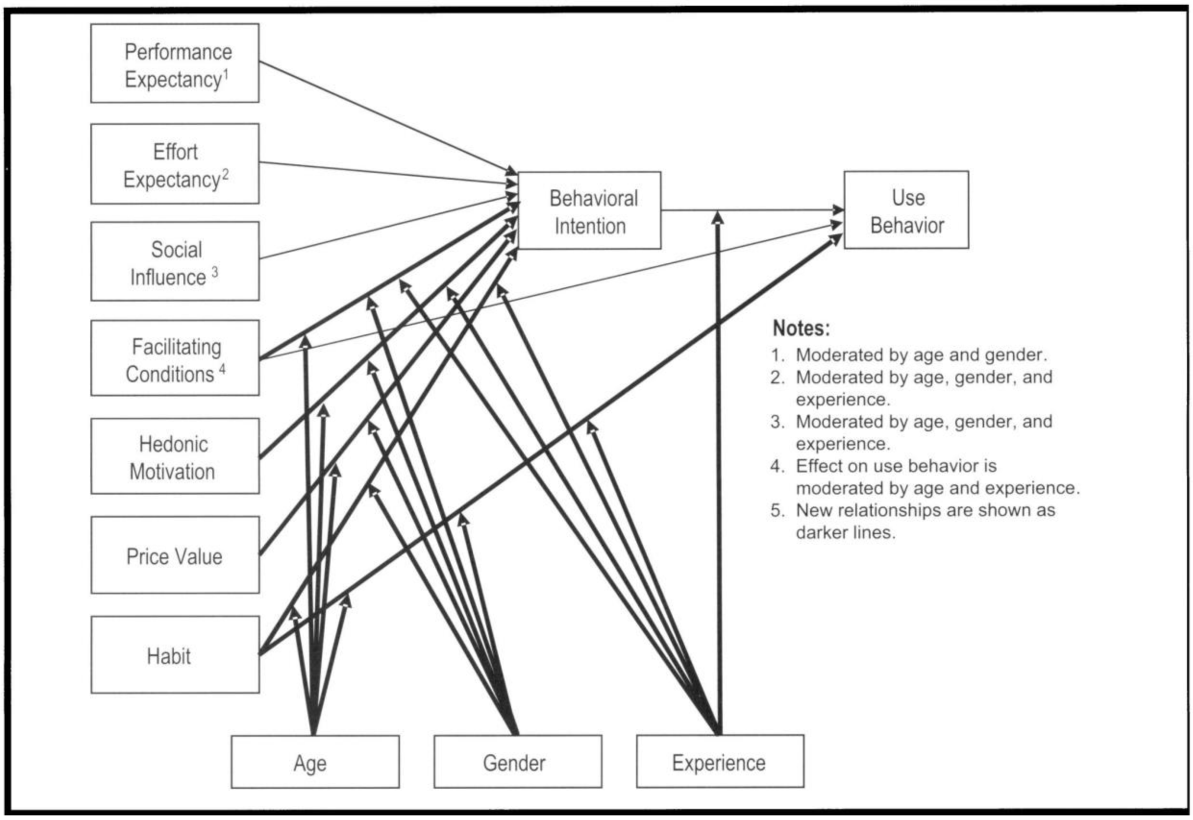

Figure 1: UTAUT 2 model (Venkatesh et al., 2012)

2.6 Hypothesis development based on UTAUT 2 model and previous studies

This study utilised the UTAUT 2 model and findings from previous studies to explore communication professionals' attitudes and intentions towards using Generative AI tools in their work.

Various studies have been conducted to understand the factors that affect users' behavioural intentions behind the use of AI. There are several overlapping findings as well as unique findings across different sectors and countries. Kelly et al. (2023) conducted a systematic review of 60 studies on user acceptance of artificial intelligence across multiple industries. They found that perceived usefulness, performance expectancy, attitudes, trust, and effort expectancy are the most common independent variables that significantly and positively predicted the intention, willingness, and use behaviour of AI. However, the researchers also found that even though AI demonstrates clear advantages in terms of usefulness and ease of use, certain cultural contexts rely heavily on the irreplaceable element of human contact. This finding suggests that AI cannot fully replace human interaction in these situations (Kelly et al., 2023).

In the context of Generative AI acceptance, many studies offered similar patterns of the contributing factors to the systematic review by Kelly et al. (2023). For instance, a study by Tiwari et al. (2023) explored factors affecting Omani university students' acceptance of ChatGPT. They found that students who perceived ChatGPT as useful, credible and fun to use tended to have positive attitudes towards the technology and a desire to use it. The study also suggested that even though some students found it challenging to use and questioned the understandability of the answers, they were still willing to adopt ChatGPT as a learning tool due to high trust in the performance (Tiwari et al., 2023). Similarly, Andrews et al. (2021) found that performance expectancy has a significant impact on the acceptance of AI technologies among librarians. They found that librarians' willingness to adopt AI depended on two key factors: how useful they perceived AI to be (performance expectancy) and their overall attitude towards using it (attitude toward use). The study also suggested that librarians, regardless of whether they work in academic or public libraries, need to be convinced of the practical benefits of AI before they consider adopting it to improve services for their users (Andrews et al., 2021). Therefore, the effect of PE variable on the users' behavioural intention toward the use of Generative AI technology has been proven in previous literature.

H1: Performance Expectancy (PE) has a statistically significant positive influence on the Behavioral Intention (BI) to use Generative AI among Cambodian communication practitioners.

Besides the emphasis on performance expectancy, several studies revealed that Effort Expectancy (EE) and Social Influence (SI) factors also played an essential role in influencing user intention to adopt Generative AI technologies. De Andrés-Sánchez and Gené-Albesa (2023) found that users' willingness to try the AI chatbots in the insurance sector is strongly influenced by how easy they perceive them to be and how much others recommend them. Interestingly, unlike other studies, the perceived effectiveness of the chatbots (performance expectancy) did not show a significant impact on user adoption attention. Similar findings were also shown in the study by Moriuchi (2021), which revealed that effort expectation has a significant positive impact on consumers' usage experience of the

AI virtual assistant hubs. Additionally, Social Influence (SI), known to impact technology adoption, also showed a positive correlation with user experience in the study. The study showed that social influence appears to primarily shape user expectations of enjoyment when using voice assistants (Moriuchi, 2021). The impact of both EE and SI factors on the attitude toward the adoption of AI technology has been recorded in previous studies (De Andrés-Sánchez & Gené-Albesa, 2023; Moriuchi, 2021).

H2: Effort Expectancy (EE) has a statistically significant positive influence on the Behavioral Intention (BI) to use Generative AI among Cambodian communication practitioners.

H3: Social Influence (SI) has a statistically significant positive influence on the Behavioral Intention (BI) to use Generative AI among Cambodian communication practitioners.

Another factor to notice is the Facilitating Condition (FC). A study on the acceptance of Enterprise Chatbots by Brachten et al. (2021) showed that users' perceived behavioural control could also be influenced by facilitating conditions and efficacy factors. In other words, having the right tools and training (facilitating conditions) and feeling capable of using the system (efficacy) contribute to users believing they can control and make use of the chatbot. This finding highlights the importance of providing support and building user confidence, especially when dealing with complex technologies like enterprise chatbots (Brachten et al., 2021). Therefore, the impact of the FC on the acceptance of AI technologies has been captured in the previous studies.

H4: Facilitating Conditions (FC) has a statistically significant positive influence on the Behavioral Intention (BI) to use Generative AI among Cambodian communication practitioners.

As many studies highlight the importance of utilitarian motivation as the key factor behind the acceptance of new technology, several studies argued that hedonic motivation is important for the users to accept or adopt new technologies. The study by Dinh and Park (2023) found that hedonic motivation plays a vital role in increasing consumer willingness to adopt AI chatbots. Their research suggests that focusing on enjoyment and fun (hedonic motivation) is more important than practicality (utilitarian motivation) in creating a sense of interaction with the chatbot (social presence). This feeling of social presence ultimately leads to a greater willingness to use the chatbot service. Interestingly, the study also found that fear of COVID-19 made people value social interaction with chatbots even more (Dinh & Park, 2023). Similar findings were also found in the study on the generative AI technology adoption model for entrepreneurs by Gupta and Yang (2023). They emphasised that successful technology adoption hinges on a balance between practicality and enjoyment. They suggested that beyond offering functional advantages, new technologies need to consider ethical and legal implications while creating a positive, fun and engaging user experience (Gupta & Yang, 2023). Therefore, the impact of the HM on the acceptance of Generative AI technologies has been proven in the previous study.

H5: Hedonic Motivation (HM) has a statistically significant positive influence on the Behavioral Intention (BI) to use Generative AI among Cambodian communication practitioners.

Other studies also suggested a positive link between perceived price value and user adoption of new technologies. A study by Wang and Weining (2023) investigated the influencing factors behind the use of Generative AI for art design. They found that price value is one of the key influencing factors behind the adoption of Generative AI for art designing among Generation Z. The study suggests that Generation Z users are more likely to embrace Generative AI design tools if they see a clear value proposition, particularly in terms of cost. Generation Z could get special discounts on student prices. These cost-effective options might incentivise Generation Z to explore and adopt Generative AI design tools for their projects (Wang & Weining, 2023). A study on Internet banking adoption by Almaiah and Al-Rahmi (2022) revealed a positive effect of price value on user behavioural intention. They suggested that price value is a key factor influencing customer adoption of Internet banking. When customers see that Internet banking is a free application that offers value (like saving time or money), they are more likely to use it (Almaiah & Al-Rahmi, 2022). Similarly, Palau-Saumell et al. (2019) emphasised that price-saving orientation is one of the eight drivers of user intentions to use mobile applications for restaurant searches and/or reservations (MARSR). The research suggests a positive connection between perceived economic benefits and user behaviour intention. In simpler terms, when technology allows consumers to use a free application to acquire products or services at lower prices, this contributes to both their intention to use the application and their actual usage frequency (Palau-Saumell et al., 2019). These findings showed that affordability plays a role in user adoption. The lower the cost of a new technology is acquired, plus the advantages the technology can offer, the higher the willingness of the user to use it. Therefore, previous studies have confirmed the effect that price saving and value have on Generative AI technology adoption.

H6: Price Value (PV) has a statistically significant positive influence on the Behavioral Intention (BI) to use Generative AI among Cambodian communication practitioners.

Studies on Generative AI technology acceptance revealed a diversity of factors at play. While findings differ somewhat, several factors consistently emerge that potentially influence users' willingness to adopt Generative AI (behavioural intention). These include how well users trust and expect it to perform (performance expectancy), how easy they perceive it to be (effort expectancy), the influence of others (social influence), the availability of resources and support (facilitating conditions), enjoyment and fun (hedonic motivation), affordability and economic benefit (price value) are determined factors commonly found in Generative AI adoption studies. These findings also confirmed the validity of the UTAUT 2 model for the study of Generative AI acceptance among Cambodian communication professionals.

However, some adjustments have been made to the UTAUT 2 model to suit the current study better. One key adjustment is the change of the dependent constructs. “User behaviour” was disregarded since Generative AI is a relatively new technology, and there is no evidence or previous study on the use of Generative AI among communication professionals in Cambodia. Therefore, focusing on existing user behaviour would not be relevant to understanding their initial adoption intentions. In this sense, this study only considered the “Behavioural Intention (BI)” as the dependent construct. In relation to this, the independent construct of habit (HA) was not included in this study. Similar to the exclusion of user behaviour as a dependent variable, this limitation is justified by the novelty of Generative AI. Since it is a new technology, it cannot be presumed that communication professionals have established consistent habits or routines involving its use. Finally, the four moderating variables, gender, age, voluntariness, and experience, included in the original model have not been taken into consideration. This delimitation is made due to the study's scope, which implies a limited time frame for the in-depth cross-factor analysis. Investigating the relationship of moderating variables with the other key constructs would require a larger number of respondents to the survey to draw generalisable conclusions. Moderators add complexity to the model, requiring even larger sample sizes to detect their effects with sufficient power. With a niche target group, even if age or gender truly influences the core UTAUT 2 relationships, the study might not be able to pick up on these effects due to statistical limitations (Venkatesh et al., 2003, p. 457).

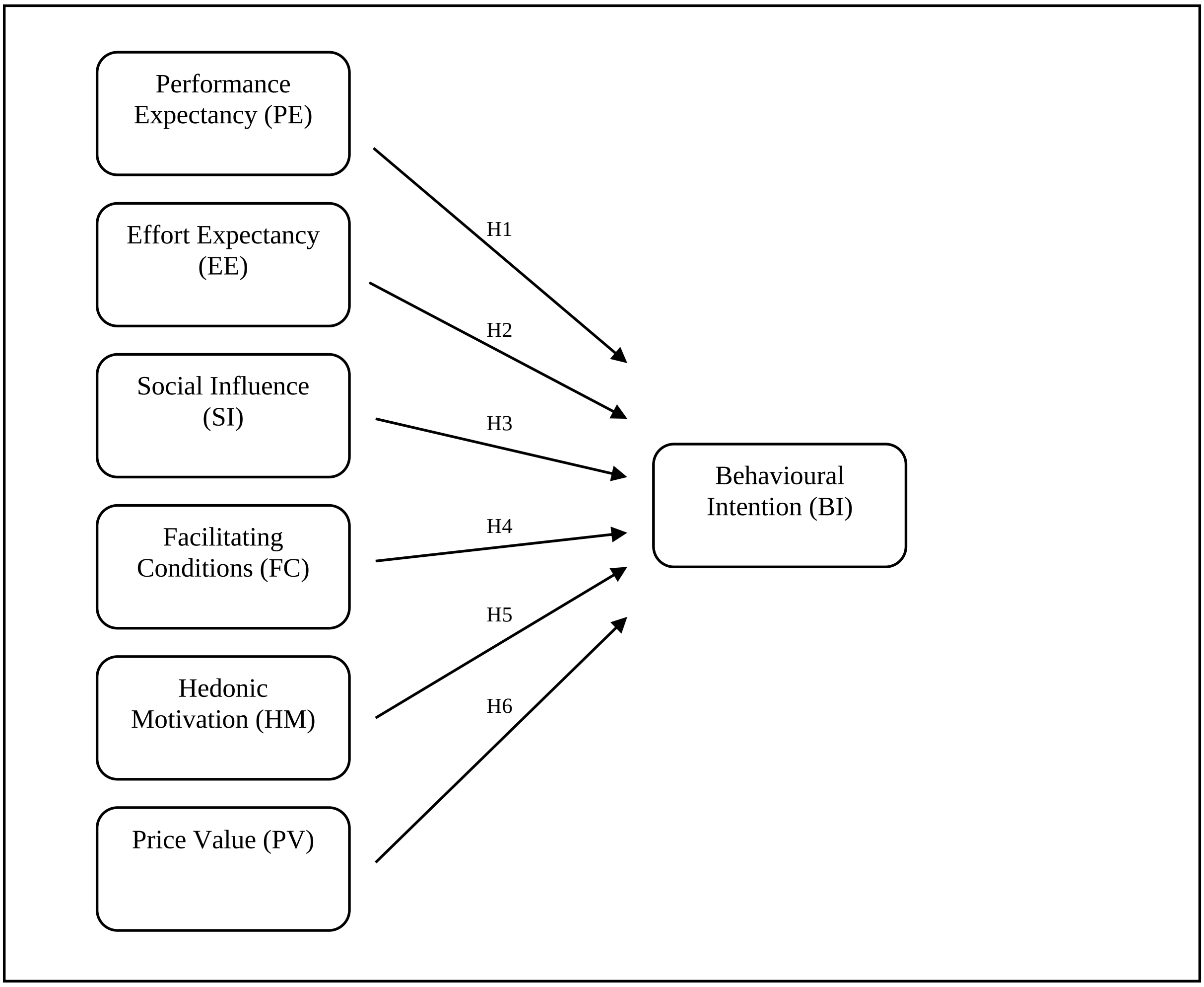

Figure 2: Research model and compilation of hypotheses

This figure showcases the research model, including its constructs and the independent variables. It emphasises the hypothesised causal relationships between these variables and their ultimate impact on behavioural intention (BI).

3. Methodology

This section begins by outlining the existing scientific literature that informs this study's approach. Subsequently, the research design will be presented, detailing the methods employed. Following this, the analysis strategy used to interpret the findings will be described. Finally, a reflection will discuss the rationale behind the chosen methods and how they align with the principles of quantitative research.

3.1 Scientific philosophical assumptions

The study was designed with a positivist approach, which means that the researcher assumed there is a single, objective reality the researcher could uncover through data collection and analysis. The knowledge would come from quantifiable observations and statistical tests, similar to scientific experiments (Bryman, 2012). The study will not be concerned with researcher bias or subjective interpretations; it will focus on the statistical data. The researcher chose this approach because the research will only depend on objective data (facts and figures). Additionally, the research used a deductive method. This means the researcher started with existing theories and hypotheses from prior studies to guide our investigation (6, P & Bellamy, 2012). Therefore, this research will employ a quantitative research method to obtain an objective and comprehensive understanding of the factors influencing the behavioural intention of Generative AI among Cambodian communication practitioners.

This study followed a deductive approach, which is commonly used in quantitative research, according to 6, P and Bellamy (2012). In this study, a pre-existing theory, UTAUT 2, is tested through data collection. A single quantitative data collection method, a survey, was used to gather data. Quantitative methods are ideal for measuring relationships between variables (6, P & Bellamy, 2012). In this case, the research aimed to quantify how specific factors influence the acceptance of Generative AI. Therefore, the empirical data was collected through a survey designed to test the chosen theory and the conceptual model presented in Figure 2.

3.2 Data collection instrument

The questionnaire was the primary data collection instrument for this study. The researcher created a questionnaire and survey items for this study—the survey items measured both the independent and dependent variables. The six independent variables include Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, and Price Value. The only dependent variable is Behavioural Intention. Since the data collection instrument needs to collect the correct data, the researcher needs to operationalise the variables. When one is operationalising variables, one makes sure that the indicators for the variables can be measured (Leavy, 2017). To operationalise the questionnaire items, the researcher adapted the items from the original UTAUT2 model (Venkatesh et al., 2012) and previous AI adoption studies (Yilmaz et al., 2023; Sebastián et al., 2022; Van, D. & Van, H., 2021). The statements on Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions and Behavior Intention were adopted from Venkatesh et al. (2012) and Yilmaz et al. (2023). Additionally, the statements on Hedonic Motivation and Price Value were adopted from Venkatesh et al. (2012) Sebastián et al. (2022) and Van et al. (2021) to operationalise the constructs into the Generative AI adoption context. The full survey statement on these constructs can be found in Appendix 1, survey item section 3.

The researcher used a Likert scale for the questions measuring the items for the independent and dependent variables. The 5-point Likert scale method was used, ranging from 1 (totally disagree) to 5 (totally agree). This scale was designed to minimise confusion and bias, ensuring the researcher can collect high-quality data. Its clear structure makes it a recommended tool for reliable results (Revilla et al., 2014). Even though the study did not include moderate variables as part of the hypothesis development, the researcher also collected demographic data such as gender, age, education and other variables that might be interesting to compare in order to see if there were correlations between different variables apart from the model to be identified (Leavy, 2017). The questionnaire (see Appendix

1) were divided into three parts: the first is demographic, the second is about the use of Generative AI, and the third is about perceptions toward Generative AI for their work.

3.3 Data collection method

An online survey was used to collect the primary data. Surveys are the most used form of data collection within quantitative social science research, as well as in market research and opinion polls (Leavy, 2017). Moreover, the survey makes it easier to collect data from standardised questions and allows the researcher to analyse the data statistically in the later stage (Leavy, 2017). Using a survey also makes it possible to collect data from a larger sample, which allows for the generalisation of the results to the general population (Leavy, 2017). The online survey was self-administered, meaning that the survey did not take place in front of the researcher, which allows for a more honest and less stressful situation for the participants of the survey (Leavy, 2017).

This online study was conducted using an online survey software called Google Forms. The choice to use Google Forms was to ensure that the study does not have one person submit multiple survey responses, as Google Forms has an automatic respondent inventory in its software (Leavy, 2017). Another main reason was that Google Forms supported many language options, including Khmer, the official language for Cambodians, which the research used for this online survey.

3.4 Research design and analysis strategy

After the data was collected through an online survey method, the researcher used the SPSS (Statistical Package for the Social Sciences) programme to analyse the data, which involves a six-step data analysis process.

The first step was Data Screening. Before diving into analysis, the data underwent a screening process to ensure its quality. This process involved checking for any unusual values or outliers that could skew the results. Additionally, the researcher verified that all participants correctly followed the survey instructions.

The second step was Demographic Statistics. In this stage, the researcher ran the analysis to find the overview of the respondents' information, such as age, gender, education, types of communication speciality, and years of communication experience. In addition, the researcher also used the descriptive statistic method to see how many per cent of the respondents have used Generative AI, what type of Generative AI they used, and what they used the technology for.

The third step was Descriptive Analysis of the research model. This stage of the analysis focused on descriptive statistics, a way of summarising the collected data, rather than testing specific predictions. This method helps present the collected information in a clear and understandable manner (Bhandari, 2021). Instead of testing theories, it focuses on describing the data itself. Descriptive statistics included measures like average scores (mean), how spread out the data is (standard deviation), and the most frequent values (mode and variance) (Bhandari, 2021).

The fourth step was Reliability Analysis. In this step, the researcher evaluated the consistency of the identified factors using Cronbach's alpha coefficient. This statistical test helped the researcher assess a scale's internal consistency, meaning that it measures how well different items within a factor measure the same underlying concept. This test was conducted to see whether the variables are suitable for combining into an index. The researcher inspected the table Reliability Statistics. After testing for the reliability of the variables, the researcher created Combined Summative Indexes based on the research model. Summative indexes were created for each element of the research model (performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and behavioural intention). In this stage, the research calculated survey items into a summative index for each variable based on the research model.

Finally, the researcher conducted the Multiple Linear Regression (MLR). This analysis was used to test the hypotheses. The technique helped uncover relationships between the various variables. By analysing these connections, the researcher could determine whether the dependent variable can be influenced by various independent variables.

3.5 Sampling method

The sample size can be determined by the research approach, number of variables, analytical method, model complexity and other things such as time and resources (Memon et al., 2020). Based on Roscoe's (1975) guidelines, in order to conduct multivariate data analysis (e.g. regression analysis), the sample size should be ten times greater than the number of variables (Memon et al., 2020). VanVoorhis and Morgan (2007) also suggested that an absolute minimum of 10 participants per predictor variable is appropriate for regression analysis using six or more predictors. Green (1991) and Tabachnick and Fidell (2013), as cited in Memon et al. (2020), proposed a more systematic rule of thumb for sampling size by using the formula of "$N \geq 50+8m$", where "m" is the number of predictors in the model. Since this study used six predictors, a minimum sample size of 98 should be sufficient for multiple regression analysis. However, to ensure higher validity and greater accuracy of the study, the researcher aimed to increase the sample size to at least 150 respondents.

3.6 Sample recruitment

Since this study requires respondents from a specific professional background and nationality, a purposive sampling method was employed to recruit target respondents. The criteria for being selected are (1) being a Cambodian citizen and (2) being a communication professional during the time of this study.

Since the population of Cambodian communication practitioners has not been recorded, nor was there any association or platform of the profession in Cambodia, the researcher could not use a random sample method in this study. This study adopted a convenience sampling method, a type of non-probability sampling technique. Convenience sampling relied on the researcher's judgment to select readily available participants who were easily accessible at the time of the study (Malhotra et al., 2017). In addition, the study also employed a snowballing sampling method. Instead of a random selection, snowball sampling enabled the researcher to ask the existing participants to recommend potential participants. This was helpful for reaching niche groups, like people with uncommon characteristics (Nikolopoulou, 2022).

To reach the target group, a virtual network sampling method was conducted since the Internet could provide certain opportunities, including quick access to the target respondents, enabling the fast realisation of surveys at low costs (Kozłowski et al., 2021; Dusek et al., 2015). However, when conducting scientific research involving groups associated with a specific industry and profession, the challenge arises in reaching and selecting an appropriate sample, even with the help of the Internet. Therefore, choosing the right platform for recruitment is necessary. Studies by Kozłowski et al. (2021) and Dusek et al. (2015) suggested that one solution is to recruit respondents via LinkedIn since it is the largest platform for employees from diverse industries worldwide. Kozlowski et al. (2021) suggest that there are three steps in the LinkedIn virtual network sampling procedure: (1) building a list of potential respondents belonging to the study population, (2) Acquiring respondents from the created list as direct contacts of the researcher, (3) Distributing invitations to participate in the study (Kozłowski et al., 2021).

Therefore, to ensure the 150 respondents, the researcher sent the survey to the researcher's networks of Cambodian communication professionals, such as the university alumni network and communication professionals working in civil society organisations, government entities and companies. The researcher compiled a list of communication professionals and reached out to them via social media and email. Since their names and contact information are confidential, the researcher chose not to disclose in this study. The researcher also used a snowball sampling method by approaching the target respondents directly and asking the respondents to forward the survey to their network. Additionally, to ensure a diverse respondent outside the researcher's network, survey recruitment public anoucements were posted on social media. The survey public announcements on Linkedin and Facebook can be found in Appendix 2.

3.7 Validity and reliability

This section addresses the validity and reliability of the study, mainly the theoretical relevance of the study, by assessing how well the survey questions capture the intended concepts. The researcher employed established survey items based on the well-validated UTAUT2 model (Venkatesh et al., 2012) and previous studies on users' behavioural intentions in Generative AI. Some modifications were made to ensure the items regarding Generative AI were contextually relevant and understandable to the participants. A concise explanation of Generative AI with examples was included within the survey itself (see Appendix 1 for details). After the survey was collected, the researcher also ran an internal consistency test to measure the strength of the constructs using Cronbach's alpha coefficient. These measures were taken to strengthen the alignment between the survey instrument and the research goals, leading to a high degree of construct validity and reliability for the study.

3.7.1 Pilot test

The researcher also conducted a pilot test to test whether the survey items were understandable and easy for the respondents to complete. The researcher recruited participants from the researcher’s social circle for the pilot study. While this approach does not guarantee generalizability, the researcher ensured a diverse range of ages and educational backgrounds within the communication practitioners circle in Cambodia to enhance internal reliability and validity. The researcher conducted the pilot test with ten Cambodian communication professionals, five of whom are female. Overall, the respondent from the pilot test responded that the questionnaire was understandable and easy to complete. Most of them spent around five minutes to complete the survey. The participants also suggested several minor comments, such as wording and translation errors. In summary, the pilot test provided valuable feedback for the researcher to refine the questionnaire, leading to the final version used in this study (see Appendix 1).

3.8 Ethical consideration

Google Forms can be a convenient tool for conducting academic research due to its ease of use and accessibility to a wide range of audience. However, the researcher observed that there are several limitations and privacy concerns associated with using Google Forms for academic research. Although Google claims to anonymise this data before providing it to the researcher, there is still a risk of potential identification, especially when combined with other publicly available information. For instance, Google's Privacy Policy states that they may collect information such as IP addresses, device information, and location data for various purposes, including providing and improving their services, personalised content, and ads. In the case of this study, it was unavoidable for the researcher to choose Google Forms as the tool for data collection. The main reason why the Google Forms was used in the study was because the tool is capable of using the Khmer language, while another survey tool, Sunet Survey, provided by Lund University, does not include the Khmer language option. To ensure a transparent disclosure, the researcher provided clear instructions and a research consent form to the respondents (see Appendix 1). In addition, the research also informed that the respondent could choose to participate or not participate or quit in the middle of the survey without any intervention from the researcher.

4. Findings

This chapter presents the survey results and analysis. First, the researcher examines the demographics of the respondents, including their experience with Generative AI. Second, the researcher presents the findings from descriptive and frequency analysis, which provide a summary of the data. Finally, the researcher focuses on testing the hypotheses formulated earlier and conducts a multiple regression analysis to explore the potential relationships between various factors.

4.1 Demographic

The survey data was collected from March 05, 2024, to March 18, 2024. Since the survey items were in Khmer, the researcher conducted an initial screening process on Microsoft Excel to translate the survey into English and check if all the respondents fully complied with the research criteria. Out of 152 initial survey participants, two responses were excluded. This decision was made because the two respondents did not fit the recruitment criteria. One respondent responded that he or she does not have Cambodian citizenship, and another does not identify him or herself as a communication professional. Excluding these two respondents left a final sample size of 150 participants. The data was later checked for abnormalities and unengaged responses on SPSS. Overall, the standard deviation for all responses was greater than 0.5 and well distributed. Thus, no response was considered disqualified.

Of the 150 respondents, 49.3 per cent (n=74) identified as female, 50 per cent (n=75) as male, and 0.7 per cent (n=1) as other. Most of the respondents, 68.7 per cent, were between 24 and 35 years old, followed by 18 to 24 (16 per cent) and 35 to 44 (15.3 per cent). For education level, 61.3 per cent responded that they finished a Bachelor's Degree, 33.3 per cent finished a Master's Degree, and only a small percentage of the respondents finished high school, vocational training and doctorate level.

Table 2: Demographic results

Demographic results	Item	Frequency	Percentage
Gender	Female	74	49.3
	Male	75	50
	Other	1	0.7
Age	18-24	24	16
	25-34	103	68.7
	35-44	23	15.3
Education	High school	4	2.7
	Vocational training	2	1.3
	Bachelor	92	61.3
	Master	50	33.3
	PhD	2	1.3

The largest group of respondents worked in the field of Public Relations (n=38) and Internal Communication (n=38), followed by Marketing Communication (n=31), Social Marketing Communication (n=19), Technical Communication (n=16) and Political Communication (n=8). Within their communication field of expertise, 36 per cent of the respondents answered that they are in a Mid-level position (n=85), followed by 30.7 per cent in Senior-level (n=46), and 12.7 per cent in an Entry-level position (n=19). Regarding their working experience, 38 per cent of them responded that they have been working for more than five years (n=57), followed by 36 per cent (n=54) with 3-5 years of experience, 16 per cent (n=24) with 1-2 years of experience and 10 per cent (n=15) has less than one year of experience. Statistics are presented in Table 3.

Table 3: Profession results

Profession results	Item	Frequency	Percentage
Communciation Specialty	Internal Communication	38	25.3
	Marketing Communication	31	20.7
	Public Relation Communication	38	25.3
	Technical Communication	16	10.7
	Political Communication	8	5.3
	Social Marketing Communication	19	12.7
Position	Entry-level	19	12.7
	Mid-level	85	56.7
	Senior-level	46	30.7
Year of experience	Less than a year	15	10
	1 – 2 years	24	16
	3 – 5 years	54	36
	More than 5 years	57	38

4.1.1 Use of Generative AI

80 per cent (n=120) of the total respondents responded that they had used Generative AI before. Since this study focused on the behaviour intention of the Cambodian communication professionals, not the use behaviour, all respondents (n=150) were included for further analysis. The majority of those who have used Generative AI responded that they had used ChatGPT (n=103), followed by Google Gemini/Bard (n=57), Microsoft Co-pilot (N=37), Mid-journey (n=21), Dall-E (n=15) and others (n=19) which includes Microsoft Bing AI, Grammarly,

QuiltBot, Claude, Canva, You.com, Writesonic, Capcut, Perplexity AI and Baichat. In addition, the majority of those who had used Generative AI responded that they used Generative AI to generate text (n=115), followed by generating picture/graphic (n=32), generating video (n=15), generating code (n=10), generating sound (n=8) and others (n=6) including brainstorming idea, creating slide and checking grammar.

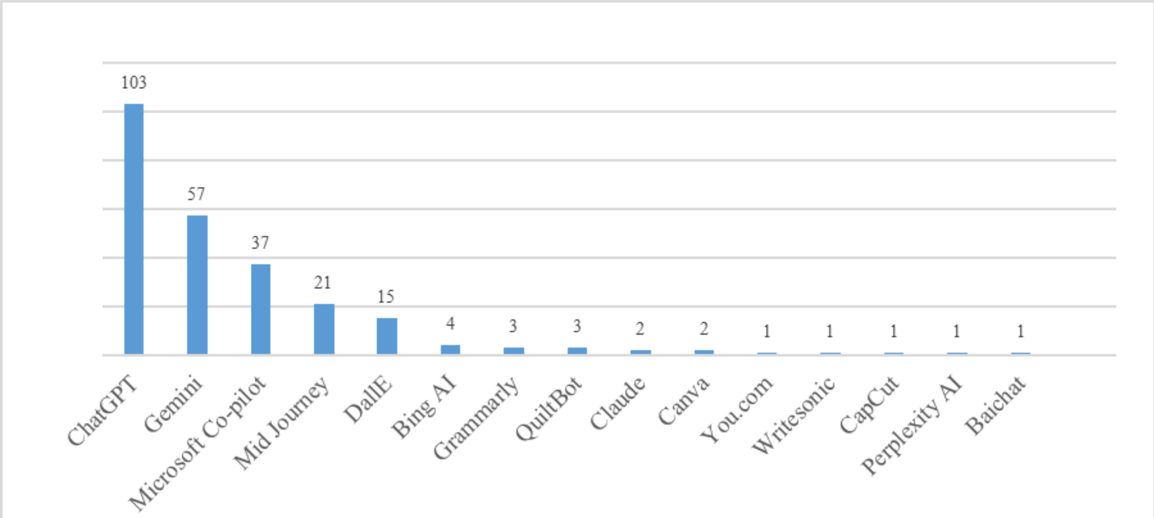

Figure 3: Generative AI tools used by the respondents

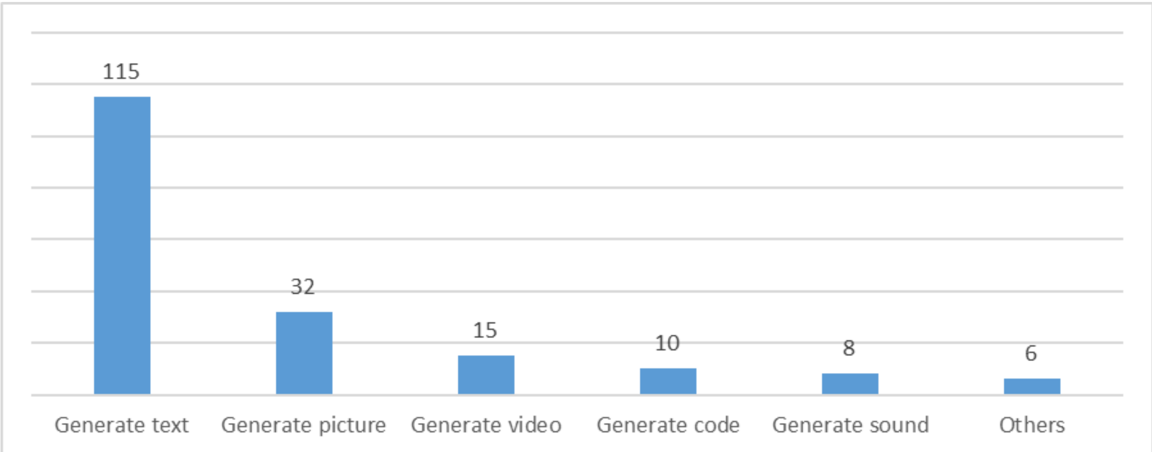

Figure 4: Purpose of using Generative AI

4.2 Descriptive statistics

In this section, the researcher ran the descriptive statistics analysis on the research model. In this stage, the researcher focused on describing and summarising the data of the research model, which includes an overview of the data, average scores (mean), and how the data is spread out (standard deviation).

The results regarding Performance Expectancy are presented in Table 5. Most respondents either agreed or strongly agreed with the statements related to Performance Expectancy. Generative AI was considered useful, and the respondents agreed that it allows them to accomplish tasks more quickly. Additionally, the majority of the respondents thought that Generative AI increases their productivity. There was slightly less agreement regarding whether Generative AI applications can increase the chances of solving the problems they face at work.

Table 5: Performance Expectancy statistics

	Completely disagree	Disagree	Neutral	Agree	Completely agree	N	Mean	Std. Deviation
I think that Generative AI can increase my job performance.	1	9	34	66	40	150	3.9	0.888
I think that Generative AI would increase my job productivity.	1	6	21	85	37	150	4.01	0.781
I think that generative AI applications are easy to use for my work.	1	6	21	76	46	150	4.07	0.816
I think that using Generative AI applications can increase my chances of solving the problems I face at work.	3	13	44	63	27	150	3.56	0.951

Based on the results regarding Effort Expectancy presented in Table 6, Generative AI is perceived as easy to learn and easy to use. Though most of the respondents responded that the instructions for Generative AI are considered clear and understandable, a notable number of people disagree with that. Similarly, while there was general agreement that becoming skilled in using Generative AI is feasible, there were also a number of people who disagreed with this statement. In general, Generative AI appeared to be considered user-friendly and relatively easy to learn.

Table 6: Effort Expectancy statistics

	Completely disagree	Disagree	Neutral	Agree	Completely agree	N	Mean	Std. Deviation
I think that learning how to use generative AI applications is easy for me.	5	6	41	61	37	150	3.79	.971
I think generative AI application instructions are clear and understandable.	4	16	65	47	18	150	3.38	.926
I think that generative AI applications are easy to use for my work.	3	11	42	68	26	150	3.69	.913
I think that it is easy for me to become skilled in using generative AI applications.	3	17	74	34	22	150	3.37	.937

The statistics concerning the Social Influence Statements are presented in Table 7. A significant number of respondents either agreed or completely agreed that if most of their co-workers used Generative AI, they were likely to use it. However, there was also a significant number of people who disagreed with the statement. Similarly, although a high number of people agreed that they are likely to use Generative AI if their superiors and close friends use it, there is also a significant number of people who disagreed with the statement. Interestingly, many respondents agreed that they would use generative AI if their superiors or close friends encouraged them to use it. In summary, the means of the Social Influence statistics are slightly higher than 3.0, which means the influence from colleagues, superiors, and close friends does not show much significance.

Table 7: Social Influence statistics

	Completely disagree	Disagree	Neutral	Agree	Completely agree	N	Mean	Std. Deviation
I would use Generative AI if most of my co-workers used the application.	14	29	36	48	23	150	3.25	1.204
I would use Generative AI if the people who are important to me (employer, close friend) are using generative AI applications.	17	26	35	46	26	150	3.25	1.254
I would use Generative AI if people who are important to me (employer, close friend) think I should use generative AI applications.	14	20	41	50	25	150	3.25	1.181
I would use Generative AI if the people who are important to me (employer, close friend) encourage the use of generative AI applications.	8	15	42	55	30	150	3.56	1.084

The statistics related to Facilitating Conditions are presented in Table 8. Most respondents agreed that they have the necessary resources to use Generative AI. Many respondents also agreed that they have the necessary knowledge to use generative AI and agreed that they can find solutions by themselves if they encounter problems with Generative AI. However, a noticeable number of people disagreed that they can get help from others when they have difficulties using generative AI applications in their workplace.

Table 8: Facilitating Condition statistics

	Completely disagree	Disagree	Neutral	Agree	Completely agree	N	Mean	Std. Deviation
I think that I have the necessary knowledge to use the Generative AI.	4	18	42	58	28	150	3.59	1.011
I think that my workplace has the necessary resources (e.g. computer, smartphone, Internet) to use generative AI.	4	17	17	60	52	150	3.93	1.075
I think that I can get help from others when I have difficulties in using generative AI applications at my workplace.	10	30	47	47	16	150	3.19	1.085
If I experience any problems while using generative AI applications, I can easily access the necessary information for a solution.	7	18	49	53	23	150	3.45	1.040

The statistics related to Hedonic Motivation are presented in Table 9. Most respondents agreed that using Generative AI for their work could be fun, enjoyable and interesting. There were some disagreements that using Generation AI could be fun, but the level of disagreement is not significant.

Table 9: Hedonic Motivation statistics

	Completely disagree	Disagree	Neutral	Agree	Completely agree	N	Mean	Std. Deviation
I believe that using Generative AI could be fun for my work.	7	21	44	58	20	150	3.42	1.038
I expect using Generative AI to be enjoyable.	7	11	35	72	25	150	3.65	.998
I expect using Generative AI to be interesting for my work.	4	12	21	78	35	150	3.85	.958

The statistics related to Price Value are presented in Table 10. Most respondents agreed that they can use Generative AI for free, while many respondents disagreed that Generative AI premium subscription is reasonably priced for their work. In addition, many of them also disagreed on the price options provided by Generative AI companies to provide good value for their work.

Table 10: Price Value statistics

	Completely disagree	Disagree	Neutral	Agree	Completely agree	N	Mean	Std. Deviation
I believe I can use generative AI for free.	6	14	37	46	47	150	3.76	1.115
I believe the generative AI premium subscription is reasonably priced for my work.	23	44	54	20	9	150	2.65	1.081
I believe that Generative AI provides a good value for my work at the current price option.	15	31	45	42	17	150	3.10	1.157

The statistics related to Behavioural Intention are presented in Table 11. Most respondents agree that they intend to use and continue to use Generative AI in the future. The majority of respondents also agree that they are willing to try new types of Generative AI for their work in the future.

Table 11: Behavioural Intention statistics

	Completely disagree	Disagree	Neutral	Agree	Completely agree	N	Mean	Std. Deviation
I intend to use generative AI in the future.	3	7	30	57	53	150	4.00	.962
Assuming I already use generative AI, I intend to continue using it for my work in the future.	2	8	26	62	52	150	4.03	.926
My plan is to continue using generative AI for my work more often.	6	12	36	55	41	150	3.75	1.068
I am willing to try new types of Generative AI for my work in the future.	6	5	25	55	59	150	4.04	1.029

4.3 Hypotheses testing

Multiple Linear Regression (MLR) was conducted to test the study's hypotheses. This section outlines the entire analytical process, encompassing the methodology and the key results obtained.

4.3.1 Validity and Reliability of the Constructs

The analysis began by assessing the internal consistency of the research model constructs using Cronbach's alpha coefficient. This coefficient measures the interrelatedness of the various items within a construct, ensuring they capture the same underlying concept. A Cronbach's alpha value of at least 0.7 is considered acceptable, with values exceeding 0.8 indicating preferable reliability (Pallant, 2003, p. 97). The specific Cronbach's alpha values for each construct in this study are presented in the table below.

Table 12: Cronbach's Alpha

Constructs	PE	EE	SI	FC	HM	PV	BI
Cronbach's alpha	.820	.854	.916	.823	.892	.451	.932

The Cronbach's alpha values of almost all constructs were above 0.8 except for the value of the PV construct, which showed only .451. In such cases, Pallant (2003) suggests calculating and reporting the mean inter-item correlation, which provides a more accurate measure of internal consistency for short scales. Optimal values for mean inter-item correlations typically range from .2 to .4 (Pallant, 2003, p. 97).

Table 13: Inter-item correlation of PV variants

	use_genai_for_free	genai_premium_is_reasonably_priced	genai_provide_goodvalue_at_current_price_option
use_genai_for_free	1.000	-.047	.066
genai_premium_is_reasonably_priced	-.047	1.000	.624
genai_provide_goodvalue_at_current_price_option	.066	.624	1.000

Table 14: PV items statistic

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
use_genai_for_free	5.75	4.066	.012	.767
genai_premium_is_reasonably_priced	6.86	2.752	.403	.123
genai_provide_goodvalue_at_current_price_option	6.41	2.298	.493	-.099[a]

a. The value is negative due to a negative average covariance among items. This violates reliability model assumptions. You may want to check item codings.

The result from the mean inter-item correlation (see Table 13) showed less than 0.2 on the first item, indicating a low level of correlation. The result of the PV item statistic (see Table 14) indicated a high level of Cronbach's Alpha if removing the first item. The first statement was about the level of agreement on whether the respondents believed that they can use Generative AI for free. The other two variants were about the level of agreement on whether the respondent thought that the price of the Generative AI premium subscription is acceptable and offers good value at the price point. Since the PV construct mainly focused on the perceived benefits of the applications and the monetary cost, the researcher decided to exclude the first variants of the PV construct, which is the level of agreement that the respondents believed that they can use Generative AI for free. As a result, the Cronbach's alpha value of the PV construct increased to 0.767, indicating an acceptable reliability level.

Table 15: Cronbach's Alpha (PV construct after removing one variant)

Constructs	PE	EE	SI	FC	HM	**PV**	BI
Cronbach's alpha	.820	.854	.916	.823	.892	**.767**	.932

4.3.2 Multicollinearity test

Prior to conducting the multiple regression analysis, multicollinearity, a phenomenon of high correlation between independent variables, must be addressed. This correlation can lead to inflated standard errors of the regression coefficients, hindering interpretation and potentially generating misleading conclusions (Pallant, 2003, p. 158). To ensure reliable results, the researcher conducted a multicollinearity test to identify any concerning correlations among the independent variables within the model.

Table 16: Pearson Correlation

		PE_Index	EE_Index	SI_Index	FC_Index	HM_Index	PV_Index	BI_Index
PE_Index	Pearson Correlation	1	.633**	.391**	.564**	.692**	.257**	.684**
	Sig. (2-tailed)		<.001	<.001	<.001	<.001	.001	<.001
	N	150	150	150	150	150	150	150
EE_Index	Pearson Correlation	.633**	1	.245**	.667**	.513**	.178*	.490**
	Sig. (2-tailed)	<.001		.003	<.001	<.001	.029	<.001
	N	150	150	150	150	150	150	150
SI_Index	Pearson Correlation	.391**	.245**	1	.375**	.570**	.213**	.487**
	Sig. (2-tailed)	<.001	.003		<.001	<.001	.009	<.001
	N	150	150	150	150	150	150	150
FC_Index	Pearson Correlation	.564**	.667**	.375**	1	.582**	.251**	.548**
	Sig. (2-tailed)	<.001	<.001	<.001		<.001	.002	<.001
	N	150	150	150	150	150	150	150
HM_Index	Pearson Correlation	.692**	.513**	.570**	.582**	1	.295**	.809**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001		<.001	<.001
	N	150	150	150	150	150	150	150
PV_Index	Pearson Correlation	.257**	.178*	.213**	.251**	.295**	1	.273**
	Sig. (2-tailed)	.001	.029	.009	.002	<.001		<.001
	N	150	150	150	150	150	150	150
BI_Index	Pearson Correlation	.684**	.490**	.487**	.548**	.809**	.273**	1
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001	
	N	150	150	150	150	150	150	150

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

*. Correlation is significant at the 0.05 level (2-tailed).

First, Pearson's correlation coefficient was calculated to assess the strength and direction of the relationships between the research variables (Pallant, 2003, p. 134). The results from the correlation test (see Table 16) showed that almost all Pearson correlation coefficient values were below 0.7 between the independent variables, except the value between the HM index and BI index, which has .8. This result indicated only the HM index showed a high level of correlation to the dependent variable.

Next, to assess the multicollinearity concern, the researcher examined tolerance and variance inflation factor (VIF). Tolerance values below 0.1 and VIF values exceeding 10 indicate potential multicollinearity issues (Pallant, 2003, p. 158). The result (see Table 17) confirmed that multicollinearity is not a significant concern in this case. The tolerance values were above 0.1, and the VIF values were below 10. These values suggested that the independent variables in the research model are not excessively correlated, and the model is appropriate for further multiple regression analysis.

Table 17: Multicollinearity test

	Collinearity Statistics	
Model	**Tolerance**	**VIF**
PE_Index	.413	2.420
EE_Index	.450	2.222
SI_Index	.661	1.514
FC_Index	.466	2.148
HM_Index	.383	2.613
PV_Index	.897	1.115

4.3.3 Mean, standard deviation, skewness and kurtosis

Central tendency and dispersion of the data were assessed through analysis of the mean and standard deviation. This analysis provided insight into both the average value of the survey responses and the degree of variability within the data set. Additionally, for continuous variables, the distribution of scores was evaluated using skewness and kurtosis. Skewness indicates the symmetry of the distribution, with a value of 0 reflecting a perfectly normal distribution (Pallant, 2003). Similarly, kurtosis measures the extent to which scores cluster at the centre or tails of the distribution, with a value of 0 representing a normal distribution (Pallant, 2003). As seen in Table 18, skewness and kurtosis indicated small deviations in all indexes. Therefore, the analysis showed that the data were normally distributed.

Table 18: Mean, standard deviation, skewness and kurtosis

	N	Minimum	Maximum	Mean		Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic	Std. Error	Statistic	Std. Error
PE_Index	150	6.00	20.00	15.6267	.22615	2.76980	-.602	.198	.828	.394
EE_Index	150	4.00	20.00	14.2400	.25500	3.12315	-.276	.198	.500	.394
SI_Index	150	4.00	20.00	13.4067	.34513	4.22695	-.266	.198	-.676	.394
FC_Index	150	5.00	20.00	14.1533	.27785	3.40299	-.513	.198	.184	.394
HM_Index	150	3.00	15.00	10.9200	.22175	2.71590	-.778	.198	.571	.394
BI_Index	150	4.00	20.00	15.8200	.29720	3.63995	-.884	.198	.417	.394
PV_Index	150	2.00	10.00	5.7533	.16465	2.01650	.064	.198	-.408	.394
Valid N (listwise)	150									

4.3.4 Normal P-P Plot and Scatterplot

The researcher also used a Normal PP plot and Scatterplot analysis (see Figure 5 & 6) to check for normality and homoscedasticity of the data. The model's graphical representation was presented in two key figures. Figure 4 depicted the Normal P-P plot, which visualised the distribution of residuals (the difference between actual and predicted values). A satisfactory P-P plot would exhibit residuals arranged close to a diagonal line, indicating normality. This condition was met in Figure 5. Additionally, Figure 6 illustrates the scatterplot, displaying standardized predicted values on the X-axis and standardized residuals on the Y-axis. Homoscedasticity, a crucial assumption for well-performing models, was assessed by inspecting the scatterplot for a random distribution of points around a rectangular shape (Pallant, 2003). Figure 6 revealed a sufficient degree of homoscedasticity, with residuals displaying a near-rectangular pattern around the predicted values.

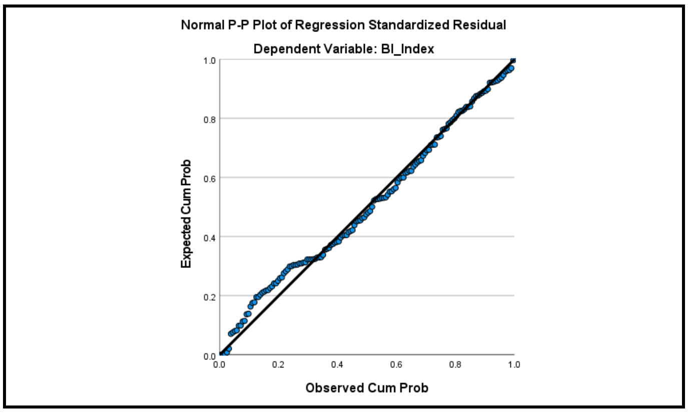

Figure 5: Normal P-P Plot of Regression Standardised Residual

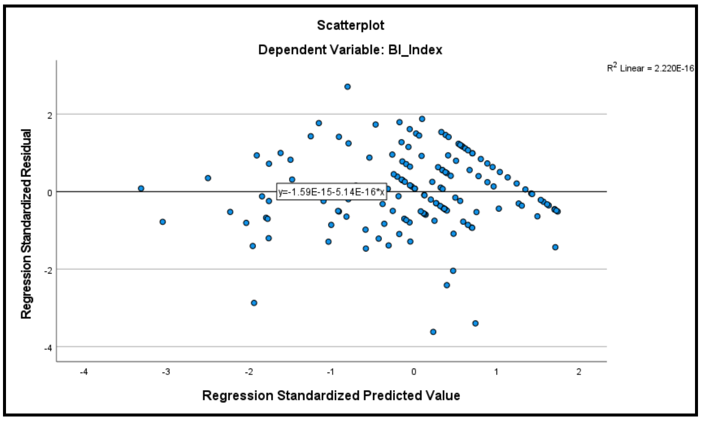

Figure 6: Scatterplot

4.3.5 Standard multiple regression analysis

The final step of the analysis is to identify significant relationships between independent and dependent variables, and subsequently evaluate the study's hypotheses, a multiple regression analysis. This technique allows the researcher to conduct an assessment of each independent variable's contribution to predicting the dependent variable.

Table 19: Model summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.829[a]	.688	.675	2.07593	.688	52.515	6	143	<.001

a. Predictors: (Constant), PV_Index, EE_Index, SI_Index, PE_Index, FC_Index, HM_Index

b. Dependent Variable: BI_Index

To analyse the hypothesis, the research employed the multiple linear regression analysis at 95 per cent confidence intervals. First, the researcher calculated the R Square and P value of the model. The R-squared (R^2) value indicates the proportion of variance in the dependent variable, behavioural intention (BI), that can be attributed to the independent variables included in the research model. It reflects how well the model explains the factors influencing behavioural intention. According to the model summary, the Adjusted R Square was .675, which means that 67.5 per cent of the variance in the dependent variable was explained by the independent variables. The level of significance of the model was <.001, which was below 0.05, indicating the statistical significance of the research model.

Table 20: ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1357.884	6	226.314	52.515	<.001[b]
	Residual	616.256	143	4.309		
	Total	1974.140	149			

a. Dependent Variable: BI_Index

b. Predictors: (Constant), PV_Index, EE_Index, SI_Index, PE_Index, FC_Index, HM_Index

The researcher also conducted an Analysis of Variance (ANOVA) test to further evaluate the overall statistical significance of the research model. A significant model ($p < .05$) indicates that the independent variables, taken together, have a statistically meaningful relationship with the dependent variable (Pallant, 2003, p. 161). The result showed that the Sig.-value (p-value) was .001, indicating the significant level of the research model.

Table 21: Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
1	(Constant)	1.138	1.048		1.086	.279	-.933	3.209
	PE_Index	.293	.096	.223	3.067	.003	.104	.482
	EE_Index	-.017	.081	-.015	-.212	.833	-.178	.143
	SI_Index	.028	.050	.032	.563	.574	-.070	.126
	FC_Index	.072	.073	.067	.983	.327	-.073	.217
	HM_Index	.804	.101	.600	7.942	<.001	.604	1.004
	PV_Index	.031	.089	.017	.346	.730	-.145	.207

a. Dependent Variable: BI_Index

The table above presents the results of the structural model testing. To delve deeper into the influence of each independent variable on the dependent variable (behavioural intention), the researcher focused on the standardised beta coefficients (β) in the Beta column. As explained by Pallant (2003, p. 161), the absolute value of a beta coefficient indicates the strength of the relationship between a specific independent variable and the dependent variable. Higher values correspond to a greater impact of that variable on the dependent variable. The result showed that Hedonic Motivation (HM) ($\beta = 0.600$) and Performance Expectancy (PE) ($\beta = 0.223$) are subsequently the constructs with the highest values.

To validate the construct's impact on the dependent variable, the researcher examined the significance column (Sig. or p-value) to evaluate the statistical significance of each independent construct's influence on the dependent variable. If the p-value is greater than 0.05 ($p > 0.05$), it suggests that the relationship between that specific construct and the dependent variable is not statistically significant (Pallant, 2003, p. 161). The result showed only that the P-values associated with PE and HM were less than 0.05 and thus had statistically significant contributions to the dependent variable (BI). Therefore, PE and HM were the only two independent constructs that have a statistically significant effect on predicting the dependent variable (BI).

5. Discussion and conclusions

In this section, the researcher will examine the findings and hypotheses of the study in comparison to prior research. Additionally, the researcher also highlights the study's contributions to the field of Generative AI acceptance among Cambodian communication practitioners. Finally, recommendations for future research on this topic will be provided to conclude this section.

The survey results showed that the majority of the respondents expressed strong behavioural intention toward adopting Generative AI for their work (see Table 11). The findings also indicated that the significant predictors of Cambodian Communication professionals' intentions to use Generative AI in order of relevance are hedonic motivation and performance expectancy. Therefore, the intention to use Generative AI highly depended on the user's fulfilment of hedonic motives expected from using the technology and the level of performance and productivity that the users expect to get from it.

Out of the six hypotheses in this study, two hypotheses (H1 and H5) were confirmed, while the remaining four (H2, H3, H4, and H6) were not supported by the data. A detailed overview of the structural model results and hypothesis testing is presented in the table below.

Table 22: Confirmed hypothesis

No.	Hypothesis	β -value	*t*-value	*p*-value
H1	PE → BI	.223	3.067	.003
H2	EE → BI	-.015	-.212	.833
H3	SI → BI	.032	.563	.574
H4	FC → BI	.067	.983	.327
H5	HM → BI	.600	7.942	<.001
H6	PV → BI	.017	.346	.730

5.1 Confirmed hypothesis

Hypothesis 1 postulated a significant positive influence of performance expectancy on Cambodian communication professionals' intention to use Generative AI for their work. The results strongly supported this hypothesis ($\beta = .223$, $t = 3.067$, $p = .003$). This indicated that a higher level of perceived usefulness and performance expectancy regarding the use of Generative AI for work significantly increases Cambodian communication professionals' intention to adopt this technology. Performance expectancy had a strong effect on behavioural intention, which is in line with previous findings on Generative AI adoption that found performance expectancy as a potential core motivator (Brachten et al., 2021; Andrews et al., 2021; Tiwari et al., 2023). The previous studies suggested that with an increased number of digital tools and available choices, users prioritise solutions that can enhance their productivity and contribute to their work and study (Brachten et al., 2021; Andrews et al., 2021). The study findings and the previous studies proved that the higher the user perceives the technology can facilitate greater performance and productivity, the higher their intention to adopt the technology, as claimed in the UTAUT 2 theoretical framework by Venkatesh et al. (2012).

To answer why performance expectancy had a significant effect, the researcher examined the descriptive results. The descriptive results of the survey (see Table 5) showed that Generative AI is considered to be a useful tool, and it allows the respondents to accomplish tasks more quickly and increases their work productivity. This result aligned with the previous studies on the practical values of Generative AI among communication practitioners. According to Haleem et al. (2022), Generative AI has a significant advantage in producing original content that can be utilised within the creative industry; hence, it increases the productivity and performance of marketing and communication practitioners. Other studies also suggested that Generative AI can enhance efficiency in tasks such as content creation, writing, coding, and debugging, thereby increasing the users' productivity associated with these tasks (Eloundou et al., 2023; Ouyang et al., 2022). In the case of this study, the majority of the respondents who had used Generative AI responded that they used Generative AI to generate text, followed by generating pictures/graphics, generating videos, generating code, generating sounds and others, including brainstorming ideas, creating slides and checking grammar. These utilitarian factors could also likely be the determinants of why performance expectancy plays such an important role in Cambodian communication professionals' intention of using Generative AI. However, further research should be conducted to determine key activities that contributed to the effect of performance expentency.

Another hypothesis confirmed by the findings was Hypothesis 5, which predicted a significant and positive influence of hedonic motivation on Cambodian communication professionals' intention to use Generative AI for their work. The findings provided strong support for this hypothesis (H5: $\beta = .600$, $t = 7.942$, $p < .001$). This suggested a significant positive relationship between Cambodian communication professionals' hedonic motivation associated with using Generative AI for work and their intention to adopt this technology. In other words, the more enjoyable or fun they perceive using Generative AI to be in their work, the more likely they are to incorporate it into their professional practices. Previous studies on acceptance of Generative AI technologies also showed that hedonic motivation had a strong effect on users' behavioural intention (Tiwari et al., 2023; Gupta & Yang, 2023; Wang & Zhang, 2023; Dinh & Park, 2023). Their results suggested that hedonic motivation is a fundamental driver that may include elements of surprise, excitement, novelty and fun from engaging or interacting with Generative AI technology. In the case of this study, The survey's descriptive results (see Table 9) also showed that most respondents agreed that using Generative AI for their work could be fun, enjoyable and interesting. Therefore, these factors could also likely be the determinants of why hedonic motivation plays such an important role in Cambodian communication professionals' intentions to use Generative AI. However, further research should be conducted to explore key factors that contributed to the effect of hedonic motivation.

5.2 Rejected hypothesis

Contrary to expectations, the findings rejected four hypotheses. Hypothesis 2, Effort Expectancy, was not found to be a significant factor influencing Cambodian communication professionals' adoption of the communication tool. This finding aligned with the findings of Tiwari et al. (2023), where users (students) reported difficulty in using ChatGPT and questioned its effectiveness in enhancing their skills. Complexity, high mental effort required for operation, and unclear or uninterpretable responses from the tool were identified as potential reasons for this perception (Tiwari et al., 2023). These factors might discourage users from seeking quick solutions to adopt the technology. In the case of this study, the descriptive result on EE (see Table 6) showed that most respondents chose neither agree nor disagree on the four statements, which could reflect their uncertainty on whether they considered Generative AI to be easy to use. Considering that Generative AI was in its early adoption, users might still experiment with and test the technology. Therefore, uncertainty and scepticism about the technology's ease of use should be expected.

Hypothesis 3 was not supported which means that Social Influence was found to be an insignificant factor influencing Cambodian communication professionals' intentions to use Generative AI. In a study on user acceptance of mobile restaurant apps, Palau-Saumell et al. (2019) suggested two reasons social influence has a weaker effect on mobile service adoption. First, because mobile apps were already commonly used, social pressure from friends, family and other important people (reference groups) to adopt them might be a less important factor in their acceptance. Second, the study suggests habit is the biggest factor influencing users' decision to use mobile services. In this line of thought, familiarity with the technological tool lessens the connection of Social Influence to the acceptance of the technological tool. In the case of this study, it could be explained that due to the nature of communication work, communication professionals need to keep themselves up-to-date with fast-paced technology as well as other communication platforms and tools. As communication professionals might have gained familiarity with new technologies, the impact of social norms regarding the intention to use these AI technologies has become less important over time.

Hypothesis 4, which predicted that facilitating conditions would influence behavioural intention, was not supported by the findings. This descriptive result on FC (see Table 8) suggested that for individuals possessing the necessary skills and abilities to utilise Generative AI without additional technical support, facilitating conditions may not be a significant determinant of user intention. This finding aligned with the study by Sebastián et al. (2022) on factors influencing behavioural intention in the use of artificial intelligence virtual assistants (VAs), in which they suggested that in scenarios where users possess the requisite skills and capabilities to effectively utilise VAs without requiring additional technical support, facilitating conditions become less influential determinants in shaping user adoption intentions. Considering that Generative AI such as ChatGPT or Google Germini is a web-based application that does not require advanced setup, structural support is not necessarily needed during installation or application use. While the result (see Table 8) also showed that the respondents generally perceived themselves as having the resources and knowledge necessary for Generative AI use, a clear link between facilitating conditions and behavioural intention to use could not be established.

Hypothesis 6, which predicted that Price Value would influence behavioural intention, was not supported by the findings. This finding also aligned with the study by Sebastián et al. (2022) as they suggested that price/value was not a significant factor due to two key factors. Firstly, the installation of these technology-assisting devices, like central speakers, often incurs no additional cost. Secondly, users perceive the overall cost of access to be affordable. In the case of this study, a similar argument could be made that many Generative AI applications offer free-of-charge options for users to use. In addition, users did not need to spend extra on purchasing or upgrading their gadgets to use the application. These factors could contribute to why the price value factor would not be so impactful in the acceptance of Generative AI.

5.3 The effect of performance expectancy and hedonic motivation

Noticeably, in this study, the researcher found that among the two impactful predictors, the effect of hedonic motivation (H5: $\beta = .600$, $t = 7.942$, $p < .001$) is significantly higher than the effect of performance expectancy ($\beta = .223$, $t = 3.067$, $p = .003$) on Cambodian communication professionals' behavioural intention on adopting Generative AI. This finding was also confirmed by previous studies on Generative AI adoption (Wang & Zhang, 2023; Dinh & Park, 2023). The research by Wang & Zhang (2023) highlighted the significant influence of hedonic motivation on users' intention to use Generative AI for art designing among Chinese Generation Z; however, performance expectancy did not show a statistically significant effect. They found that Generation Z users were more driven by their enthusiasm for technology and eagerness to adopt new technology like Generative AI. When engaging with the Generative AI platform, they might prioritise the novelty and excitement it offers over its practical advantages (Wang & Zhang, 2023). Similarly, a study by Dinh and Park (2023) also found that hedonic motivation is vital in increasing consumer willingness to adopt AI chatbots, while utilitarian motivation did not show a significant effect. Their findings suggested that focusing on enjoyment and fun (hedonic motivation) is more important than practicality (utilitarian motivation) in creating a sense of interaction with the chatbot. They concluded that excitement and social presence ultimately lead to a greater willingness to use the chatbot service (Dinh & Park, 2023).

The studies that highlighted the impact of hedonic motivation over utilitarian motivation appeared to focus on or include the young generation cohort as the target respondent (Wang & Zhang, 2023; Dinh & Park, 2023; Tiwari et al., 2023). In the case of the current study, even though the researcher focused on Cambodian communication professionals without targeting a specific age group, the majority of respondents (68.7%) appeared to be in the age between 25 and 34 years old, which could be considered a young generation cohort (Generation Y and Z, born between 1980-2010). In this sense, young populations could demonstrate a stronger influence of technological enthusiasm and a propensity for early adoption on their intention to use Generative AI platforms. This suggested that the novelty and excitement associated with this technology may be a more significant driver for their engagement, potentially even outweighing the perceived practical benefits. According to the Generational Cohort theory, individuals' thoughts and behaviours are significantly influenced by the socio-historical events they experience during their formative years (Moss, 2014). As a result, Moss (2014) suggested that individuals born within a similar timeframe tend to share common experiences that shape their values, beliefs, and expectations. These shared experiences ultimately contribute to the development of a distinct generational identity (Moss, 2014). The significance of the age factor was also addressed by Venkatesh et al. (2003) as one of the key moderators of the UTAUT 2 model. Therefore, the age factor could also have a moderate effect on why hedonic motivation shows a higher effect than performance expectancy among Cambodian communication professionals' intentions to use Generative AI.

5.4 Conclusions and suggestions for further research

Considering the growing popularity of Generative AI technologies among communication professionals around the world (Mariani et al., 2023; Dwivedi et al., 2023) and its economic potential for developing nations like Cambodia (Mannuru et al., 2023), this study aimed to examine what important factors and drivers for Cambodian communication professionals to accept Generative AI for their work by using UTAUT2 as the theoretical framework. This study has contributed to both theoretical and practical knowledge of the field of strategic communication.

From a theoretical point of view, the current study theoretically addressed several gaps in the existing literature on Generative AI adoption intention. Previous research on Generative AI adoption's intention has focused on examining users in the academic, enterprise, art design, and consumer contexts (Brachten et al., 2021; Andrews et al., 2021; Tiwari et al., 2023; Gupta & Yang, 2023; Wang & Zhang, 2023; Dinh & Park, 2023). Several studies on Generative AI and communication practitioners have investigated the potential of the technology in the profession (Valin, 2018; Anderson & Rainie, 2023; Mariani et al., 2023; Dwivedi et al., 2023). However, this study performed an empirical examination of 150 communication professionals' intentions to use Generative AI, expanding the literature related to Generative AI adoption's intention among communication professionals. Secondly, this research also provided valuable insights from the UTAUT2 model perspective by confirming the significance of key factors such as Performance Expectancy and Hedonic Motivation in influencing the acceptance and intention to use Generative AI technology. Additionally, the research was done to provide insights into how Generative AI is perceived among communication professionals in a developing nation. The results of this study could contribute to the literature on technology adoption in Cambodia.

From a practical perspective, these findings could inform the potential acceptance of Generative AI among communication professionals in Cambodia. The results showed a positive behavioural intention toward Generative AI, indicating the potential mass utilisation of the technology within the communication field in Cambodia in the future. The findings also addressed strategies to promote the adoption of new technology among communication professionals in Cambodia. This study found that user Performance Expectancy and Hedonic Motivation are essential drivers of technology acceptance among Cambodian communication professionals. The results highlight the potential of Generative AI in the communication field and its capability to enhance the productivity of communication professionals, as well as the need to address hedonic elements to promote wider adoption.

Like other research, this study also has limitations that pave the way for further exploration. One area for future research could be a deeper investigation into the concept of habit formation within the UTAUT2 model. Additionally, the moderating variables such as age, gender, voluntariness, and experience, which were excluded in this study, could be examined to understand their influence on technology adoption. Furthermore, the research focused solely on factors encompassed by the UTAUT2 framework. Future studies could benefit from analysing the impact of external constructs specific to Cambodian communication professionals' acceptance of Generative AI. These constructs might include their existing knowledge of the technology, individual personality traits, and technology self-efficacy. By incorporating such variables, future research has the potential to develop more accurate models for predicting both acceptance and utilisation of Generative AI tools.

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Appendices

Appendix 1 - Survey

A. Survey Introduction

You are being invited to participate in a research study titled “The Contributing Factors to the Acceptance of Generative AI among Cambodian Communication Practitioners”. This study is being done by Singhtararith Chea as part of his Master’s Degree graduation criteria at Lund University, Sweden.

The purpose of this research study is to investigate the factors that influence the acceptance of Generative AI (e.g. ChatGPT, Google Barn, Mid Journey …) among Cambodian communication professionals. By understanding these contributing factors, this study can provide insights into the decision-making processes, as well as challenges and opportunities in the adoption of this technology within the country’s communication industry. This, therefore, contributes to the understanding of the current landscape and the future of the communication profession in Cambodia.

This survey will take you approximately five minutes to complete. Your participation in this study is entirely voluntary, and you do not have to answer any questions you do not want to. I believe there are no known risks associated with this research study; however, as with any online-related activity, the risk of a breach is always possible. To the best of our ability, your participation in this study will remain confidential, and only anonymised data will be published.

If you have any questions or concerns about this study, please contact the researcher via email: singhtararith.chea@gmail.com or mobile: +46 729 943 841.

If you understand and would like to do the survey, please tick in the box and proceed to the next page to start.

B. Survey item (translated in English)

Section 1: Demographic

Do you have a Cambodian Nationality?

- Yes
- No

Gender

- Female
- Male
- Other

Age

- 18 to 24
- 25 to 34
- 35 to 44
- 45 to 54
- 55 or older

Education level

- Secondary
- Vocational training
- University
- Master
- PhD

Please choose the communication specialty that you are most fit with

- management communication (e.g. internal communication staff)
- marketing communication (e.g. marketing, advertising staff)
- public relations (e.g. stakeholder relations, press relations staff)
- technical communication (e.g. customer support staff)
- political communication (e.g. politician, activist)
- social marketing campaign (e.g. social campaigner)
- Other (specify)

Which position are you working in?

- Entry-level or junior position (assistant)
- Mid-level position (officer)
- Senior-level position (manager)

How long have you been working as a communication professional?

- ☐ Less than a year
- ☐ 1-2 years
- ☐ 3-5 years
- ☐ More than 5 years

In the next section, you will be asked about Generative AI. Here is a brief definition of generative AI by Google Cloud: “Generative AI or generative artificial intelligence refers to the use of AI to create new content, like text, images, music, audio, and videos.” Here are some examples of generative AI: ChatGPT, Google Bard, Mid Journey, Dall-E, and Microsoft Co-pilot.

Section 2: Use of generative AI

Have you ever used Generative AI? (If yes, please complete all the questions in this section. If no, please proceed to another section.)

- ☐ Yes
- ☐ No

Please choose your usage frequency for each of the following:

(5 points high-frequency scale: Never, Twice a month or less, Once a week, Twice a week, Daily)

- ChatGPT
- Google Bard / Gemini
- Microsoft Co-pilot
- Mid journey
- Dall-E
- Other (specify)

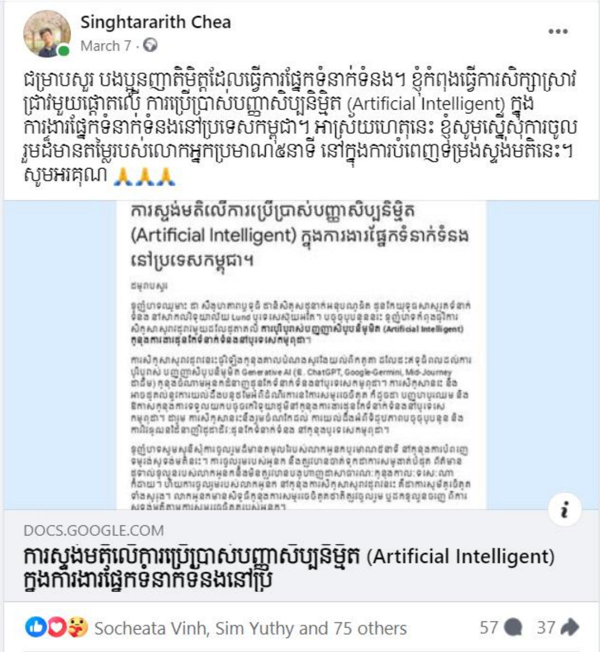
Section 3: Perception toward the adoption of Generative AI in communication Please choose the level of your agreement for each of the following statements:

(1-Strongly Disagree, 2-Disagree, 3-Undecided, 4-Agree, 5-Strongly Agree)

Factor	Code	Statement (English)
Performance expectancy (Venkatesh et al., 2012; Yilmaz et al., 2023)	PE1	I think that Generative AI can increase my job performance.
	PE2	I think that Generative AI would increase my job productivity.
	PE3	I think that Generative AI could decrease the time I need to do my work-related tasks.
	PE4	I think that using Generative AI applications can increase my chances of solving the problems I face at work.
Effort expectancy (Venkatesh et al., 2012; Yilmaz et al., 2023)	EE1	I think that learning how to use generative AI applications is easy for me.
	EE2	I think generative AI application instructions are clear and understandable.
	EE3	I think that generative AI applications are easy to use for my work.
	EE4	I think that it is easy for me to become skilled in using generative AI applications.
Social influence (Venkatesh et al., 2012; Yilmaz et al., 2023)	SI1	I would use Generative AI if most of my co-workers used the application.
	SI2	I would use Generative AI if the people who are important to me (employer, close friend) are using generative AI applications.
	SI3	I would use Generative AI if people who are important to me (employer, close friend) think I should use generative AI applications.
	SI4	I would use Generative AI if the people who are important to me (employer, close friend) encourage the use of generative AI applications.
Facilitating conditions (Venkatesh et al., 2012; Yilmaz et al., 2023)	FC1	I think that I have the necessary knowledge to use the Generative AI.
	FC2	I think that my workplace has the necessary resources (e.g. computer, smartphone, Internet) to use generative AI.
	FC3	I think that I can get help from others when I have difficulties in using generative AI applications at my workplace.
	FC4	If I experience any problems while using generative AI applications, I can easily access the necessary information for a solution.
Hedonic Motivation (Venkatesh et al., 2012; Sebastián et al., 2022; Van et al., 2021)	HM1	I believe that using Generative AI could be fun for my work.
	HM2	I expect using Generative AI to be enjoyable.
	HM3	I expect using Generative AI to be interesting for my work.
Price Value (Venkatesh et al., 2012; Sebastián et al., 2022; Van et al., 2021)	PV1	I believe I can use generative AI for free.
	PV2	I believe the generative AI premium subscription is reasonably priced for my work. (e.g. ChatGPT Plus subscription is $20/month; Mid Journey basic plan is $10/month)
	PV3	I believe that Generative AI provides a good value for my work at the current price option.
Behaviroural intention (Venkatesh et al., 2012; Sebastián et al., 2022; Van et al., 2021)	BI1	I intend to use generative AI in the future.
	BI2	Assuming I already use generative AI, I intend to continue using them for my work in the future.
	BI3	My plan is to continue using generative AI for my work more often.
	BI4	I am willing to try new types of Generative AI for my work in the future.

Appendix 2 – Survey Announcement

A. Facebook announcement



B. Linkedin Announcement