FACTORS INFLUENCING THE ACCEPTANCE AND USE OF GENERATIVE ARTIFICIAL INTELLIGENCE IN THAI STARTUP COMPANIES

BY

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ABSTRACT

This study investigates the determinants of Generative AI acceptance and usage among personnel within Thai startup companies. The primary objective is to elucidate the critical organisational and psychological factors driving adoption in this specific, high-agility context. To achieve this, the study proposes and tests a conceptual framework by extending the Unified Theory of Acceptance and Use of Technology (UTAUT) model. This extension incorporates three psychological constructs comprising Hedonic Motivation (HM), Trust in AI (TAI), and AI Anxiety (AIA).

Employing a quantitative methodology, the research gathered 343 valid responses from employees and founders across the Thai startup ecosystem through a multi-channel strategy comprising online communities, on-site data collection at industry events, and direct outreach. The data was analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM).

The results demonstrate that the model possesses moderate explanatory power, accounting for 49.2% of the variance in Behavioural Intention (BI) and 60.1% of the variance in Use Behaviour (UB). The analysis confirmed five hypotheses where Performance Expectancy (PE), Social Influence (SI), and Hedonic

Motivation (HM) were identified as significant positive drivers of Behavioural Intention. Furthermore, Facilitating Conditions (FC) and Behavioural Intention (BI) served as significant predictors of actual Use Behaviour

Conversely, three key hypotheses were not supported where Effort Expectancy (EE), Trust in AI (TAI), and AI Anxiety (AIA) were found to have an insignificant effect on Behavioural Intention. Consequently, the study concludes that adoption in this context is distinctively pragmatic. Users are motivated primarily by utility (PE), social norms (SI), and enjoyment (HM). These drivers prove sufficiently potent to override low trust and functional anxieties, resulting in a "Pragmatic Adoption" model. This behaviour reinforces a "Human-in-the-Loop" approach, wherein users verify AI output due to a lack of absolute trust. The findings offer practical guidelines for startup leaders, suggesting a strategic pivot in training from the "how" (ease of use) to the "why" (utility), alongside the implementation of formal "Human-in-the-Loop" policies to effectively manage user anxiety.

Keywords: Generative AI, Artificial Intelligence, Technology Acceptance, UTAUT, Startups, AI Anxiety, Trust in AI, PLS-SEM

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Kittisak Kanokbusabarn

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

Symbols/Abbreviations	Terms
AI	Artificial Intelligence
GenAI	Generative AI
TAM	Technology Acceptance Model
UTAUT	Unified Theory of Acceptance and Use of Technology
LLMs	Large Language Models
PE	Performance Expectancy
EE	Effort Expectancy
SI	Social Influence
FC	Facilitating Conditions
HM	Hedonic Motivation
TAI	Trust in AI
AIA	AI Anxiety
BI	Behavioural Intention
UB	Use Behaviour
PLS-SEM	Partial Least Squares Structural Equation Modelling
AVE	Average Variance Extracted
CR	Composite Reliability
HTMT	Heterotrait-Monotrait Ratio
VIF	Variance Inflation Factor
MGA	Multi-Group Analysis
DEPA	Digital Economy Promotion Agency
NIA	National Innovation Agency
MDES	Ministry of Digital Economy and Society
NSC	National Startup Committee

CHAPTER 1
INTRODUCTION

This chapter provides an introduction to the study, outlining the background and the primary research problem. Subsequently, it details the research objectives and the significance of the study.

1.1 Background and Rationale

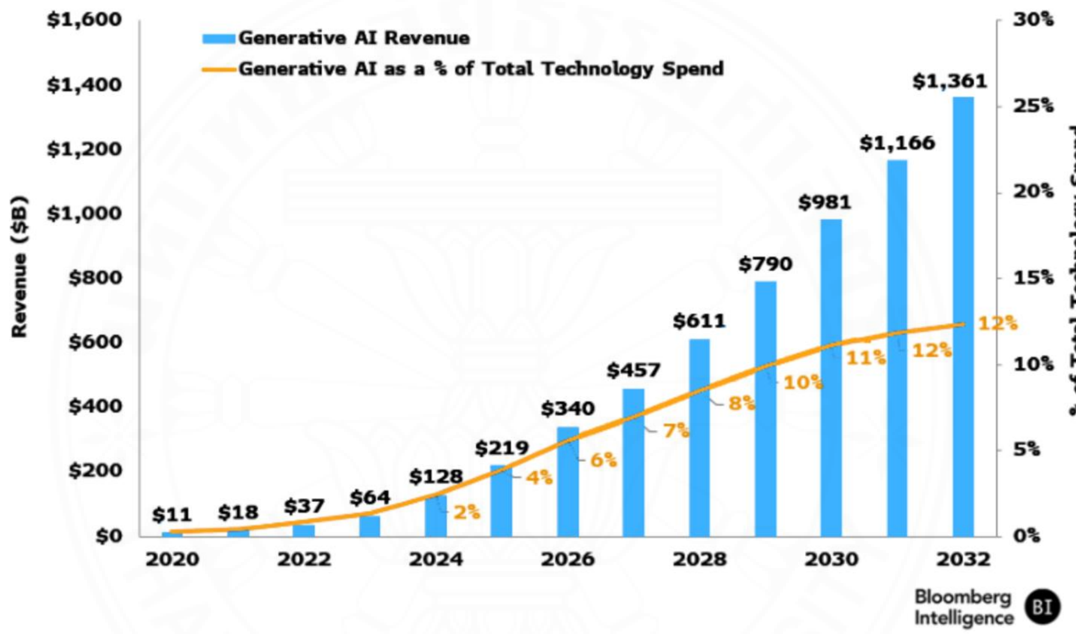
In recent years, artificial intelligence (AI) has experienced exponential growth and fundamentally transformed numerous facets of society across both industrial sectors and daily life. The advent of powerful Generative AI (GenAI) has further accelerated this paradigm shift. Unlike earlier technologies, Generative AI tools such as ChatGPT and Gemini transcend mere automation. They possess the advanced capability to facilitate complex decision-making, foster innovation, and generate novel forms of content.

These distinctive capabilities have democratised access to AI and expanded its user base far beyond specialists and engineers. Today, a diverse array of individuals utilises these tools for various tasks. This group includes educators, students, and office professionals who use the technology for purposes ranging from lesson planning to academic research. This widespread adoption underscores the status of GenAI as a critical technology for both modern business and broader society. Indeed, the integration of AI into varied environments such as retail stores, hospitals, and automotive systems demonstrates its pervasive reach. It also highlights the importance of analysing its usage across different contexts.

Technological advancement in this field is rapid as new AI tools and systems enter the market annually. Developers also continuously update their flagship products. According to Singh & Rana (2024), the global market for generative AI is projected to reach USD 1.3 trillion by 2032. This figure accounts for approximately 12 percent of worldwide technology spending (Singh & Rana, 2024). Such data indicates substantial investment from organisations and individuals alike. However, adoption remains uneven despite the immense potential of generative AI to enhance business performance. Many organisations acquire these advanced technologies only to find that their employees lack the necessary knowledge to utilise them effectively.

Figure 1.1

Generative AI Spending

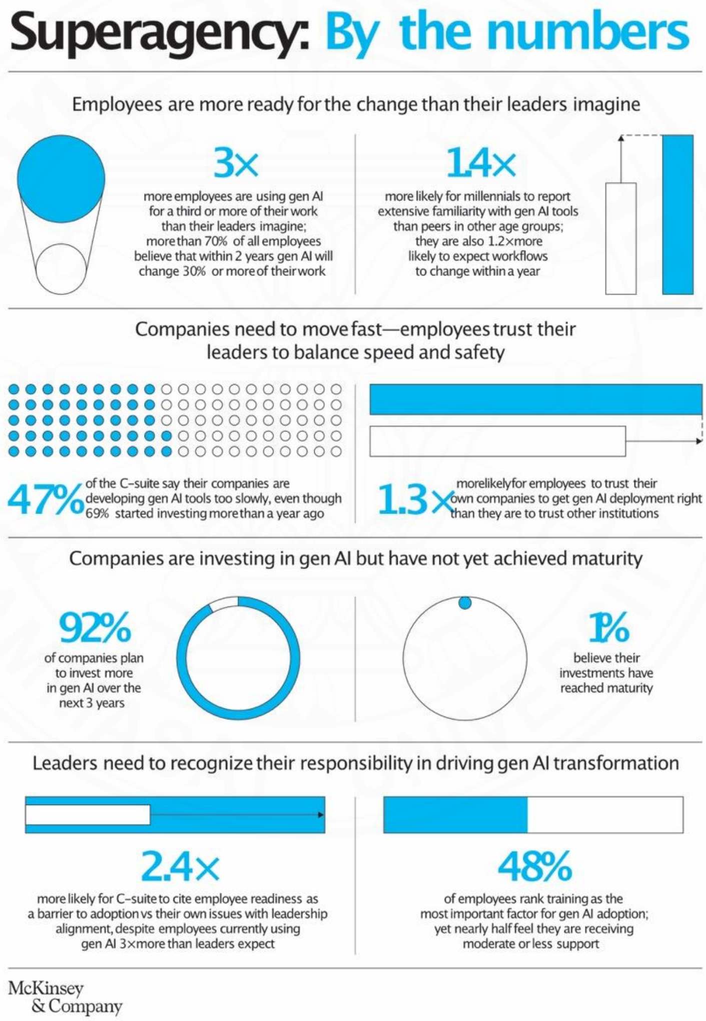


Note. *From Generative AI Outlook 2025: Assessing Opportunities and Disruptions in an Evolving Trillion-Dollar-Plus Market* (p. 6), by M. Singh and A. Rana, 2024, Bloomberg Intelligence.

A survey by Mayer et al. (2025) reveals that widespread efforts to adopt AI technology are underway across various organisations. Nevertheless, only approximately 1 percent of large companies have managed to achieve favourable results (Mayer et al., 2025). This finding underscores that the availability of advanced technology does not inherently ensure success. Employees must acquire the necessary skills to utilise AI correctly. A significant barrier to this is the current insufficiency of AI experts and dedicated training programmes. Such a deficit illustrates the disconnect between the rapid pace of technological change and the time required for organisations and individuals to adjust. Consequently, many industries face a shortage of the essential skills and knowledge needed to leverage new technologies effectively. Companies therefore experience mounting pressure to transform even as they continue to find the process challenging.

Figure 1.2

An Overview of Corporate Adaptation to the Generative AI Era



Note. From *Superagency in the workplace: Empowering people to unlock AI's full potential* (p. 3), by H. Mayer, L. Yee, M. Chui, and R. Roberts, 2025, McKinsey & Company.

Thailand presents a compelling case study characterised by both significant opportunities and distinct challenges regarding AI acceptance. The government has implemented the Thailand 4.0 vision to transform the country into a high-income and innovation-driven nation. This strategy aims to shift the economy from agriculture and manufacturing towards a knowledge-based and digital-enabled model. Key organisations such as the Digital Economy Promotion Agency (DEPA) and the National Innovation Agency (NIA) actively encourage the workforce to integrate AI into their operations. Progress is evident yet numerous obstacles persist. Urban centres like Bangkok typically enjoy access to modern technology. Rural areas face greater difficulties due to limited digital infrastructure such as computer access and stable internet connections.

Research indicates that the digital divide, bias, and privacy risks remain prevalent issues (Thanyawatpornkul, 2024). Economic disparities mean that not everyone can afford essential hardware or subscriptions to premium generative AI services. This situation creates a tangible gap between different demographic groups. Furthermore, studies within the context of Thai government information services highlight that factors such as social influence, perceived usefulness, ease of use, and trust are critical for AI adoption (Noonpakdee, 2024). These findings suggest that psychological and social dimensions are just as important as technical capabilities. Cultural habits can sometimes hinder the adoption of new systems. Users are unlikely to adopt technology they do not trust. Consequently, society requires comprehensive education and clear explanations regarding these new technologies to foster acceptance.

Startups represent a particularly intriguing subject for the study of AI acceptance. They differ significantly from large corporations primarily because they face severe constraints on financial capital and a persistent shortage of high-skilled talent. These factors create a fundamentally different risk landscape. Startups often operate with small teams and limited management experience. The utilisation of generative AI in this context serves purposes beyond mere speed. It is often a necessity for business continuity within an unpredictable and fast-changing environment. Some startups employ generative AI for customer service or advertising generation as an alternative to hiring additional staff. However, budget limitations can make it difficult to purchase the necessary AI technology and prepare the supporting facilities.

Facing these pressing challenges of limited funding and a pronounced talent gap means that accepting technologies like Generative AI is no longer optional. It has become a strategic imperative necessary for survival in a competitive business environment.

Thai startups frequently struggle to secure sufficient funding to sustain their operations (Thanapongpopn et al., 2021). Possessing a novel idea does not guarantee that it will develop into a viable product for the market. Research indicates that strong networks and innovative capabilities are critical for successful performance (Peemanee et al., 2023). Startups that build positive relationships with other businesses or individuals find it easier to obtain support and access relevant information. These factors demonstrate that adoption challenges persist despite the numerous benefits of generative AI. A lack of support or expertise can complicate the adoption of new technology. Startups often require significant practice and study to utilise generative AI effectively.

1.2 Statement of the Problem

The Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT/UTAUT2) stand as prominent frameworks for elucidating technology acceptance (Davis, 1989; Venkatesh et al., 2003; Venkatesh et al., 2012). Researchers globally employ these theories to decipher the underlying reasons for the acceptance or rejection of new technologies. These frameworks effectively explicate the intention to utilise technology, but they were conceived prior to the market introduction of generative AI. Furthermore, the startup environment diverges significantly from that of traditional large corporations. This discrepancy suggests that the TAM and UTAUT frameworks may not always be entirely appropriate within the specific contexts of generative AI or startups. Startup businesses operate under unstable and rapidly changing conditions where they often lack the fixed rules and formal procedures characteristic of large organisations.

Previous scholarship has applied TAM and UTAUT to investigate AI acceptance within Thailand, yet the focus has largely remained on general consumers or traditional public sectors. For instance, research regarding ChatGPT users revealed that perceived usefulness and perceived ease of use strongly influenced attitudes toward the technology (Teerawongsathorn, 2023). Similarly, an investigation involving employees in state enterprises discovered that demographic factors such as age, education, tenure, and income exerted a significant effect on the adoption of generative (Sri-ar-sa & Rassameethes, 2025).

Within the field of human resources, research conducted in Thailand indicates that multiple determinants drive the intention to adopt AI. Individuals demonstrate a higher likelihood of adoption when they perceive the technology as valuable and when they possess autonomy in its usage. Additional critical factors include the requirement for minimal effort and the presence of a supportive environment (Tanantong & Wongras, 2024). Conversely, factors such as trust and social influence do not exert a direct impact on intention. Trust instead positively affects effort expectancy while social influence indirectly shapes value perception (Tanantong & Wongras, 2024). Such dynamics illustrate that AI adoption is a complex process involving various psychological dimensions.

European research further suggests that startup companies possess distinct characteristics that differentiate them from large organisations. Employees within startups often initiate AI usage from the bottom up and frequently operate without direct managerial oversight. Findings indicate that these entities utilise AI primarily to enhance operational efficiency. Personnel tend to prioritise the functional benefits of the technology over ethical considerations (Sammet et al., 2024). Additional scholarship in this context highlights a scarcity of research regarding the acceptance of ChatGPT by entrepreneurs. Consequently, a gap remains in our understanding of how startups utilise generative AI (Gupta & Yang, 2024). The combination of the niche environment of startups and the nascence of generative AI technology necessitates a tailored approach. It is therefore crucial to develop a framework capable of elucidating both the specific context of startups and the psychological factors pertinent to acceptance.

1.3 Towards an Integrated Framework

To address the identified research gap, this study proposes an integrated model grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT). This framework is further expanded by the inclusion of three distinct constructs known as Trust in AI (TAI), AI Anxiety (AIA), and Hedonic Motivation (HM).

Trust in AI (TAI) serves as a critical determinant in the acceptance process. While it does not always influence users directly, it frequently operates in concert with other variables. Research indicates that trust impacts both perceived usefulness and attitude to foster a more positive reception of AI technology (Choung et al., 2023). Conversely, other studies have found that while trust exerts a significant effect on behavioural intention, it lacks a direct connection to actual use behaviour (Rana et al., 2024). This suggests that trust can effectively motivate the intention to adopt a technology without guaranteeing its actual usage. A comprehensive literature review further identifies several essential elements for cultivating trust. These include AI capability, anthropomorphism, individual factors, and explainability (Dang & Li, 2025). The necessity of trust in the acceptance process is particularly acute given that AI often functions as a "black box" where the internal logic of answers or decisions remains difficult to discern.

Research conducted in Sweden applied the UTAUT framework to examine employee perceptions of AI within technology organisations. The study demonstrated that while employees maintained a predominantly positive outlook and expected AI to enhance both individual work and organisational performance, they simultaneously expressed concerns regarding ethics, trust, and risk (Yunita, 2025).

Second, AI Anxiety (AIA) refers to the uneasiness or worry that individuals experience when interacting with AI. This phenomenon frequently stems from the "black box" nature of AI making decision processes difficult to understand or from the fear that AI will replace employment. A recent study categorises AI anxiety into two primary types. These are anticipatory anxiety which arises from concerns about future disruptions and annihilation anxiety which relates to threats against human identity and autonomy (Frenkenberg & Hochman, 2025). Both forms can significantly alter the decision-making process regarding AI usage. Furthermore, separate research indicates that anxiety is negatively correlated with other constructs within the Technology Acceptance Model (TAM) (Mohamed et al., 2025). This finding highlights AI anxiety as a formidable barrier to acceptance and complicates the overall adoption process.

Third, Hedonic Motivation (HM) encompasses the enjoyment and curiosity individuals derive from using generative AI. This sentiment differs significantly from the feelings associated with traditional work tools. Generative AI serves not only to enhance task efficiency but also to generate creative ideas and foster a sense of fun. Research indicates that HM exerts a positive effect on both perceived effort expectancy and perceived individual benefits (Noerman et al., 2025). Another study conducted within the banking industry found that HM, performance expectancy (PE), and effort expectancy (EE) are significant drivers for AI usage, whereas social influence (SI) proved insignificant (Papathomas et al., 2025). Furthermore, investigations into ChatGPT adoption highlight HM as a critical factor influencing adoption and usage (Paudel & Acharya, 2025). These findings underscore the importance of HM as a catalyst for AI adoption. This is particularly relevant within the startup context where individuals are often inclined to experiment with new technologies and explore creative possibilities.

Age also presents a significant variable. The original UTAUT framework posits that age can moderate the effect of various constructs (Venkatesh et al., 2003). Consequently, this research incorporates age as a variable to explore these potential differences. For the purposes of discussion, findings related to age will be interpreted through the conceptual groupings of generational cohorts such as Generation X, Y, and Z. Individuals from different generations may hold distinct perspectives regarding AI adoption. For instance, younger cohorts may be more attracted to the hedonic and social aspects of the technology. Conversely, older groups may prioritise the trust and usefulness that AI can provide.

1.4 Research Questions

The research questions are outlined as follows.

1) What are the key factors that influence the behavioural intention and actual use of Generative AI among personnel in startups located in Thailand?

2) What specific role does psychological factors, such as Trust, Anxiety, and Hedonic Motivation, play in shaping the acceptance of Generative AI within this startup context?

1.5 Research Objectives

The research objectives are outlined as follows.

1) To identify the key factors that influence the acceptance and use of Generative AI in startups located in Thailand.

2) To investigate how specific psychological factors shape the behavioural intention to adopt Generative AI within the startup context.

3) To propose practical guidelines enabling startup leaders in Thailand to foster the effective and responsible adoption of Generative AI.

1.6 Significance of the Study

This study is important both in theory and in practice as follows.

1) Theoretically this research contributes to the existing literature by exploring the key factors that influence the acceptance and use of Generative AI in the unique context of startups in Thailand. Furthermore, it investigates the specific role of psychological factors such as trust and anxiety to provide a deeper understanding of the human side of technology adoption. This study provides a more balanced view

showing not only the positive drivers but also the challenges for Generative AI acceptance.

2) Practically, the findings from this study can offer valuable insights for startup leaders in Thailand. By understanding which factors are most critical managers can make more informed decisions when introducing Generative AI.

For instance, by recognising the impact of key psychological factors they can create better strategies. Understanding the roles of trust and anxiety can help them improve their communication and support plans. At the same time knowing that hedonic motivation or the enjoyment of using the technology is a key driver can help them introduce AI to their personnel in a more positive and engaging way.

The results can also help developers to design AI that is easier and more transparent for people to use. For startups having this knowledge is very important as understanding the key drivers of acceptance can be essential for a successful technology implementation and survival in a competitive business environment.

CHAPTER 2
REVIEW OF LITERATURE

This chapter presents a comprehensive review of the literature pertinent to the research. The initial section elucidates the research context by examining the Thai startup ecosystem and global trends in AI acceptance. The subsequent section details the theoretical framework, incorporating the UTAUT model and additional constructs employed in this study. Building upon this foundation, the chapter concludes by presenting the conceptual framework and the associated research hypotheses.

2.1 Research Context

To situate the study effectively, this section delineates the specific environment of the Thai startup ecosystem which serves as the primary focus of this research.

2.1.1 Thai Startup Ecosystem

The Thai government actively seeks to transform the nation into a value-based, innovation-driven economy, aligning with the "Thailand 4.0" vision (Kraivichien & Pruetipibultham, 2024). This long-term strategy covers the period from 2017 to 2036. The framework emphasises the critical importance of supporting entrepreneurs and fostering new innovative businesses (Kraivichien & Pruetipibultham, 2024). Within this context, startups are viewed as "new business warriors" essential for driving the Thai economy forward (Khong-khai & Wu, 2018).

Despite this ambitious strategic vision, the Thai startup ecosystem faces significant challenges and has not experienced rapid expansion. A discernible gap remains between government policy and tangible outcomes. According to the Global Startup Ecosystem Index 2025, Thailand ranks 53rd globally. Although this represents a slight improvement from the 54th position in 2024, it remains lower than the 50th rank achieved in 2021. The ecosystem currently exhibits an annual growth rate of 12.7% which indicates a lack of strong momentum (StartupBlink, 2025). Nevertheless, Thailand maintains its standing as the 4th largest ecosystem in Southeast Asia, trailing Singapore, Indonesia, and Malaysia (StartupBlink, 2025).

Figure 2.1

Global Ranking of Thailand's Startup Ecosystem

Note. From *Global Startup Ecosystem Index 2025* (p. 225), by StartupBlink, 2025.

Bangkok stands as the undisputed centre of Thailand's startup landscape while Phuket trails significantly in second place. The disparity between the two cities is stark. Data from the Global Startup Ecosystem Index 2025 reveals that Bangkok's ecosystem score exceeds that of Phuket by a factor of more than 30 (StartupBlink, 2025). In terms of global standing, the capital currently ranks 81st after experiencing a minor decline of one position this year (StartupBlink, 2025).

Resources and activities critical to business development are concentrated predominantly within the capital. Key infrastructure includes True Digital Park which is recognised as the largest digital innovation hub in Southeast Asia. This facility hosts over 5,800 startups, tech entrepreneurs, and organisations and boasts a community of more than 14,000 active members (StartupBlink, 2025). Such figures clearly demonstrate that startup development in Thailand remains overwhelmingly centralised within Bangkok.

Figure 2.2

Ranking of the Startup Ecosystem by Thai Prefecture

National Rank & Change (from 2024)	City	Global Rank & Change (from 2024)	Total Score	Ecosystem Growth (Annual)	Top Industry Global Rank
1 –	**Bangkok**	81 −1	10.800	+15.1%	Blockchain 32
2 –	**Phuket**	641 +21	0.343	+25.2%	–
3 –	**Chiang Mai**	716 −31	0.274	+6.0%	–

Note. From *Global Startup Ecosystem Index 2025* (p. 226), by StartupBlink, 2025.

2.1.1.1 The Genesis and Evolution of the Ecosystem

The evolution of the Thai startup ecosystem represents a transition from disparate private sector activities to a more formalised, government-supported infrastructure. The initial phase during the 2000s witnessed the organic emergence of small software clusters. At this stage, state intervention was minimal (Juasrikul & Vandenberg, 2022). Consequently, many of these early ventures faced significant hurdles in achieving scalability and were forced to experiment extensively with various business models.

A pivotal shift occurred in 2011 driven by the private sector rather than public policy. The major telecommunications provider AIS organised an event known as "AIS Startup Weekend" (Juasrikul & Vandenberg, 2022). This initiative served as a catalyst that ignited broader interest in the potential of the startup model.

By the mid-2010s, the Thai government recognised the strategic importance of the sector. A watershed moment arrived with the organisation of "Startup Thailand 2016" (Juasrikul & Vandenberg, 2022). This event facilitated the launch of new ventures and coalesced the fragmented community. Subsequently, the state formalised its involvement through the establishment of key institutions. These included the Ministry of Digital Economy and Society (MDES) and the National Startup Committee (NSC) in 2016 followed by the Digital Economy Promotion Agency (DEPA) in 2017 (Juasrikul & Vandenberg, 2022). This period marked the official entry of the government into the ecosystem. However, this intervention lagged approximately five years behind the private sector. The government layered its new system atop the existing structure which occasionally resulted in operational inefficiencies. Notably, certain government agencies were established with similar mandates leading to a redundancy of task (Juasrikul & Vandenberg, 2022; Thawesaengskulthai et al., 2024).

2.1.1.2 Determinants of Thai Startups' Success and Survival

Numerous studies indicate that several pivotal factors contribute to the success or survival of a new company. These determinants generally fall into three primary categories comprising human capital, internal organisation, and external networks.

Existing literature consistently underscores human capital as the paramount determinant of business success (Khong-khai & Wu, 2018). This domain encompasses several specific capabilities. First, Entrepreneurial Capability relates to the founder's competence in business management and their ability to manage change alongside the possession of a clear strategic vision (Khong-khai & Wu, 2018). Second, Innovation Capability refers to the utilisation of knowledge to create new products, services, or solutions that effectively address customer pain points (Khong-khai & Wu, 2018; Peemanee et al., 2023).

Beyond these functional abilities, the personal character of the founder is significant for survival. Various studies on Thai startups suggest it is essential to possess a resilient mindset, effort, a clear vision, relevant experience, and an elevated motivation or hunger for success (Kraivichien & Pruetipibultham, 2024). These attributes assist a founder in overcoming complex problems and uncertain situations during the initial stages of a business.

Recent studies indicate that entrepreneurship education involving experiential learning, extracurricular activities, and networking is crucial for fostering entrepreneurial skills in Thai startups (Nititham & Phillips, 2024). Additionally, the quality of the startup team is vital. The team should possess experience, skills, and a shared vision aligned with that of the founder (Khong-khai & Wu, 2018).

Beyond human capital, internal organisational factors are pivotal for survival. A company must possess a clear and flexible business plan to navigate the market effectively (Kraivichien & Pruetipibultham, 2024). Adequate financial resources and specifically steady cash flow are often regarded as critical determinants of a startup's survival during its nascent. Furthermore, a robust company culture is essential for fostering teamwork and maintaining the motivation required for arduous work (Kraivichien & Pruetipibultham, 2024).

Finally, the establishment and utilisation of an external network constitute a significant success factor. Research suggests that startup networks provide essential knowledge, partners, and resources which can directly assist innovation and enhance overall company performance in other ways (Peemanee et al., 2023).

Nevertheless, a significant dichotomy exists when comparing these positive success factors with the prevailing negative conditions in the Thai startup ecosystem. The ecosystem requires skilled human capital such as experienced and creative entrepreneurs. However, it faces a shortage of skilled technology professionals and concerns regarding entrepreneurial quality while universities fail to teach effectively (Juasrikul & Vandenberg, 2022; Thawesaengskulthai et al., 2024). Consequently, the primary factor limiting the growth potential of the Thai startup ecosystem is a lack of talent.

2.1.1.3 Systemic Challenges and Barriers to Growth

The intricate interplay of various systemic issues within Thailand currently impedes the rapid expansion of its startup ecosystem. These challenges originate from diverse sources including policy, regulation, human capital, market dynamics, and cultural norms. Collectively these factors generate a negative cycle that causes the ecosystem to stagnate and hinders significant progress.

First, the ecosystem faces numerous challenges derived from government policies and regulatory frameworks. The bureaucratic structure in Thailand is notably rigid and involves multi-layered procedural workflows where inter-departmental collaboration remains ineffective (Thawesaengskulthai et al., 2024). For instance, certain agencies such as the NIA and DEPA possess similar mandates which occasionally results in functional overlap (Juasrikul & Vandenberg, 2022). Furthermore, government processes are often characteristically slow and complex. This lethargic pace is fundamentally ill-suited to startups which thrive on an agile and fast-moving culture (Juasrikul & Vandenberg, 2022; Thawesaengskulthai et al., 2024).

Second, a significant deficit exists regarding human capital due to a shortage of skilled technology professionals such as software engineers and data scientists. It is also difficult to identify experienced entrepreneurs capable of teaching or serving as role models for the younger generation (Juasrikul & Vandenberg, 2022; Thawesaengskulthai et al., 2024). This issue stems largely from an education system that frequently fails to equip students with sufficient practical skills or the entrepreneurial mindset required to launch new ventures (Nititham & Phillips, 2024).

Third, market and cultural contexts significantly contribute to the existing challenges. Research indicates that the private sector in Thailand frequently favours foreign technologies over local solutions (Thawesaengskulthai et al., 2024). Consumer spending remains limited in specific sectors such as education technology and health technology because a large portion of the customer base has low income. Furthermore, innovations introduced by startups to public institutions like schools and hospitals require government approval and must undergo public procurement procedures which are often complex and protracted (Juasrikul & Vandenberg, 2022). Additionally, some startup founders lack a global mindset and focus exclusively on the domestic Thai market rather than the global market. This narrow focus severely limits their potential for significant growth (Thawesaengskulthai et al., 2024).

These primary obstacles involving the lack of skilled human capital, insufficient financial support, and strict regulations create a negative cycle that is difficult to escape. Consequently, only a small number of successful individuals can utilise their own capital and experience to assist new startups as advisers or investors. The scarcity of mentors and early-stage financiers exacerbates the existing talent and funding shortages and causes the cycle to perpetuate itself.

This persistent cycle elucidates why the Thai startup ecosystem remains smaller and exhibits slower growth compared to global trends. These challenges persist despite the implementation of long-term government initiatives such as "Thailand 4.0" which have been in place for several years yet have not achieved the desired level of success.

The acceptance of AI and specifically generative AI assumes critical importance within this context. Generative AI offers a potential solution to the shortage of skilled human capital by enhancing work efficiency under resource constraints and by supporting the innovation process. Consequently, examining the factors that influence the implementation of generative AI within Thai startups is crucial. Such an analysis provides valuable insights for overcoming structural constraints while improving competitiveness and fostering more sustainable ecosystem expansion.

2.1.2 Global Perspectives on AI Acceptance

This section broadens the scope of the study to encompass the global landscape. It elucidates diverse perspectives regarding how AI is adopted across various countries and organisational contexts.

2.1.2.1 The Changing Perspective of AI Acceptance

AI has recently proliferated globally and fundamentally altered numerous aspects of daily life including business operations and strategic decision-making (Gansser & Reich, 2021; Rizomyliotis et al., 2025). The adoption of AI technologies is no longer a futuristic concept but a present reality for organisations ranging from small startups to large corporations (Rizomyliotis et al., 2025; Söderberg & Stenmark, 2025). The acceptance of such disruptive technologies is a complex process. This complexity stems from a variety of influencing factors including technical, organisational, environmental, and social dynamics alongside individual psychological factors (Gupta & Yang, 2024; Kim et al., 2024; Mohamed et al., 2025).

Academic studies frequently utilise established theories such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) to account for technology acceptance. However, generative AI is distinct from other technologies because it can generate responses in natural human-like language and sustain two-way conversations which significantly enhances its perceived usefulness (Gupta & Yang, 2024). This capability creates an interaction where the user feels the machine communicates similarly to a human.

It is crucial to consider psychological and emotional factors in addition to technical or organisational determinants when studying the acceptance of generative AI. For instance, anxiety regarding job replacement, privacy issues, or algorithmic bias has been found to influence the intention to use generative AI (Mohamed et al., 2025). Consequently, traditional models such as TAM and UTAUT may prove insufficient to fully explain the acceptance of this disruptive technology if they fail to incorporate these critical psychological factors.

This evolution in research across different regions demonstrates a significant shift in the conceptualisation of AI acceptance. A study involving nursing students in the Middle East identified anxiety as a critical moderating factor. This finding suggests that strong emotional responses are integral to the acceptance process (Mohamed et al., 2025). Additionally, multi-national research incorporating anthropomorphism into models for entrepreneurs revealed that the human-like characteristics of AI systems exercise a direct effect on user perceptions (Gupta & Yang, 2024). Furthermore, various studies in Europe and other regions indicate that ethical considerations and safety security represent pivotal themes. These factors significantly influence user trust and the willingness to adopt AI (Gansser & Reich, 2021; Rizomyliotis et al., 2025; Yunita, 2025). Consequently, a comprehensive understanding of AI acceptance in diverse contexts requires more than a simple analysis of costs and benefits. It necessitates a careful consideration of the complex relationships existing between the user, the organisation, and the unique characteristics of the technology itself.

2.1.2.2 Organisational and Startup Contexts

The decision to adopt AI within a company is rarely an individual choice but is significantly influenced by the broader organisational environment (Alateeg et al., 2024). This dynamic is particularly acute for startups and small and medium-sized enterprises (SMEs) which operate under conditions of rapid change and limited resources (Rizomyliotis et al., 2025). These entities possess distinct motivations for AI acceptance and face unique challenges. Consequently, their approach differs markedly from that of large corporations which typically benefit from established systems and abundant resources.

2.1.2.3 The Startup Imperative

For startups, the utilisation of AI is driven primarily by practical necessity and often by the imperative of survival. Research indicates that the primary drivers for adoption are the goals of increasing efficiency, reducing costs, and improving internal processes (Sammet et al., 2024). Numerous startups utilise AI for repetitive tasks, market analysis, and customer service to conserve time and resources (Sammet et al., 2024). Furthermore, additional studies suggest that the acceptance of generative AI depends not merely on resources or technical expertise but also on how the organisation manages and learns from the new technology which implies that AI is integral to growth within such dynamic environments (Söderberg & Stenmark, 2025).

A startup environment necessitates conditions that foster independent work and encourage experimentation and risk-taking. Research on a Swedish AI startup indicates that a leadership style characterised as “permissive, direction-light” enabled employees to rapidly test new AI tools from the nascent stages (Söderberg & Stenmark, 2025). Similarly, a study from the United Kingdom determined that organisational culture and values play a pivotal role in shaping employee attitudes. Specifically, a culture that embraces experimentation and risk-taking is essential for the adoption of AI technology by startup employees (Rizomyliotis et al., 2025). Such environments empower employees to autonomously explore how AI can enhance their specific tasks.

The widespread availability of powerful and affordable AI tools presents a novel challenge for startups. This issue transcends mere deficits in skills or financial capital and instead centres on management and organisational coordination. The study of the Swedish AI startup posits that off-the-shelf large language models (LLMs) function as “a shortcut to AI maturity” because they are accessible to virtually any user (Söderberg & Stenmark, 2025). Conversely, independent AI usage by employees may result in coordination gaps and the formation of knowledge silos. This fragmentation limits collaboration and hinders the collective development of ideas (Söderberg & Stenmark, 2025). The same study identifies the phenomena of “AI noise” and “information overload” where an excessive volume of ideas obscures valuable insights and thereby complicates the development of robust strategic AI capabilities (Söderberg & Stenmark, 2025). Research from Germany corroborates this trend and reveals that numerous startups utilise AI on an individual basis without integrating it into the broader organisational structure (Sammet et al., 2024). Consequently, the primary challenge lies not in acquiring AI but rather in deploying it through a deliberate and strategic approach.

2.1.2.4 The Reality of Using AI in Startups

While many perceive AI primarily as a driver of disruptive innovation, the practical reality within startups centres on its utility for supporting human effort. Research indicates that most startups regard AI as a powerful instrument to augment human creativity and knowledge rather than as a replacement for the workforce. A notable study of German entrepreneurs utilising Q-methodology found that AI is widely employed for translation and content creation. However, it is not yet considered a tool for “innovative and unforeseen solutions” (Sammet et al., 2024).

A global survey of entrepreneurs corroborates this view. The study suggests that AI should be conceptualised as a “knowledge collaborator” (Gupta & Yang, 2024). Under this perspective, AI-generated outputs are treated as hypotheses which require human expert review and approval. This methodology is known as the human-in-the-loop approach. It enables startups to leverage the processing speed and data capabilities of AI while mitigating risks such as inaccurate outcomes or biased results. Consequently, the consensus among these studies is that optimal adoption strategies are human-centric. They focus on how technology can enhance human skills rather than replace humans.

2.1.2.5 A Comparative View of Different Regional and Cultural Factors

The global adoption of AI exhibits distinct variation across different geographical and cultural landscapes. These disparities arise from a confluence of factors including national policies, regulatory frameworks, cultural norms, and economic priorities. Collectively, these elements shape how organisations and individuals conceptualise and utilise AI technology.

(1) European Perspectives (Sweden, UK, Germany)

Research originating from European nations, specifically Sweden, the United Kingdom, and Germany, indicates a collective emphasis on internal organisational operations and ethical standards regarding artificial intelligence.

In Sweden, a significant debate surrounds the acceptance of AI. Technology companies encounter intense pressure to adopt AI rapidly to maintain global competitiveness and address talent requirements (Yunita, 2025). This drive is counterbalanced by a strong societal and governmental mandate for caution and the implementation of AI in an ethical and trustworthy manner. Swedish technology workers identify several critical factors for successful acceptance. These include building a supportive organisational culture, establishing robust data governance that adheres to regulations such as the General Data Protection Regulation (GDPR), and formulating clear internal guidelines for AI usage (Yunita, 2025). Another study focusing on a Swedish AI startup identified a primary challenge in balancing employee autonomy with the necessity for strategic alignment and collective learning (Söderberg & Stenmark, 2025).

The United Kingdom is renowned for its vibrant startup culture and substantial investment in artificial intelligence. Within this context, the key determinants of acceptance represent a confluence of technical, organisational, and ethical elements. A study involving employees in UK startups identified the primary factors influencing AI acceptance as technical infrastructure, data quality, organisational culture, employee attitudes, available resources, and legal and ethical challenges (Rizomyliotis et al., 2025).

Conversely, researchers in Germany emphasise the utilisation of AI to enhance operational efficiency (Sammet et al., 2024). A study of German startups identified a distinct cohort of founders known as "Dedicated Optimisers" who may overlook legal and ethical challenges if AI significantly boosts efficiency. This tendency stems from a strong focus on operational optimisation and reveals that some entrepreneurs prioritise efficiency over broader governance concerns. However, the study further notes that most individuals do not permit AI to execute final decisions. The process invariably involves a human review of the AI's output which implies that ethical factors are consequently given less weight (Sammet et al., 2024).

(2) Asian Perspectives (South Korea, Thailand)

Research originating from the Asian region reveals a distinct set of priorities. Social dynamics and fundamental usability take precedence particularly within organisational settings. A study of employees in South Korea presents a compelling contrast to Western models. The findings indicate that social influence serves as the most potent determinant of an employee's intention to adopt AI while Performance Expectancy proved insignificant during the initial stages (Kim et al., 2024). This suggests that social acceptance and the behaviour of colleagues and superiors act as the primary gateways for adoption in this context. Individuals are likely to adopt AI due to encouragement from their professional circle rather than a belief in its ability to enhance job performance. This phenomenon is likely linked to a collectivist culture where group harmony and adherence to norms hold significant value.

Conversely, a study focused on ChatGPT users in Bangkok, Thailand demonstrated that the classic Technology Acceptance Model (TAM) remains highly effective and direct (Teerawongsathorn, 2023). Unlike the findings from Korean corporate environments, this research on a consumer-facing generative AI system revealed that both perceived usefulness and ease of use were significant predictors of user attitudes. These attitudes subsequently predicted the intention to utilise the technology. This indicates that the fundamental concepts of usability and utility remain relevant and capable of predicting user behaviour among modern consumers in Bangkok.

(3) Middle Eastern Perspectives (Saudi Arabia & Region)

In the Middle East, the acceptance of AI appears to be strongly influenced by two primary determinants comprising top-down national strategies initiated by the government and individual psychological factors.

In Saudi Arabia, AI acceptance within startup ecosystems is intricately linked to the nation's ambitious economic framework known as Vision 2030 (Alateeg et al., 2024). Due to the significant government impetus, factors such as observability or witnessing successful AI examples and trialability or the opportunity to experiment with AI have become crucial for fostering positive attitudes among entrepreneurs. Active government promotion creates a supportive ecosystem that encourages adoption (Alateeg et al., 2024).

A comprehensive analysis of nursing students across several countries including Egypt, Jordan, Saudi Arabia, and Yemen reveals two principal findings (Mohamed et al., 2025). First, the study demonstrates significant disparities in access to technology and infrastructure across the region which directly impacts AI readiness. Second, it identifies anxiety as a powerful psychological variable. This factor exerts a significant impact on the intention to use AI. Such findings underscore that emotional and psychological readiness act as key determinants of AI acceptance in the Middle East region (Mohamed et al., 2025).

2.1.2.6 The Universal Consensus on Human-in-the-Loop

Another consistent conclusion emerges across various studies which posits AI as a tool for augmentation rather than human replacement.

This concept is presented by researchers through a variety of explanations. A global study of entrepreneurs suggests that AI should be viewed as a "knowledge collaborator" where its results are regarded as hypotheses that human experts must examine and approve (Gupta & Yang, 2024). Similar research on German startups corroborates this finding. Founders view AI as a tool for supporting human creativity rather than a replacement (Sammet et al., 2024). Furthermore, a Swedish study highlights that it is crucial to establish distinct roles for both employees and AI while emphasising the ability of AI to enhance human capabilities (Yunita, 2025).

This "human-in-the-loop" concept implies that effective AI strategies must be human-centric. It is critical to design systems that leverage the respective strengths of both people and AI. Humans possess skills in areas such as critical thinking, creativity, and ethical judgment while AI demonstrates effectiveness in speed, pattern recognition, and big data processing. The ultimate goal focuses on combining these capabilities into a synergistic partnership to enhance work outcomes.

2.1.2.7 Towards a Context-Aware Model of AI Acceptance

A synthesis of various studies provides a comprehensive overview of global AI utilisation. While fundamental concepts of technology acceptance such as usefulness and ease of use remain relevant, they are insufficient to explain the full scope of the phenomenon because AI acceptance is highly complex and varies significantly across different regions. These core determinants are modified and influenced by a multitude of variables including the user profile, organisational context, and the surrounding cultural or societal framework.

Empirical results demonstrate that no single model of AI acceptance is universally applicable. The most critical determinant varies depending on the specific context. For instance, within organisations characterised by a collectivist culture such as South Korea, social influence emerges as the strongest factor (Kim et al., 2024). Conversely, in a nation driven by a robust government agenda such as Saudi Arabia, observing AI success and aligning with national goals are of paramount importance (Alateeg et al., 2024). In European startups, internal organisational factors such as culture and the management of innovation take precedence (Rizomyliotis et al., 2025; Söderberg & Stenmark, 2025). Regarding students entering the workforce, psychological factors such as anxiety can significantly affect AI usage patterns (Mohamed et al., 2025).

This perspective holds particular relevance for the Thai startup ecosystem. Thai startups currently face challenges including a lack of skilled human capital, limited financial resources, and evolving regulations. Consequently, psychological and emotional factors may significantly influence behavioural intention. Understanding these dynamics helps explain the unique situation in Thailand and provides insight into how AI can support sustainable growth within the startup ecosystem.

2.2 Theoretical Framework

Based on the research context previously reviewed, this section elucidates the theoretical foundation for the study. It introduces the primary theory utilised to construct the research model and formulate the associated hypotheses.

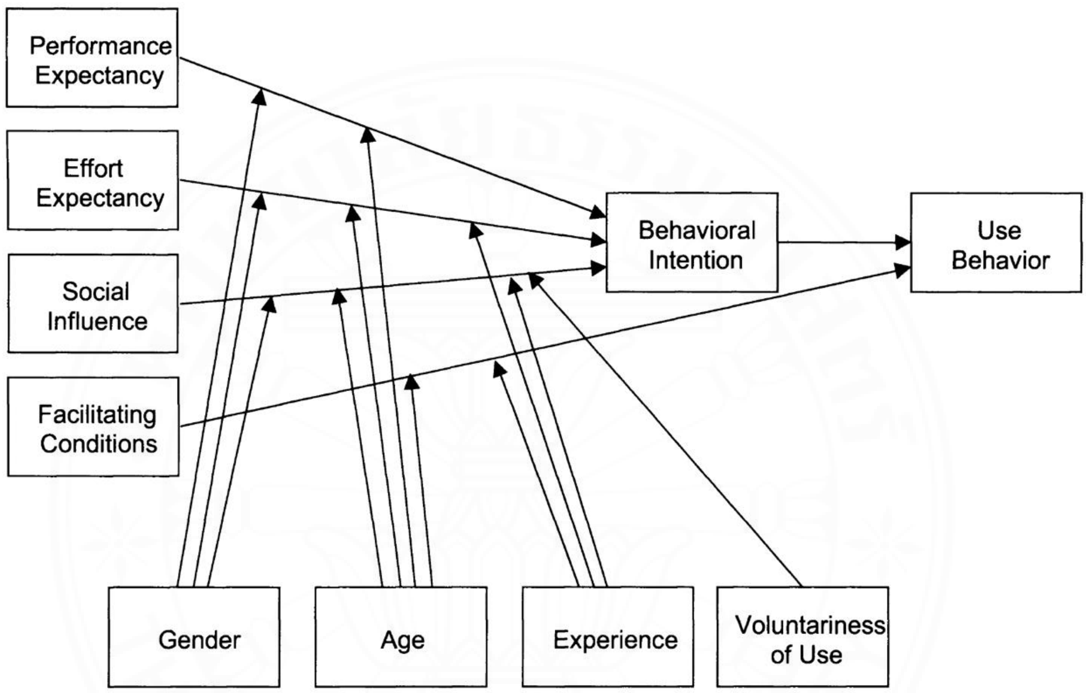
2.2.1 The UTAUT Model: A Foundational Framework for Technology Acceptance

To comprehend why technologies are accepted within an organisation, it is necessary to establish a robust theoretical foundation. A prominent example of such a foundation is the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). The development of this model relied on the analysis and integration of eight prominent models within the technology acceptance literature. These included the Theory of Reasoned Action (TRA), the Technology Acceptance Model (TAM), and Innovation Diffusion Theory (IDT) (Venkatesh et al., 2003).

The principal objective of UTAUT was to function as a unified and streamlined model capable of explaining a user's intention to utilise an information system and their subsequent usage behaviour, particularly within an organisational environment (Venkatesh et al., 2003). Initial research demonstrated the high efficacy of the model and revealed its capacity to explain up to 70 percent of the variance in user intention. This result represented a substantial improvement when compared with any of the previous single models (Venkatesh et al., 2003).

Figure 2.3

Unified Theory of Acceptance and Use of Technology Model



Note. From “User Acceptance of Information Technology: Toward a Unified View,” by V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, 2003, *MIS Quarterly, 27*(3), p. 447.

2.2.1.1 The Four Core Concepts of Intention and Behaviour

The UTAUT model identifies four key constructs directly influencing behavioural intention and use behaviour. The definition for each construct is based on the main ideas from the models that it integrated (Venkatesh et al., 2003).

(1) Performance Expectancy (PE)

Performance expectancy 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). This concept acts as the strongest predictor of behavioural intention within the model. It synthesises ideas such as perceived usefulness (from TAM and TAM2), job-fit (from MPCU), relative advantage (from IDT), extrinsic motivation (from MM), and outcome expectations (from SCT) (Venkatesh et al., 2003). It represents the utilitarian value a user associates with a technology and focuses on whether it can improve their efficiency, productivity, and general effectiveness at work.

H1: Performance expectancy (PE) has a positive effect on behavioural intention (BI)

(2) Effort Expectancy (EE)

Effort expectancy is defined as "the degree of ease associated with the use of the system" (Venkatesh et al., 2003). This concept aligns with the ideas of perceived ease of use (from TAM and TAM2), complexity (from MPCU), and ease of use (from IDT) (Venkatesh et al., 2003). It reflects the user's perception of the effort required for technology acceptance. Effort expectancy significantly impacts the initial stages of technology acceptance, although its influence tends to fade into insignificance over extended periods.

H2: Effort expectancy (EE) has a positive effect on behavioural intention (BI)

(3) Social Influence (SI)

Social influence 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). This concept demonstrates the extent to which a person's decision to adopt technology is affected by their social environment. It integrates constructs such as subjective norm (from TRA, TAM2, TPB/DTPB, and C-TAM-TPB), social factors, and image (from IDT) (Venkatesh et al., 2003). Social influence proves particularly significant in situations where usage is mandatory because compliance with organisational norms and meeting the expectations of supervisors and colleagues serve as critical drivers for behavioural intention.

H3: Social influence (SI) has a positive effect on behavioural intention (BI)

(4) Facilitating Conditions (FC)

Facilitating Conditions is defined as "the degree to which an individual believes that an organisational and technical infrastructure exists to support use of the system" (Venkatesh et al., 2003). This concept pertains to an individual's perception of available resources and support including technical assistance, training, and compatibility with existing systems. It is grounded in concepts such as perceived behavioural control (from TPB/DTPB and C-TAM-TPB), facilitating conditions (from MPCU), and compatibility (from IDT) (Venkatesh et al., 2003). A key distinction lies in the fact that Facilitating Conditions is posited to directly determine usage behaviour rather than behavioural intention. This implies that even when a strong intention to use a technology exists, actual usage can be significantly hindered or supported by the level of practical support available within the user's environment.

H7: Facilitating Conditions (FC) has a positive effect on Use Behaviour (UB)

2.2.1.2 The Role of Intentions and Behaviour in the UTAUT Model

According to the UTAUT model, to understand technology acceptance, it is necessary to examine two primary outcome variables comprising Behavioural Intention and Use Behaviour.

(1) Behavioural Intention (BI)

Behavioural intention is defined as the measure of a person's plan or intention to utilise a technology in the future. It serves as the most immediate predictor of actual behaviour. This model suggests that behavioural intention is influenced by the key constructs of performance expectancy (PE), effort expectancy (EE), and social influence (SI) (Venkatesh et al., 2003).

(2) Use Behaviour (UB)

Use behaviour is defined as the tangible and actual usage of the technology. It represents the ultimate result that the researcher seeks to comprehend. The model indicates that this behaviour is primarily driven by the user's behavioural intention. Additionally, facilitating conditions can directly influence this use behaviour (Venkatesh et al., 2003).

H8: Behavioural intention (BI) has a positive effect on use behaviour (UB).

2.2.1.3 The Role of Age as a Supplementary Analysis

The original UTAUT model posits that technology acceptance patterns vary based on individual differences such as age. The theory identifies age as a significant moderator. For instance, younger workers often prioritise performance expectancy while older workers are typically more influenced by effort expectancy and social influence (Venkatesh et al., 2003).

This research primarily focuses on the core UTAUT constructs involving PE, EE, SI, and FC. However, a supplementary descriptive analysis will be conducted to explore the role of age. This secondary analysis is not intended to test a core hypothesis but aims to provide additional context and richer insights into the findings.

Age will be interpreted through the lens of generational cohorts for the purpose of this supplementary analysis. This approach is valuable because recent studies on Generative AI indicate that generational differences are significant. For example, younger individuals or Generation Z often exhibit more positive attitudes towards using Generative AI compared to older cohorts or Generation X who may possess heightened concerns regarding ethics and technology dependence (Chan & Lee, 2023). In the specific context of Thailand, Generation Y and Generation Z employees utilise tools such as ChatGPT more frequently than their Generation X counterparts (Navarattanapaiboon, 2024). Younger demographics have also demonstrated a more favourable perception of AI-generated content (Bakumenko, 2024).

Consequently, exploring age from this generational perspective allows this research to offer a more detailed discussion regarding how distinct life experiences may impact the acceptance of Generative AI within the Thai startup environment.

2.2.2 Application and Contextual Nuances of UTAUT in AI Acceptance Study

Since its inception in 2003, the UTAUT model has served as a robust and widely employed framework for examining technology acceptance. It remains highly relevant for studying modern AI technologies such as generative AI (Abdalla, 2025; Ayeni et al., 2024; Kim et al., 2024; Yakubu et al., 2025). Its structured methodology provides a solid foundation for understanding the key determinants of user acceptance. However, a review of recent scholarship indicates that the predictive influence and significance of its core constructs are not uniform across all scenarios. Instead, they depend heavily on the specific technology, the user demographics, and the socio-organisational context under investigation.

This dependency on context becomes evident when comparing recent studies that utilise UTAUT for generative AI acceptance. A study of Korean companies found that effort expectancy and social influence were significant predictors of employees' intention to use generative AI. Conversely, performance expectancy and facilitating conditions did not demonstrate a significant impact (Kim et al., 2024). This suggests that during the initial stages of corporate adoption within a collectivist culture such as Korea, the primary drivers were ease of use and influence from colleagues and managers.

In contrast, a study on Omani students utilising ChatGPT for learning data analytics revealed that performance expectancy was the most influential predictor followed by facilitating conditions. In this specific context, all four core UTAUT constructs along with an additional variable of self-efficacy were found to be significant (Abdalla, 2025). Similarly, research on Nigerian students determined that performance expectancy, effort expectancy, and social influence were significant for behavioural intention while facilitating conditions proved insignificant (Yakubu et al., 2025).

Similarly, a study involving students in Nepal introduces further complexity by identifying System Quality which is closely related to Effort Expectancy as the most influential predictor of ChatGPT acceptance (Paudel & Acharya, 2025).

Hedonic motivation and social influence also proved significant in this context while perceived usefulness related to performance expectancy demonstrated a weaker direct impact as it was fully mediated by user attitude. This reinforces the notion that practical usability and social factors can occasionally outweigh perceived performance benefits during the initial stages of acceptance depending on the user group and their immediate goals (Paudel & Acharya, 2025).

Studies from Thailand further illustrate the critical importance of local context. Research regarding AI acceptance in recruitment among Thai human resource professionals identified effort expectancy and facilitating conditions as significant drivers of intention alongside extended factors such as perceived value and perceived autonomy. Conversely, social influence did not directly affect intention within this specific professional setting (Tanantong & Wongras, 2024).

A qualitative study focusing on Swedish technology organisations prior to adoption offers a divergent perspective. Although employees generally held positive views regarding the potential of AI to enhance performance or performance expectancy, their motivation stemmed less from internal social pressure and more from external global trends and media narratives or social influence. A particularly significant finding was the profound concern regarding trust which originated from the "black-box" nature of AI. The lack of transparency regarding how AI generates outputs fostered scepticism and a reluctance to fully rely on the technology (Yunita, 2025). This underscores that factors outside the original UTAUT model such as trust and transparency become critical issues even before formal acceptance commences within a technologically advanced and ethically conscious context like Sweden.

These divergent findings do not imply that the UTAUT model is incompatible with the context of modern AI technology. Instead, they demonstrate its sensitivity to situational variables and reveal deeper patterns within the psychology of technology acceptance. Variations in the significance of these constructs can be understood by examining the underlying differences between study groups and their respective circumstances. For instance, the reason Facilitating Conditions may act as a critical factor for Omani students and Thai human resource professionals but not for

Korean employees or Nigerian students pertains to resource accessibility. For students and professionals adopting new tools, facilitating conditions often entail personal access to adequate facilities or digital infrastructure such as computers, stable internet, and software resources which might not be universally available and thus present significant barriers (Abdalla, 2025). Conversely, these resources are likely standardised and provided by the organisation for employees in Korean companies, rendering them a constant rather than a variable that influences acceptance (Kim et al., 2024). When a resource becomes universally available, it ceases to function as a differentiating factor and consequently loses its predictive power.

The Omani students utilised ChatGPT for a highly specific purpose such as learning data analytics or simplifying complex statistics where the utility was clear and instantaneous (Abdalla, 2025). This has led various researchers to conclude that the foundational UTAUT model remains robust for examining technology acceptance. However, it often requires extension to provide a comprehensive picture within the specific context of AI acceptance. For instance, several studies have incorporated domain-specific factors such as convenience, health, and sustainability regarding AI (Gansser & Reich, 2021) or added AI-specific psychological concepts like algorithmic aversion to explain user hesitation stemming from a lack of trust and transparency in AI decision-making (Ayeni et al., 2024). This comparative analysis demonstrates that UTAUT alone may prove insufficient for the AI acceptance context. A detailed investigation must carefully consider contextual nuances to understand why certain factors gain or lose importance. This necessity explains why many contemporary studies focus on highly specific contexts and explore factors tailored to those unique environments.

Additional studies further illustrate these distinct variations. Research conducted in Oman revealed that performance expectancy directly influenced the continued use of AI services, while hedonic motivation played a pivotal role in driving user engagement. Interestingly, effort expectancy was not significant in predicting continuance intention (Salih et al., 2025). This finding suggests that when users perceive high utility and enjoyment in a technology, the ease of use becomes a secondary concern. In Turkey, a separate study examining AI anxiety determined that specific anxiety related to learning AI served as a potent negative predictor of user attitude. This predictor proved even stronger than general personality traits (Kaya et al., 2024). This underscores the critical importance of studying emotional and psychological factors within the AI context.

2.2.3 Extending the UTAUT Framework for generative AI in the Startup Context

While the UTAUT model serves as a robust and essential framework, a more comprehensive theoretical perspective is required to fully grasp generative AI acceptance within the Thai startup context. This necessity arises from the distinct characteristics of generative AI combined with the specific operational dynamics of startups in a developing economy like Thailand. Generative AI differs significantly from conventional information systems due to its creative capabilities and autonomous functionality. Furthermore, it operates as a "black box" where the internal decision-making processes remain opaque to the user (Yunita, 2025).

Startups are characterised by high agility, a culture of innovation, and openness to experimentation. However, they frequently operate under the constraint of limited resources (Rizomyliotis et al., 2025; Söderberg & Stenmark, 2025). These factors engender specific psychological and organisational dynamics that the original UTAUT constructs may not fully explicate. Consequently, an extended model is proposed to achieve a holistic understanding of generative AI acceptance in this specific context. This study incorporates three additional constructs comprising hedonic motivation, trust in AI, and AI anxiety into the foundational UTAUT concepts.

2.2.3.1 Hedonic Motivation (Perceived Enjoyment) (HM)

Hedonic motivation is defined as the pleasure or satisfaction a person derives from using a technology (Noerman et al., 2025; Salazar & Rivera, 2025). This construct was originally introduced in the UTAUT2 model to better address consumer contexts (Venkatesh et al., 2012). Its significance is confirmed in numerous recent studies within the technology acceptance literature.

Many studies have demonstrated it to be a significant factor influencing user intention. Examples include research on media content creators in the Arab Gulf states (Ali et al., 2024), employees in Indonesian SMEs (Noerman et al., 2025), and stakeholders in the Greek banking sector (Papathomas et al., 2025). Perceived enjoyment serves as a key driver for entrepreneurs. They are initially motivated by enjoyment or the playful use of technology before transitioning to task-oriented usage. This progression suggests that hedonic motivation constitutes an essential factor (Gupta & Yang, 2024). When a tool appears enjoyable and interesting, individuals are more likely to experiment with it regardless of immediate performance advantages. This is particularly relevant in startup cultures characterised by an experimental environment (Rizomyliotis et al., 2025; Söderberg & Stenmark, 2025).

This pleasure-driven interaction helps build familiarity and user skill while positively influencing other perceptions such as improving emotional value (Kang et al., 2025) and reducing perceived effort (Salazar & Rivera, 2025). Consequently, hedonic motivation is a critical factor for understanding generative AI acceptance in the startup context.

H4: Hedonic motivation (HM) has a positive effect on behavioural intention (BI)

2.2.3.2 Trust in AI (TAI)

The UTAUT model was originally developed for the information systems sector where operational mechanics were predominantly clear and results were predictable. Generative AI differs fundamentally from this paradigm. Its outputs are probabilistic and its internal decision-making processes are frequently opaque, earning it the designation of a "black box" (Yunita, 2025). This lack of clarity necessitates a significant degree of user trust. This is a critical dimension that constructs such as Facilitating Conditions or Effort Expectancy fail to address. When a user cannot discern how a result was generated, they must trust that the output is reliable, accurate, and free from bias.

The importance of trust is a recurring theme in recent AI acceptance literature. This is strongly corroborated by a large-scale systematic review of 562 empirical studies which identified trust as a "central mechanism" that shapes behavioural intention, system usage, and long-term acceptance of AI (Dang & Li, 2025). Furthermore, a qualitative study on AI acceptance in Swedish technology companies identified trust as a primary concern for employees (Yunita, 2025).

According to another study, trust in AI exerts a significant indirect effect on the intention to use the technology. This effect occurs mainly by improving the user's attitude towards the technology and enhancing their perception of its usefulness (Choung et al., 2023). These researchers further conceptualised trust into two dimensions comprising functionality trust which relates to competence and reliability and human-like trust which relates to benevolence and fairness. Both dimensions are deemed essential for user acceptance (Choung et al., 2023).

A study regarding AI acceptance in academia within a developing country determined that trust served as a significant positive predictor of user behavioural intention and reaffirmed its critical role during the initial stages of the acceptance decision (Rana et al., 2024).

This concept aligns with a study on generative AI acceptance in Sub-Saharan Africa which extended the UTAUT model by incorporating the construct of algorithmic aversion (Ayeni et al., 2024). This is defined as a user's reluctance or scepticism regarding reliance on or acceptance of algorithmic decision-making systems. This sentiment stems directly from a lack of trust and concerns regarding transparency and the potential for errors (Ayeni et al., 2024).

This concept suggests it is difficult for a user to believe a tool will enhance their job performance if they do not trust the results it provides. For instance, although using AI offers the opportunity to complete tasks more rapidly which relates to performance expectancy, the knowledge that generative AI can occasionally generate errors or biased information will reduce the employee's level of trust. Consequently, they may perceive a need to invest significant time and effort to rigorously verify every result generated by the AI.

This additional burden can diminish the anticipated efficiency benefits and thereby reduce the level of performance expectancy. Therefore, superior performance cannot be realised without a foundational level of trust. This renders trust in AI an essential additional construct for utilising UTAUT in the study of generative AI acceptance.

H5: Trust in AI (TAI) has a positive effect on behavioural intention (BI)

2.2.3.3 AI Anxiety (AIA)

The decision to adopt a disruptive technology such as AI represents more than a mere logical calculation of benefits. It also constitutes an emotional process. A significant barrier to AI acceptance is AI anxiety which is defined as the fear or apprehension individuals experience regarding AI and its potential societal impacts (Hatos, 2025; Lemay et al., 2020).

This anxiety stems from various concerns including job loss, the devaluation of human skills, loss of personal control, and data privacy issues (Cengiz & Peker, 2025; Mohamed et al., 2025). A recent study offers a more nuanced perspective and suggests two primary dimensions of AI anxiety. The first is anticipatory anxiety which relates to fears of future issues such as job displacement. The second and deeper dimension is annihilation anxiety. This pertains to existential concerns such as the loss of human identity and autonomy due to advanced AI (Frenkenberg & Hochman, 2025).

AI anxiety acts as a potent counterforce to acceptance. Numerous studies demonstrate a negative correlation between anxiety and the intention to adopt AI (Mohamed et al., 2025; Salazar & Rivera, 2025). These anxieties can undermine the positive influence of the core UTAUT constructs. For instance, long-term fears regarding job security may outweigh the short-term benefits associated with performance expectancy and effort expectancy (Mohamed et al., 2025). The original UTAUT model was not designed to address such complex emotional dynamics. Consequently, including AI anxiety is essential for achieving a comprehensive understanding of scenarios where AI acceptance fails.

H6: AI anxiety (AIA) has a negative effect on behavioural intention (BI)

2.3 Summary of the Foundation model and Additional factors

In summary, this review has established that the UTAUT model provides a robust foundation for examining technology acceptance. However, its direct application to generative AI reveals significant variations depending on the contextual nuances. Evidence from diverse studies indicates that the predictive power of the key UTAUT constructs fluctuates based on the user demographic, the maturity of the technology, and the organisational culture.

Given the distinct characteristics of generative AI including its creative capabilities, its opaque black box nature, and its capacity to evoke emotional responses, combined with the agile and innovative nature of startups, a more comprehensive theoretical model is required. Consequently, this study extends the original UTAUT framework by integrating Hedonic Motivation (HM) adapted from the UTAUT2 model to capture enjoyment-based drivers, Trust in AI (TAI) to address concerns regarding reliability and the black box phenomenon, and AI anxiety (AIA) to account for significant emotional barriers such as the fear of job displacement. This integrated model synthesises these factors to provide a nuanced understanding of generative AI adoption within Thai startups.

Table 2.1

Summary of the core constructs of the UTAUT model, including their definitions, and theoretical origins

Construct Name	Definition	Theoretical origin
Performance Expectancy (PE)	The degree to which an employee or entrepreneur in a startup believes that using a generative AI system will boost their work efficiency, productivity, and overall job performance.	(Venkatesh et al., 2003)

Table 2.1

Summary of the core constructs of the UTAUT model, including their definitions, and theoretical origins (Cont.)

Construct Name	Definition	Theoretical origin
Effort Expectancy (EE)	How easy an employee or entrepreneur in a startup finds it to learn and use generative AI tools.	(Venkatesh et al., 2003)
Social Influence (SI)	The extent to which an employee or entrepreneur in a startup feels that important people around them, such as their manager, colleagues, or investors, believe they should be using generative AI.	(Venkatesh et al., 2003)
Facilitating Conditions (FC)	The belief of an employee or entrepreneur in a startup that their company has the necessary infrastructure and support, like technical assistance and training, to use generative AI effectively.	(Venkatesh et al., 2003)
Behavioural Intention (BI)	The employee's or entrepreneur's stated plan and willingness to use generative AI in the future, which is a strong indicator of their actual usage.	(Venkatesh et al., 2003)
Use Behaviour (UB)	The actual, tangible use of generative AI technology for work-related tasks by an employee or entrepreneur in a startup.	(Venkatesh et al., 2003)

Table 2.2

Summary of the extended constructs proposed for this research framework, including their definitions and theoretical origins

Construct Name	Definition	Theoretical origin / Key Literature
Hedonic Motivation (HM)	The sense of fun, pleasure, and curiosity that a startup employee or entrepreneur gets from using generative AI, which is separate from its practical work benefits.	(Ali et al., 2024; Gupta & Yang, 2024; Kang et al., 2025; Noerman et al., 2025; Venkatesh et al., 2012)
Trust in AI (TAI)	The psychological state where an employee or entrepreneur feels they can depend on generative AI, trusting that it is reliable, accurate, and fair, even though its internal workings are often unclear, like a "black box".	(Ayeni et al., 2024; Choung et al., 2023; Rana et al., 2024; Yunita, 2025)
AI Anxiety (AIA)	Feelings of fear, worry, or discomfort an employee or entrepreneur has about AI, including concerns about losing their job, their skills becoming redundant, or a loss of human identity and control.	(Cengiz & Peker, 2025; Frenkenberg & Hochman, 2025; Hatos, 2025; Lemay et al., 2020; Mohamed et al., 2025; Rana et al., 2024; Salazar & Rivera, 2025)

Table 2.3

Summary of Literature on Factors Influencing generative AI Acceptance

No.	Author	Performance	Effort	Social Influence	Facilitating	Hedonic	Trust in AI	AI Anxiety
1	(Teerawongsathorn, 2023)	●	●					
2	(Navarattanapaiboon, 2024)	●	●	●				
3	(Abdalla, 2025)	●	●	●	●			
4	(Kim et al., 2024)	◐	●	●	◐			
5	(Yakubu et al., 2025)	●	●	●	◐			
6	(Alateeg et al., 2024)	●	◐		◐			
7	(Rizomyliotis et al., 2025)	○		○	○			
8	(Gansser & Reich, 2021)	●	●	●		●		
9	(Noerman et al., 2025)	●	●	●		●		
10	(Papathomas et al., 2025)	●	●	◐		●		
11	(Kang et al., 2025)	●	●		●	●		
12	(Tanantong & Wongras, 2024)	●	●	○	●		○	
13	(Paudel & Acharya, 2025)	◐		●		●	○	
14	(Salih et al., 2025)	●	●	●		●	●	
15	(Ali et al., 2024)	●	●	●	●	●	●	
16	(Rana et al., 2024)	●	●	●	●		●	
17	(Gupta & Yang, 2024)	●	●	●		●	●	
18	(Dang & Li, 2025)						○	
19	(Choung et al., 2023)						○	
20	(Salazar & Rivera, 2025)	●	●	●			●	●
21	(Frenkenberg & Hochman, 2025)	○					○	●

Table 2.3

Summary of Literature on Factors Influencing generative AI Acceptance (Cont.)

No.	Author	Performance Expectancy	Effort Expectancy	Social Influence	Facilitating Conditions	Hedonic Motivation	Trust in AI	AI Anxiety
22	(Yunita, 2025)	○			○		○	○
23	(Sammet et al., 2024)				○		○	○
24	(Söderberg & Stenmark, 2025)				○		○	○
25	(Lemay et al., 2020)						○	●
26	(Cengiz & Peker, 2025)	●	●	●	●			●
27	(Mohamed et al., 2025)	●	●	●	●			●
28	(Ayeni et al., 2024)	●	●	●	●			○
29	(Kaya et al., 2024)							●
30	(Hatos, 2025)							○

Note. ●: Direct Empirical Test (Significant)

◐: Direct Empirical Test (Not Significant)

○: Conceptual/Contextual Support

2.4 Conceptual Framework

This research utilises the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) as its foundational structure. It further extends this model by incorporating three additional constructs comprising Hedonic Motivation (HM), Trust in AI (TAI), and AI Anxiety (AIA). These additions reflect the unique characteristics of Generative AI and the dynamic environment inherent to Thai startups.

The framework posits that Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Hedonic Motivation (HM), Trust in AI (TAI), and AI Anxiety (AIA) influence the Behavioural Intention (BI) to adopt generative AI. This intention subsequently determines Use Behaviour (UB). Additionally, Facilitating Conditions (FC) act as a direct influence on Use Behaviour (UB) which is consistent with the original UTAUT model. Furthermore, generational cohorts comprising Generation X, Generation Y, and Generation Z are integrated as moderators.

The framework is structured as follows.

1) Direct predictors of BI: PE, EE, SI, HM, TAI, AIA.

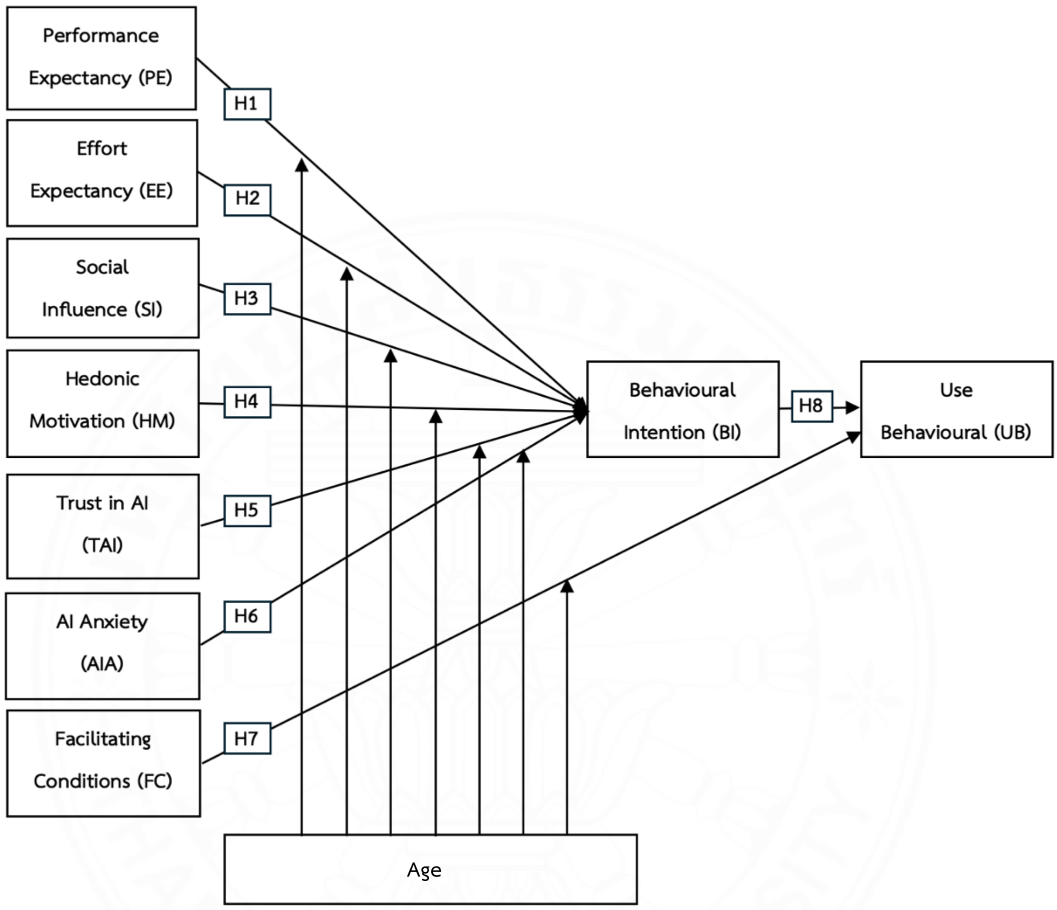
2) Direct predictors of UB: BI and FC.

3) Moderator: Age moderates the relations between predictors and BI, and between FC and UB.

This framework integrates both cognitive determinants such as PE, EE, SI, and FC and psychological determinants such as HM, TAI, and AIA. The objective is to provide a comprehensive understanding of how employees within Thai startups adopt and utilise generative AI.

Figure 2.4

Research Structural Model



2.5 Research Hypothesis

To validate the proposed model, this study employs Partial Least Squares Structural Equation Modelling (PLS-SEM) to examine the structural relationships defined in hypotheses H1 through H8.

1) Determinants of Behavioural Intention (BI)

The following hypotheses posit the factors influencing the intention to adopt generative AI.

H1: Performance expectancy (PE) has a positive effect on behavioural intention (BI).

H2: Effort expectancy (EE) has a positive effect on behavioural intention (BI).

H3: Social influence (SI) has a positive effect on behavioural intention (BI).

H4: Hedonic motivation (HM) has a positive effect on behavioural intention (BI).

H5: Trust in AI (TAI) has a positive effect on behavioural intention (BI).

H6: AI anxiety (AIA) has a negative effect on behavioural intention (BI).

2) Determinants of Use Behaviour (UB)

The following hypotheses posit the factors determining the actual usage of the technology.

H7: Facilitating conditions (FC) has a positive effect on use behaviour (UB).

H8: Behavioural intention (BI) has a positive effect on use behaviour (UB).

CHAPTER 3
RESEARCH METHODOLOGY

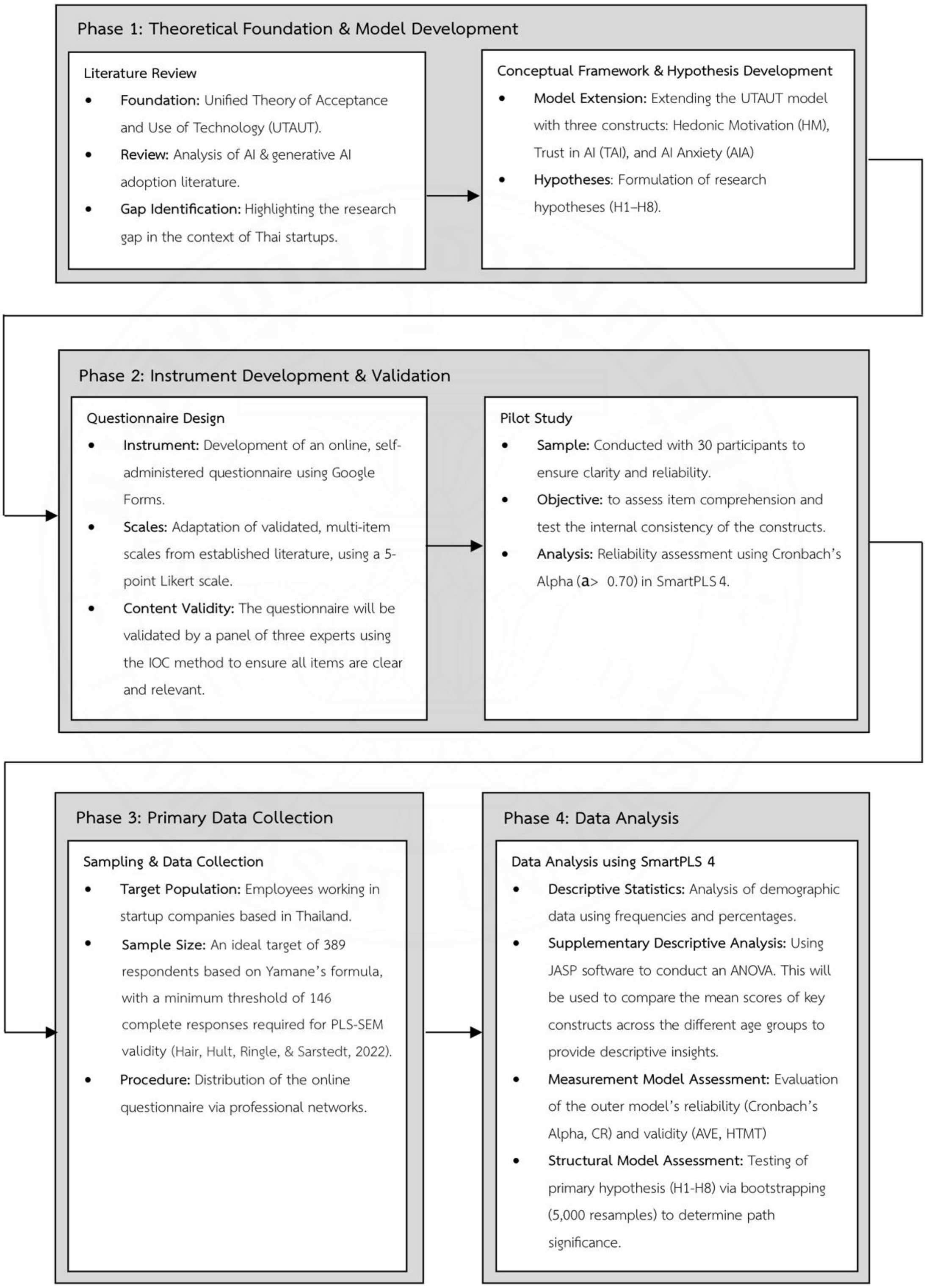
This chapter presents the research methodology employed in this study. The primary purpose is to provide a clear and systematic explanation of the procedures used to investigate the research questions introduced in Chapter 1. The chapter is organised to present the research design followed by the population and sampling methods. It subsequently details the data collection instrument and the measurement of variables. Finally, the chapter outlines the rigorous procedures established to ensure validity and reliability as well as the statistical techniques utilised for data analysis.

3.1 Research Design

This research employs a quantitative approach to collect and analyse numerical data which allows for the testing of hypotheses in a structured manner. The procedure utilises deductive reasoning and begins with the established expanded UTAUT theory to formulate specific and testable hypotheses. The overall research process ranges from theoretical model development to data analysis and is systematically illustrated in Figure 3.1.

Figure 3.1

Overview of the Research Process



The primary method for data collection involves a self-administered online questionnaire distributed via Google Forms. Following the refinement of the research instrument through a pilot study, the final questionnaire link will be disseminated across professional networks and online startup communities. The data collection phase is scheduled to span three to four weeks during which the researcher will actively monitor responses to track progress toward the target sample size.

3.2 Population and Sampling

This section describes the target population of the study and explains the sampling plan along with the method utilised to determine the sample size.

3.2.1 Target Population

The target population for this research is defined as employees or entrepreneurs currently employed in startup companies based in Thailand. Participants must meet specific criteria to be eligible for the study. First, the individual must be an employee or entrepreneur of a startup company situated in Thailand. Second, the participant must possess experience using at least one generative AI tool such as ChatGPT, Gemini, or Midjourney for work-related tasks.

3.2.2 Sampling plan

The primary method for distributing the questionnaire involves sharing an online link through various channels where startup employees are concentrated. These channels include professional communities such as True Digital Park as well as online forums and startup communities on social media platforms like Facebook. Furthermore, the questionnaire will be distributed through the researcher's professional network.

3.2.3 Sample size

To ensure the statistical validity of the research findings, the determination of the sample size considered established guidelines from two perspectives comprising population representation and the specific requirements of the data analysis technique.

1) Population-Based Perspective (Yamane Formula)

From the perspective of population representation, the study referenced the formula by Yamane (1967) as a primary guideline. The formula is expressed as follows.

$$n = \frac{N}{1 + N(e^2)}$$

Where

n = sample size

N = population size

e = margin of error (set at 0.05 for a 95% confidence level)

Because the total population of startup employees in Thailand is not precisely known, this study utilises active membership of True Digital Park which is recognised as Southeast Asia's largest digital innovation hub and a central point for the Bangkok startup ecosystem. According to the Global Startup Ecosystem Index 2025 report (StartupBlink, 2025), the park has an active membership of over 14,000 individuals.

Using this figure for the population size (N = 14,000) with a 95% confidence level (e = 0.05), the sample size is calculated as follows:

$$n = \frac{14{,}000}{1 + 14{,}000(0.05^2)}$$

$$n \approx 388.89$$

This calculation indicates that an ideal target sample size for full population coverage is approximately 389 respondents.

2) Technical Requirement Perspective (PLS-SEM Guidelines: Power Analysis using G*Power 3.1.9.6)

Concurrently, the adequacy of the sample size was evaluated against the technical requirements for Structural Equation Modelling using Partial Least Squares (PLS-SEM). Following the recommendation of Hair, Hult, Ringle, & Sarstedt (2022), sample size determination for PLS-SEM should be based on statistical power analysis, using the most complex structural equation in the model (i.e., the endogenous construct with the largest number of predictors) (Hair, Hult, Ringle, & Sarstedt, 2022).

In this research model, the endogenous construct with the highest number of incoming paths is Behavioral Intention (BI), which is predicted by 6 exogenous constructs. Therefore, a power analysis was conducted in G*Power using F tests and Linear multiple regression: Fixed model, R^2 deviation from zero, with the following parameters: α = 0.05, effect size (f^2) = 0.15, power ($1-\beta$) = 0.95, and number of predictors = 6. The G*Power calculation indicated a minimum required sample size of 146 respondents to achieve adequate statistical power for detecting effects in the structural model.

Based on the complementary approaches adopted in this study, sample size determination was guided by both a population-based reference and a statistical power–based requirement. The sample size estimated using the Yamane formula serves as an ideal reference value, reflecting the desirable level of population coverage under optimal data collection conditions.

In contrast, the G*Power analysis, conducted in accordance with the PLS-SEM guidelines recommended by Hair, Hult, Ringle, & Sarstedt (2022), was employed to establish the minimum required sample size for statistical analysis. Using the most complex structural equation in the research model, the power analysis specifies the minimum number of observations necessary to achieve adequate statistical power for hypothesis testing.

Accordingly, this study adopts the sample size derived from G*Power as the minimum target threshold, while the Yamane-based estimate is retained as an ideal benchmark for evaluating data collection adequacy. This dual-guideline approach ensures methodological rigor by balancing statistical robustness and population representation in the research design.

3.3 Research Instrument and Measurements

This section details the research instrument utilised for data collection. It describes the design of the questionnaire and explains the measurement methodology for each construct within the research model.

3.3.1 Questionnaire Design

This research utilised an online questionnaire developed via Google Forms. The questionnaire is structured into three distinct parts.

3.3.1.1 Part 1: Introduction and Consent

This section outlines the research purpose and informs participants that their responses will remain anonymous and confidential. It further explicitly states that participation is voluntary. Participants are required to respond to an informed consent question prior to proceeding to the subsequent section.

3.3.1.2 Part 2: Demographic and Contextual Information

The objective of this section is to collect general background information from the participants. Data points include gender, age, level of education, job position, work experience, organisation size, and the frequency of generative AI usage.

3.3.1.3 Part 3: Measurement of Constructs

This section constitutes the primary component of the questionnaire. It contains the items designed to measure the nine constructs within the research model. A 5-point Likert scale is utilised for all items.

5 means strongly agree

4 means agree

3 means neutral

2 means disagree

1 means strongly disagree.

3.3.2 Construct Measurement

All constructs in this study are measured using multi-item scales. These scales were adapted from established instruments found in previous academic literature which have been rigorously validated. The specific items for each construct are presented in Table 3.1.

Table 3.1

Construct Measurement Items and Sources

Construct	Measurement item	Source
Performance Expectancy (PE)	PE1: I believe generative AI provides me with useful information and services.	(Kang et al., 2025; Kim et al., 2024; Tanantong & Wongras, 2024; Venkatesh et al., 2003)
	PE2: Using generative AI helps me boost my productivity on tasks.	(Ali et al., 2024; Kang et al., 2025; Kim et al., 2024; Papathomas et al., 2025; Venkatesh et al., 2003)
	PE3: I think generative AI assists me in solving complex problems.	(Ali et al., 2024; Kim et al., 2024; Papathomas et al., 2025)
	PE4: Generative AI helps me generate creative new ideas.	(Ali et al., 2024; Kim et al., 2024)

Table 3.1

Construct Measurement Items and Sources (Cont.)

Construct	Measurement item	Source
Effort Expectancy (EE)	EE1: I find generative AI to be simple and easy to use.	(Alateeg et al., 2024; Ali et al., 2024; Kang et al., 2025; Kim et al., 2024; Venkatesh et al., 2003)
	EE2: The features of generative AI are easy for me to operate and control.	(Kang et al., 2025; Kim et al., 2024; Venkatesh et al., 2003)
	EE3: It would not be difficult for me to become highly skilled at using generative AI.	(Alateeg et al., 2024; Ali et al., 2024; Kim et al., 2024; Venkatesh et al., 2003)
	EE4: I can flexibly use generative AI in many different situations.	(Kang et al., 2025; Kim et al., 2024; Venkatesh et al., 2003)
Social Influence (SI)	SI1: My supervisor or colleagues encourage me to use generative AI systems.	(Kim et al., 2024; Venkatesh et al., 2003)
	SI2: My colleagues generally have a positive opinion about using generative AI.	(Kim et al., 2024; Venkatesh et al., 2003)
	SI3: People who are important to me believe I should use generative AI.	(Ali et al., 2024; Kim et al., 2024; Papathomas et al., 2025; Venkatesh et al., 2003)

Table 3.1

Construct Measurement Items and Sources (Cont.)

Construct	Measurement item	Source
Facilitating Conditions (FC)	FC1: My company provides the necessary technical infrastructure and support for generative AI.	(Kim et al., 2024; Papathomas et al., 2025; Strzelecki et al., 2024; Venkatesh et al., 2003)
	FC2: There is sufficient support from AI experts in my organisation for using generative AI.	(Alateeg et al., 2024; Ali et al., 2024; Kim et al., 2024)
	FC3: My company offers adequate training for the use of generative AI.	(Gupta & Yang, 2024; Kim et al., 2024; Venkatesh et al., 2003)
Hedonic Motivation (HM)	HM1: I find using generative AI to be enjoyable.	(Gupta & Yang, 2024; Kang et al., 2025; Strzelecki et al., 2024; Venkatesh et al., 2012)
	HM2: Generative AI helps me satisfy my curiosity.	(Kang et al., 2025; Venkatesh et al., 2012)
	HM3: Using generative AI is a fun experience for me.	(Gupta & Yang, 2024; Kang et al., 2025; Strzelecki et al., 2024; Venkatesh et al., 2012)
Trust in AI (TAI)	TAI1: I trust that generative AI is designed to help users, not for personal gain.	(Choung et al., 2023; Jiang et al., 2025)
	TAI2: I believe generative AI is honest and does not misuse information or its advantages over users.	(Jiang et al., 2025; Rana et al., 2024; Tanantong & Wongras, 2024)

Table 3.1

Construct Measurement Items and Sources (Cont.)

Construct	Measurement item	Source
Trust in AI (TAI)	TAI3: Generative AI seems to be trustworthy.	(Ali et al., 2024; Rana et al., 2024; Tanantong & Wongras, 2024)
	TAI4: I can understand how generative AI reaches decisions for work tasks.	(Jiang et al., 2025)
AI Anxiety (AIA)	AIA1: I am worried that generative AI may replace human jobs.	(Aung, 2025; Hatos, 2025; Wang & Wang, 2022)
	AIA2: I fear that using generative AI too much will make me dependent on it and cause me to lose some of my critical thinking skills.	(Hatos, 2025; Wang & Wang, 2022)
	AIA3: I am concerned that generative AI might get out of control and not function properly.	(Hatos, 2025; Wang & Wang, 2022)
	AIA4: I am afraid that generative AI will replace someone's job.	(Aung, 2025; Hatos, 2025; Wang & Wang, 2022)
Behavioural Intention (BI)	BI1: I am willing to use generative AI.	(Kim et al., 2024; Venkatesh et al., 2003)
	BI2: I plan to use generative AI to improve my work performance.	(Kim et al., 2024; Venkatesh et al., 2003)
	BI3: I intend to continue using generative AI in the future.	(Ali et al., 2024; Kim et al., 2024; Papathomas et al., 2025; Venkatesh et al., 2003)

Table 3.1

Construct Measurement Items and Sources (Cont.)

Construct	Measurement item	Source
Use Behaviour (UB)	UB1: I personally use generative AI.	(Ali et al., 2024; Kim et al., 2024)
	UB2: I use generative AI to explore new ways of working.	(Ali et al., 2024)
	UB3: I use generative AI applications on various devices that I own.	(Ali et al., 2024)

3.4 Instrument Validation

The Index of Item-Objective Congruence (IOC) was employed to verify the content validity of the questionnaire prior to the pilot study (Turner & Carlson, 2003). The validation process entailed specific steps starting with an Expert Review. The questionnaire was submitted for review to a panel of three experts alongside the theoretical definitions of all constructs. These experts were selected due to their specialised knowledge in relevant fields including artificial intelligence and technology acceptance as well as the business environment for Thai startups. Regarding the Rating Scale the experts independently scored the congruence of each item using a three-point scale.

+1 : Indicates the item is relevant and measures the intended construct.

0 : Indicates the item's relevance is uncertain.

-1 : Indicates the item is not relevant to the construct.

For the Calculation and Decision Rule the scores provided by the experts were utilised to calculate an IOC value for every single item using the following formula.

$$IOC = \frac{\sum R}{N}$$

Where:

IOC = the Index of Item-Objective Congruence.

$\sum R$ = the sum of the scores from all experts.

N = the total number of experts.

Where IOC represents the Index of Item-Objective Congruence while $\sum R$ denotes the sum of the scores from all experts and N represents the total number of experts.

Items with an IOC score of 0.50 or higher were deemed valid and retained for the subsequent stage in accordance with accepted guidelines. Any items scoring below 0.50 were carefully revised based on the experts' written comments or removed if improvement was not feasible. This process constituted a necessary step to confirm the accuracy and reliability of the questionnaire prior to its deployment in the pilot study.

3.5 Pilot Study

A pilot study will be conducted prior to the commencement of the main data collection process. The purpose of this preliminary phase is to assess the quality and reliability of the questionnaire. This test entails distributing the questionnaire to a small sample group consisting of 30 participants.

The pilot test serves two primary objectives. First, it evaluates the clarity and comprehensibility of the questions to ensure that participants interpret them as intended. Second, the data collected from the pilot test will facilitate an initial reliability analysis (Hair, Hult, Ringle, & Sarstedt, 2022).

The analysis will utilise SmartPLS 4 (version 4.1.1.6) to calculate Cronbach's alpha (α) for each construct. A construct is considered reliable if the Cronbach's alpha coefficient is 0.70 or higher (Hair, Hult, Ringle, & Sarstedt, 2022). The coefficient varies from 0 to 1 where scores closer to 1 indicate greater reliability. Necessary modifications will be implemented to the questionnaire based on the results from the pilot study. This process will be concluded before the questionnaire is distributed for the primary data collection.

3.6 Data Analysis Techniques

The collected data will be analysed using the statistical software package SmartPLS 4 (version 4.1.1.6). This software was selected as it is a leading tool for Partial Least Squares Structural Equation Modelling (PLS-SEM).

3.6.1 Descriptive Statistics

Descriptive statistics will be employed to analyse the demographic data using frequency and percentage. Mean and standard deviation will be utilised for the main constructs derived from the questionnaire. Five levels of interpretation will be established using a class interval calculation to interpret the mean scores from the 5-point Likert scale.

The class interval is calculated as follows:

$$Class\ interval\ = \frac{(Maximum\ Score - Minimum\ Score)}{number\ of\ Levels}$$

$$= \frac{(5-1)}{5}$$

$$= 0.8$$

The interpretation of the mean scores will be based on the following criteria:

Mean = 1.00–1.80: Strongly Disagree

Mean = 1.81–2.60: Disagree

Mean = 2.61–3.40: Neutral

Mean = 3.41–4.20: Agree

Mean = 4.21–5.00: Strongly Agree

3.6.2 Two-Step Analytical Approach

The data analysis will employ the recommended two-step analytical approach for PLS-SEM. This procedure is widely adopted to ensure both the reliability of the measurement model and the explanatory power of the structural model (Hair, Hult, Ringle, & Sarstedt, 2022).

3.6.2.1 Step 1: Measurement Model Assessment (Outer Model)

The first step involves confirming that the measurement items accurately represent their respective latent constructs. This process in PLS-SEM is equivalent to the confirmatory factor analysis (CFA) utilised in covariance-based SEM or CB-SEM. The assessment will include four criteria as follows.

(1) Indicator reliability

Outer loadings should exceed 0.70. However, indicators with loadings between 0.40 and 0.70 may be retained if the composite reliability (CR) and average variance extracted (AVE) of the construct already meet the required thresholds (Hair, Hult, Ringle, & Sarstedt, 2022). The indicator reliability is calculated as follows.

$$IR_i = \lambda_i^2$$

Where

IR_i = Indicator reliability

λ_i = Outer loading of an observed variable on its latent construct

(2) Internal consistency reliability

Cronbach's alpha (α) and composite reliability (CR) should exceed 0.70 (Hair, Hult, Ringle, & Sarstedt, 2022). The formula for Cronbach's Alpha is expressed as follows.

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum_{i=1}^{k} \sigma_i^2}{\sigma_T^2}\right)$$

Where

k = number of items

σ_i^2 = variance of each item

σ_t^2 = total variance

Table 3.2

Cronbach's Alpha Scores' Levels.

Cronbach's Alpha	Internal Consistency
$\alpha \geq 0.9$	Excellent
$0.7 \leq \alpha < 0.9$	Good
$0.6 \leq \alpha < 0.7$	Acceptable
$0.5 \leq \alpha < 0.6$	Poor
$\alpha < 0.5$	Unacceptable

Source: Streiner, 2003.

The formula for Composite Reliability is expressed as follows.

$$CR = \frac{\left(\sum_{i=1}^{k} \lambda_i\right)^2}{\left(\sum_{i=1}^{k} \lambda_i\right)^2 + \sum_{i=1}^{k}(1 - \lambda_i^2)}$$

Where

λ_i = outer loading

$1 - \lambda_i^2$ = error variance

(3) Convergent validity

The average variance extracted (AVE) should be greater than 0.50 (Fornell & Larcker, 1981). The formula for Convergent Validity is expressed as follows.

$$AVE = \frac{\sum_{i=1}^{k} \lambda_i^2}{k}$$

Where

λ_i^2 = squared loading of each item

k = number of items

(4) Discriminant validity

The Heterotrait-Monotrait (HTMT) ratio of correlations will be utilised to assess discriminant validity. Two thresholds are applied based on the guidelines established by Henseler et al. (2015) which are also supported by Hair et al. (2022). The HTMT ratio should fall below 0.85 for conceptually distinct constructs. Conversely, a more liberal threshold below 0.90 is considered acceptable for constructs that exhibit conceptual similarity (Henseler et al., 2015).

3.6.2.2 Step 2: Structural Model Assessment (Inner Model)

Once the measurement model is confirmed as reliable and valid, the second step entails assessing the structural model. This stage evaluates the hypothesised relationships and the explanatory power of the model (Hair, Hult, Ringle, & Sarstedt, 2022).

(1) Collinearity assessment

Multicollinearity among predictors is tested using the Variance Inflation Factor (VIF). VIF values should remain below (Hair, Hult, Ringle, & Sarstedt, 2022). The formula is expressed as follows.

$$VIF = \frac{1}{1 - R_j^2}$$

Where

R_j^2 = the variance explained when predictor

j = regressed on the other predictors.

(2) Explanatory Power

The explanatory strength of the model is evaluated through the coefficient of determination (R^2). The formula is expressed as follows.

$$R^2 = \frac{Explained\ Variance}{Total\ Variance}$$

Values of 0.75, 0.50, and 0.25 are interpreted as substantial, moderate, and weak explanatory power respectively (Hair, Hult, Ringle, & Sarstedt, 2022; Hair et al., 2011). A higher R^2 value indicates that the predictor concepts possess a greater capacity to explain the changes in the endogenous constructs such as Behavioural Intention and Use Behaviour (Hair, Hult, Ringle, & Sarstedt, 2022).

This two-step approach ensures that the constructs are measured reliably before proceeding to test the structural relationships. This sequence enhances the robustness of the research findings.

3.6.3 Hypothesis Testing and Path Coefficient Analysis

A process will be conducted in SmartPLS 4 to test the primary hypotheses of this study comprising H1 to H8. The significance of the path coefficients (β) and their p-values will be determined using a bootstrapping procedure. This procedure will utilise 5,000 resamples. If the p-value for a path is less than 0.05 it is considered to be statistically significant. Each hypothesis can be supported or not supported based on these results (Hair, Hult, Ringle, & Sarstedt, 2022).

CHAPTER 4
RESULTS AND DISCUSSION

This chapter presents the empirical analysis of the factors influencing Generative AI acceptance within the Thai startup ecosystem. Utilising a quantitative approach, the study employs JASP for descriptive and comparative analysis, followed by Partial Least Squares Structural Equation Modelling (PLS-SEM) via SmartPLS 4 to test the proposed framework. The presentation of findings proceeds systematically from instrument validation and sample profiling to the rigorous two-step assessment of the measurement and structural models. The chapter concludes by synthesising these statistical results to evaluate the research hypotheses and discuss their implications for the study's objectives.

4.1 Instrument Development and Validation Results

This section presents the results of the two-step instrument validation process conducted prior to the main data collection. This process was essential to ensure the quality and reliability of the final questionnaire. The first step involved assessing the content validity through an expert or IOC review followed by the second step which was a pilot test to confirm the internal consistency reliability of the constructs. The results of each step are detailed in the following sub-sections.

4.1.1 Content Validity (IOC) Assessment and Qualitative Feedback

The questionnaire instrument was submitted to three experts for content validity verification prior to the pilot test. The standard criterion for item acceptance was an Index of Item-Objective Congruence (IOC) score greater than 0.50. Items scoring below this threshold were considered for revision or deletion based on expert comments.

The IOC results showed that all 11 demographic and contextual items passed the criterion of greater than 0.50. Most items for the main constructs comprising PE, EE, FC, HM, TAI, BI, and UB also passed. However, two items failed the threshold. These were SI3 "People who are important to me believe I should use generative AI" and the original AIA4 "I am afraid that generative AI will replace someone’s job".

Qualitative feedback from the experts provided clear direction regarding these failures and suggested further improvements as outlined below.

1) Demographics: Options for gender and position should be expanded for clarity.

2) SI & AIA: The failed items SI3 and original AIA4 were noted as redundant and unclear. Experts suggested adding items for organisational policy regarding SI and result verification anxiety regarding AIA.

3) FC & TAI: New items were suggested to cover data security for FC and data privacy for TAI.

4) HM: Merging two similar items HM1 and HM3 and adding one new item described as "excited to learn" was recommended.

5) BI & UB: New items were suggested to measure advanced usage such as recommending to colleagues for BI and strategic decision-making for UB.

Based on this feedback, the researcher implemented revisions for the final questionnaire. All item wording was adjusted for clarity. Specific structural changes are detailed below.

1) SI: The original SI3 was deleted. A new item was added as SI3: "My organisation has a policy or guidelines that encourage employees to use Generative AI." (Kim et al., 2024; Yunita, 2025).

2) FC: A new item was added as FC4: "My company has appropriate measures in place to ensure data security for the use of Generative AI." (Tanantong & Wongras, 2024).

3) HM: The original HM1 and HM3 were merged. A new item was added as HM3: "Generative AI makes me feel excited to constantly learn new things."(Ali et al., 2024; Gupta & Yang, 2024).

4) TAI: A new item was added as TAI5: "I believe that Generative AI will not disclose my information without permission." (Choung et al., 2023; Rana et al., 2024).

5) AIA: The original AIA1 and AIA4 were merged. A new item was added as AIA4: "I feel unconfident when I have to rely on results generated by Generative AI without verification." (Ali et al., 2024; Hatos, 2025).

6) BI: A new item was added as BI4: "I intend to recommend that my colleagues use Generative AI." (Papathomas et al., 2025).

7) UB: Two new items were added: UB4 ("I use Generative AI to assist in strategic decision-making or work planning.") (Kim et al., 2024) and UB5 ("I apply the output from Generative AI in work that has an organisational impact") (Kim et al., 2024).

4.1.2 Pilot Test Reliability Results

Following the content validity assessment, a pilot study was conducted to evaluate the internal consistency reliability of the research instrument. Data was collected from a sample of 55 participants within the target population for this pilot phase. This sample size was selected to ensure stable and accurate reliability estimates, exceeding the traditional recommendation of 30 participants often cited in methodological literature.

The reliability analysis was performed using SmartPLS 4 to calculate Cronbach's Alpha (α) for each construct. The criteria for acceptance was set at $\alpha > 0.70$ (Hair, Hult, Ringle, & Sarstedt, 2022). The results demonstrated that all constructs successfully met this requirement.

Table 4.1

Pilot Study Reliability Test Results (n = 55)

Construct	Number of Items	Cronbach's Alpha (α)	Result
PE	4	0.807	Good
EE	4	0.794	Good
SI	3	0.749	Good
FC	4	0.839	Good
HM	3	0.904	Excellent
TAI	5	0.879	Good
AIA	3	0.719	Good
BI	4	0.875	Good
UB	5	0.854	Good

As all constructs demonstrated acceptable internal consistency the research instrument was confirmed to be reliable and suitable for the primary data collection phase.

4.2 Sample Profile and Descriptive Statistics

This section presents the results of the primary data collection which forms the basis for the subsequent PLS-SEM analysis. The section is structured into three parts.

It begins with subsection 4.2.1 which details the researcher's data collection strategy and presents the final demographic and contextual profile of the sample. In the following section 4.2.2 a comprehensive analysis of the descriptive statistics such as mean and standard deviation for all model constructs will be provided. Finally, subsection 4.2.3 explores these constructs more deeply by presenting a comparative analysis across the key generational cohorts.

4.2.1 Data Collection and Sample Profile

The data for this study was collected between 17 October 2025 and 9 November 2025. The researcher employed a multi-pronged data collection strategy to access the target population of personnel within Thai startup companies. This approach combined online distribution, onsite data gathering, and direct professional invitations.

The primary method involved online distribution of the questionnaire through major startup communities as detailed below.

1) True Digital Park (TDPK Community) where the survey was promoted to a private group of over 1,400 startup personnel.

2) Bangkok Startup Association (BSO) where the survey was disseminated to 1,580 entrepreneurs and stakeholders.

3) Other Digital Communities which included the Chiangmai Startup group and various targeted Facebook and OpenChat groups related to Startup, AI, HealthTech, FinTech, and DeepTech.

Additionally, onsite data collection was conducted by distributing the questionnaire at relevant industry events to capture real-time responses from attendees. These events included the Bitkub Summit 2025, the AI Thailand Conference 2025 held on 25 and 26 October 2025, and TECHBITE Energy by Bangchak & KX held on 31 October 2025.

Finally, the researcher employed three additional strategies to ensure data saturation by targeting personnel and companies through direct contact.

1) Personal Connections involved leveraging the researcher's existing professional network to invite known contacts within the startup community.

2) Direct Email Outreach involved a systematic campaign sending email invitations to 806 startup companies sourced from public databases including NIA, Thai Startup, and Startup Thailand to encourage internal dissemination.

3) Direct LinkedIn Messaging involved contacting relevant startup personnel directly through the LinkedIn platform to invite their participation.

All responses were screened for completeness and validity following the data collection period. A total of n=343 usable responses were retained for the final analysis. The detailed characteristics of this sample are presented in the following tables.

Table 4.2

Sample Profile (Demographics)

Characteristic	Category	Frequency (n)	Percent (%)
Industry	FinTech	47	13.7
	HealthTech / MedTech	30	8.7
	EdTech	15	4.4
	E-commerce & Marketplace	64	18.7
	Logistics & Supply Chain	22	6.4
	FoodTech / AgriTech	20	5.8
	SaaS (Software as a Service) / Enterprise Tech	42	12.2
	Tech Consulting / Innovation Service	33	9.6
	AI / Big Data / Deep Tech	29	8.5
	Other	41	12.0
Location	Bangkok Metropolitan Region	258	75.2
	Other regions	85	24.8
Gender	Male	145	42.3
	Female	185	53.9
	LGBTQ+	9	2.6
	Prefer not to say	4	1.2
Generation (Age)	Gen Z (18–28 years old)	115	33.5
	Gen Y (29–44 years old)	203	59.2
	Gen X (45–60 years old)	20	5.8
	Baby Boomer (61 years or older)	5	1.5

Table 4.2

Sample Profile (Demographics) (Cont.)

Characteristic	Category	Frequency (n)	Percent (%)
Education	Below Bachelor's Degree	8	2.3
	Bachelor's Degree	227	66.2
	Master's Degree	97	28.3
	Doctoral Degree (PhD or equivalent)	11	3.2
Position	Founder / Co-founder	81	23.6
	Senior Executive	17	5.0
	Manager or equivalent	55	16.0
	Supervisor or equivalent	49	14.3
	Officer / Staff or equivalent	141	41.1
Experience	0–3 years	163	47.5
	4–5 years	84	24.5
	6–10 years	66	19.2
	11–15 years	12	3.5
	More than 15 years	18	5.2
Company Size	25 or fewer	164	47.8
	26–50	80	23.3
	51–200	61	17.8
	201–500	23	6.7
	More than 500	15	4.4

Table 4.3

Sample Profile (Contextual Behaviour)

Characteristic	Category	Frequency (n)	Percent (%)
Frequency of Use	Daily	225	65.6
	Several times a week	107	31.2
	Once a week	9	2.6
	1-3 times a month	2	0.6
	Less than once a month	0	0.0
Subscription Plan	Free plan	120	35.0
	Premium or Pro plan	160	46.6
	Team or Enterprise plan	63	18.4
	Pay-as-you-go (API)	0	0.0
Tools Used (Multiple responses)	ChatGPT	336	98.0
	Gemini	281	81.9
	Claude	113	32.9
	Perplexity	63	18.7
	Microsoft Copilot	62	18.1
	Grok	37	10.8
	Midjourney	28	8.2
	GitHub Copilot	36	10.5
	Etc.	18	5.2

Based on the data in Table 4.2 a detailed profile of the sample (n =343) can be established. Respondents are predominantly located in the Bangkok Metropolitan Region at 75.2%. The industry distribution is diverse among technology sectors with the largest groups being E-commerce & Marketplace at 18.7% followed by FinTech at 13.7% and SaaS or Software as a Service and Enterprise Tech at 12.2%.

The sample shows a very strong balance in gender with 53.9% identifying as Female and 42.3% as Male alongside 2.6% identifying as LGBTQ+. The sample is characterised by a strong representation from younger generations specifically Gen Y at 59.2% and Gen Z at 33.5% which together constitute 92.7% of all participants.

In terms of qualifications, the sample is highly educated. The majority hold a Bachelor’s Degree at 66.2% or a Master’s Degree at 28.3%. Professional experience levels align with the startup context as the largest group at 47.5% has 0 to 3 years of experience. Furthermore, the data captures a mix of organisational roles including Staff or Officer at 41.1% and a significant group of Founder or Co-founders at 23.6%. This indicates the insights are gathered from both end-users and strategic decision-makers. The majority comprising 47.8% work in small organisations of 25 or fewer employees which confirms the startup focus.

Regarding contextual behaviour as shown in Table 4.3 the data reveals a highly engaged and mature user base. A vast majority of respondents comprising 65.6% use Generative AI daily. ChatGPT is nearly ubiquitous at 98.0% with Gemini also showing strong adoption at 81.9%. The sample is almost evenly divided between those using a paid Premium or Pro plan at 46.6% and those on a Free plan at 35.0%. This suggests a high perceived value and willingness to pay for these tools within the Thai startup sector.

4.2.2 Descriptive Statistics of Model Constructs

This section presents the descriptive statistics for all indicators utilised to measure the nine constructs within the research model. The mean, standard deviation or SD, and the corresponding interpretation level for each item are presented in Table 4.4.

Table 4.4

Descriptive Statistics of Model Indicators

Construct	Indicator	Question item	Mean	SD	Interpretation Level
Performance Expectancy	PE1	I believe generative AI provides me with useful information and services.	4.55	0.56	Strongly Agree
	PE2	Using generative AI helps me boost my productivity on tasks (e.g., by saving time or improving the quality of my work).	4.59	0.58	Strongly Agree
	PE3	I think generative AI assists me in solving complex problems.	4.06	0.90	Agree
	PE4	Generative AI helps me develop new ideas.	4.29	0.82	Strongly Agree
Effort Expectancy	EE1	I find generative AI to be simple and easy to use.	4.34	0.75	Strongly Agree
	EE2	The features of generative AI are easy for me to operate and control.	4.21	0.74	Strongly Agree
	EE3	It would not be difficult for me to become highly skilled at using generative AI.	4.38	0.72	Strongly Agree
	EE4	I can adapt how I use Generative AI to suit different types of tasks.	4.32	0.72	Strongly Agree

Table 4.4

Descriptive Statistics of Model Indicators (Cont.)

Construct	Indicator	Question item	Mean	SD	Interpretation Level
Social Influence	SI1	My supervisor or colleagues encourage me to use generative AI systems.	4.57	0.71	Strongly Agree
	SI2	My colleagues generally have a positive opinion about using generative AI.	4.45	0.66	Strongly Agree
	SI3	My organisation has a policy or guidelines that encourage employees to use Generative AI.	4.43	0.83	Strongly Agree
Facilitating Conditions (FC)	FC1	My company provides the necessary resources and technical infrastructure (e.g., computers, budget, software) for using Generative AI.	4.23	1.00	Strongly Agree
	FC2	There is sufficient support from AI experts in my organisation for using generative AI.	3.73	1.17	Agree
	FC3	My company offers adequate training for the use of generative AI.	3.31	1.33	Neutral

Table 4.4

Descriptive Statistics of Model Indicators (Cont.)

Construct	Indicator	Question item	Mean	SD	Interpretation Level
Facilitating Conditions (FC)	FC4	My company has appropriate measures in place to ensure data security for the use of Generative AI.	3.67	1.20	Agree
Hedonic Motivation (HM)	HM1	I find using Generative AI to be enjoyable and fun.	4.35	0.77	Strongly Agree
	HM2	Generative AI helps me satisfy my curiosity.	4.53	0.65	Strongly Agree
	HM3	Generative AI makes me feel excited to constantly learn new things.	4.42	0.82	Strongly Agree
Trust in AI (TAI)	TAI1	I trust that generative AI is designed to help users, not for the personal gain of the developer.	3.75	0.90	Agree
	TAI2	I believe generative AI is honest and does not misuse information or its advantages over users.	3.13	1.12	Neutral
	TAI3	Generative AI seems to be trustworthy.	3.10	0.99	Neutral

Table 4.4

Descriptive Statistics of Model Indicators (Cont.)

Construct	Indicator	Question item	Mean	SD	Interpretation Level
Trust in AI (TAI)	TAI4	I have some understanding of how Generative AI reasons to produce its results.	3.85	0.90	Agree
	TAI5	I believe that Generative AI will not disclose my information without permission.	2.92	1.22	Neutral
AI Anxiety (AIA)	AIA1	I am worried that generative AI may replace human jobs.	3.28	1.18	Neutral
	AIA2	I fear that using generative AI too much will make me dependent on it and cause me to lose some of my critical thinking skills.	3.60	1.23	Agree
	AIA3	I am concerned that generative AI might get out of control and not function properly.	3.54	1.02	Agree
	AIA4	I feel unconfident when I have to rely on results generated by Generative AI without verification.	3.82	1.08	Agree

Table 4.4

Descriptive Statistics of Model Indicators (Cont.)

Construct	Indicator	Question item	Mean	SD	Interpretation Level
Behavioural Intention (BI)	BI1	I feel unconfident when I have to rely on results generated by Generative AI without verification.	4.63	0.62	Strongly Agree
	BI2	I plan to use generative AI to improve my work performance.	4.59	0.62	Strongly Agree
	BI3	I intend to continue using generative AI in the future.	4.71	0.50	Strongly Agree
	BI4	I intend to recommend that my colleagues use Generative AI.	4.54	0.68	Strongly Agree
Use Behaviour (UB)	UB1	I personally use generative AI.	4.59	0.69	Strongly Agree
	UB2	I use generative AI to explore new ways of working.	4.46	0.75	Strongly Agree
	UB3	I use generative AI applications on various devices that I own.	4.57	0.66	Strongly Agree
	UB4	I use Generative AI to assist in strategic decision-making or work planning.	4.24	0.91	Strongly Agree

Table 4.4

Descriptive Statistics of Model Indicators (Cont.)

Construct	Indicator	Question item	Mean	SD	Interpretation Level
Use Behaviour (UB)	UB5	I apply the output from Generative AI in work that has an organisational impact.	4.39	0.74	Strongly Agree

As shown in Table 4.4 the descriptive statistics reveal an exceptionally positive user base. A striking finding is that all indicators for Effort Expectancy (EE), Social Influence (SI), Hedonic Motivation (HM), Behavioural Intention (BI), and Use Behaviour (UB) scored unanimously in the Strongly Agree range. This indicates an overwhelming consensus where users find the technology extremely easy to use (EE), feel strong social support (SI), enjoy using it (HM), and are already using it extensively for both personal and strategic tasks (UB) with a clear intention to continue (BI).

Performance Expectancy (PE) was also rated very highly with three of its four indicators (PE1, PE2, PE4) scoring Strongly Agree. Only PE3 "I think generative AI assists me in solving complex problems" scored slightly lower though still positively in the Agree range (Mean = 4.06).

In sharp contrast, constructs related to organisational support and psychological perceptions were much more nuanced.

Facilitating Conditions (FC) revealed a clear gap in organisational support. While respondents Strongly Agree that they have technical resources (FC1, Mean=4.23), they were only Agree on expert support (FC2) and data security (FC4). The item for organisational training (FC3, Mean=3.31) scored in the Neutral range.

AI Anxiety (AIA) also showed specific and practical concerns. Interestingly, anxiety about job replacement (AIA1, Mean=3.28) was Neutral. The actual anxieties reported by users scored in the Agree range including the fear of losing critical skills (AIA2), concerns about system malfunctions (AIA3), and feeling unconfident in unverified results (AIA4).

Finally, Trust in AI (TAI) received the weakest scores overall. While TAI1 related to benevolence and TAI4 related to understanding were rated Agree, respondents remained Neutral on core trust aspects like honesty (TAI2, Mean=3.13), general trustworthiness (TAI3, Mean=3.10), and data privacy (TAI5, Mean=2.92). This suggests a significant gap between the high usage of the technology and the low trust placed in it.

4.2.3 Descriptive Analysis by Generational Cohort

To provide a deeper profile of the sample, a one-way Analysis of Variance or ANOVA was conducted using JASP (Version 0.95.4) to compare the mean scores of each construct across the different generational cohorts. Due to the very small sample size (n =5) the Baby Boomer cohort was excluded from this specific statistical comparison to ensure the validity of the ANOVA results.

Table 4.5

Descriptive Statistics and ANOVA by Generational Cohort

Construct	Generation	n	Mean	SD	p-Value
Performance Expectancy (PE)	Gen Z (18-28)	115	0.083	1.022	0.352
	Gen Y (29-44)	203	-0.027	1.002	
	Gen X (45-60)	20	-0.241	0.910	
Effort Expectancy (EE)	Gen Z (18-28)	115	0.170	0.892	< 0.001
	Gen Y (29-44)	203	0.000	0.990	
	Gen X (45-60)	20	-0.789	1.334	
Social Influence (SI)	Gen Z (18-28)	115	0.055	0.979	0.505
	Gen Y (29-44)	203	0.014	0.969	
	Gen X (45-60)	20	-0.225	1.187	
Facilitating Conditions (FC)	Gen Z (18-28)	115	0.059	1.081	0.256
	Gen Y (29-44)	203	0.011	0.909	
	Gen X (45-60)	20	-0.343	1.419	

Table 4.5

Descriptive Statistics and ANOVA by Generational Cohort (Cont.)

Construct	Generation	n	Mean	SD	p-Value
Hedonic Motivation (HM)	Gen Z (18-28)	115	0.037	1.100	0.658
	Gen Y (29-44)	203	-0.044	0.983	
	Gen X (45-60)	20	0.125	0.607	
Trust in AI (TAI)	Gen Z (18-28)	115	0.053	0.938	0.503
	Gen Y (29-44)	203	-0.024	1.047	
	Gen X (45-60)	20	-0.222	0.951	
AI Anxiety (AIA)	Gen Z (18-28)	115	0.028	1.161	0.820
	Gen Y (29-44)	203	-0.010	0.906	
	Gen X (45-60)	20	0.129	0.919	
Behavioural Intention (BI)	Gen Z (18-28)	115	0.118	1.010	0.192
	Gen Y (29-44)	203	-0.057	0.998	
	Gen X (45-60)	20	-0.235	1.025	
Use Behaviour (UB)	Gen Z (18-28)	115	0.128	0.995	0.216
	Gen Y (29-44)	203	-0.065	1.024	
	Gen X (45-60)	20	-0.136	0.832	

Note. $p<0.05$

The full comparison of mean scores for all constructs is presented in Table 4.5. The ANOVA results indicated that whilst most constructs were perceived similarly across the cohorts including Performance Expectancy (p=0.352), Social Influence (p=0.505), Trust in AI (p=0.503), and AI Anxiety (p=0.820), a notable statistical difference was found for the Effort Expectancy (EE) construct (p<0.001).

To investigate this specific difference, a Tukey HSD post-hoc analysis was performed. The results of this test provide clear details on the variation and are presented in Table 4.6 below.

Table 4.6

Post-Hoc Test (Tukey HSD) Results for Effort Expectancy (EE) by Generational Cohort

Comparison	Mean Different	SE	df	t	ptukey
Gen Z – Gen Y	0.170	0.114	335	1.484	0.300
Gen Z – Gen X	0.959	0.238	335	4.038	< 0.001
Gen Y – Gen X	0.789	0.230	335	3.435	0.002

Note. $p<0.05$

There was no statistically significant difference between the mean scores of Generation Z and Generation Y ($p=0.300$). This suggests that these two younger cohorts share a similar and positive perception regarding the ease of use of Generative AI. In contrast, a highly significant difference was found between Generation Z and Generation X ($p<0.001$). A significant difference was also present between Generation Y and Generation X ($p=0.002$). These findings confirm that Generation X perceives significantly higher effort is required compared to the younger generations ($p<0.05$).

4.3 Measurement Model Assessment

This section presents the results of the measurement model or Outer Model assessment which constitutes the first phase of the two-step analytical approach recommended for PLS-SEM. The primary purpose involves confirming the reliability and validity of the constructs prior to testing the structural model (Hair, Hult, Ringle, & Sarstedt, 2022).

During the initial analysis, the AI Anxiety (AIA) construct required significant methodological refinement. The preliminary assessment which included all four original indicators ranging from AIA1 to AIA4 failed to meet the established criteria for reliability and validity. Its Composite Reliability (CR) was 0.621 which falls below the required 0.70 threshold while its Average Variance Extracted (AVE) was 0.356 which is well below the required 0.50 benchmark.

A diagnostic check of the outer loadings revealed the source of this discrepancy. The indicator AIA1 "I am worried that generative AI may replace human jobs" yielded an extremely low loading of 0.034. This result indicated that AIA1 did not measure the same underlying concept as the other items within the construct. Based on this clear evidence the researcher removed the AIA1 indicator.

Following the removal of AIA1, the model was re-assessed using the three remaining indicators comprising AIA2, AIA3, and AIA4. This revised construct demonstrated improved metrics which met the minimum thresholds with a CR of 0.801 and an AVE of 0.588.

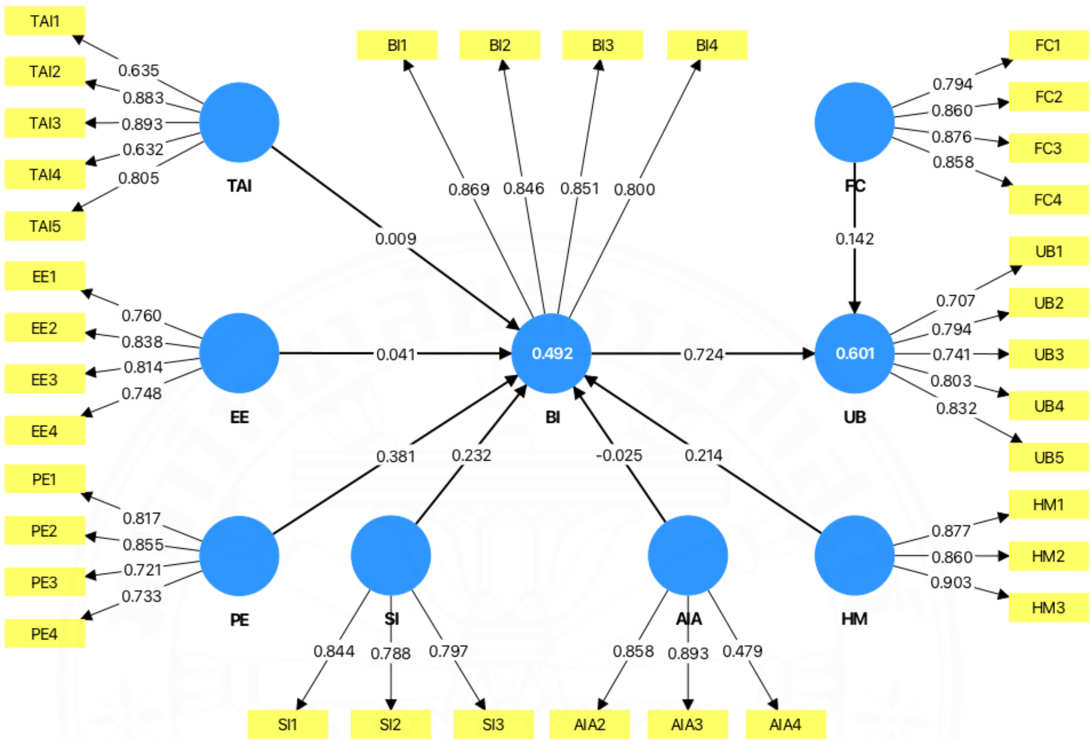
This refinement process represents a common and necessary step in model validation and remains consistent with practices in similar literature (Hair, Hult, Ringle, & Sarstedt, 2022). For example, studies conducted by German researchers (Mirbabaie et al., 2022) also removed indicators with low loadings to ensure construct validity in their study of AI identity threat. Similarly, research conducted by South Korean scholars (Kim et al., 2024) removed items to enhance model validity in their investigation of Generative AI adoption.

This refined model was analysed using the SmartPLS 4 (version 4.1.1.6) software package. Figure 4.1 below illustrates the final validated measurement model and displays the outer loadings of all remaining indicators following the removal of AIA1.

The subsequent sections present the detailed statistical validation of this final model.

Figure 4.1

PLS-SEM Result with path coefficients



4.3.1 Indicator Reliability

Indicator reliability serves as the initial test to assess the quality of the measurement items. It analyses the extent of variance an indicator shares with its associated construct. The primary rule of thumb dictates that the Outer Loading for each indicator should exceed 0.70 (Hair, Hult, Ringle, & Sarstedt, 2022).

However, a critical justification was established for indicators with loadings falling within the acceptable range between 0.40 and 0.70. According to established guidelines (Hair, Hult, Ringle, & Sarstedt, 2022) indicators within this range should be retained rather than automatically deleted provided that the construct's overall composite reliability (CR) and average variance extracted (AVE) already meet the required minimum thresholds where CR>0.70 and AVE>0.50. This approach is recommended to preserve the content validity of the construct (Hair, Hult, Ringle, & Sarstedt, 2022). The results for the outer loadings along with the reliability and validity scores for each construct are presented in Table 4.7.

Table 4.7

Construct Reliability and Convergent Validity

Construct	Indicator	Outer Loading	Cronbach's Alpha (α)	Composite Reliability (CR)	Average variance extracted (AVE)
Performance Expectancy (PE)	PE1	0.817	0.792	0.864	0.614
	PE2	0.855			
	PE3	0.721			
	PE4	0.733			
Effort Expectancy (EE)	EE1	0.760	0.801	0.870	0.626
	EE2	0.838			
	EE3	0.814			
	EE4	0.748			
Social Influence (SI)	SI1	0.844	0.737	0.851	0.656
	SI2	0.788			
	SI3	0.797			
Facilitating Conditions (FC)	FC1	0.794	0.870	0.911	0.718
	FC2	0.860			
	FC3	0.876			
	FC4	0.858			
Hedonic Motivation (HM)	HM1	0.877	0.854	0.911	0.774
	HM2	0.860			
	HM3	0.903			
Trust in AI (TAI)	TAI1	0.635	0.832	0.882	0.605
	TAI2	0.883			
	TAI3	0.893			
	TAI4	0.632			
	TAI5	0.805			

Table 4.7

Construct Reliability and Convergent Validity (Cont.)

Construct	Indicator	Outer Loading	Cronbach's Alpha (α)	Composite Reliability (CR)	Average variance extracted (AVE)
AI Anxiety (AIA)	AIA2	0.860	0.703	0.801	0.588
	AIA3	0.893			
	AIA4	0.479			
Behavioural Intention (BI)	BI1	0.869	0.863	0.907	0.709
	BI2	0.846			
	BI3	0.851			
	BI4	0.800			
Use Behaviour (UB)	UB1	0.707	0.834	0.883	0.603
	UB2	0.794			
	UB3	0.741			
	UB4	0.803			
	UB5	0.832			

As shown in Table 4.7 nearly all indicators possess outer loadings significantly higher than the 0.70 standard. However, three indicators within the Trust in AI (TAI) and AI Anxiety constructs were found to be below this 0.70 level.

1) TAI1 which states "I trust that generative AI is designed to help users, not for the personal gain of the developer" had a loading of 0.635.

2) TAI4 which states "I have some understanding of how Generative AI reasons to produce its results" had a loading of 0.632.

3) AIA4 which states "I feel unconfident when I have to rely on results generated by Generative AI without verification" had a loading of 0.479.

Following methodological guidelines (Hair, Hult, Ringle, Sarstedt, et al., 2022) indicators with loadings in this range between 0.40 and 0.70 are not subject to automatic removal provided the overall reliability and validity of the construct are strong.

The CR and AVE values for the respective constructs were confirmed to validate this decision.

AI Anxiety (AIA) The construct including AIA2, AIA3, and AIA4 demonstrated acceptable reliability and validity with CR=0.801 and AVE=0.588.

Trust in AI (TAI) This construct including all TAI items also showed strong reliability and validity with CR=0.882 and AVE=0.605.

Since both constructs clearly met the required statistical thresholds, the decision was made to retain all three indicators comprising TAI1, TAI4, and AIA4. This action ensures a consistent methodological rule was applied across the entire model (Hair, Hult, Ringle, Sarstedt, et al., 2022).

4.3.2 Internal Consistency Reliability

The internal consistency reliability was assessed to ensure that all items measuring the same construct are consistent. This assessment utilised two metrics comprising Cronbach's Alpha (α) and Composite Reliability (CR) where the accepted level for both exceeds 0.70 (Hair, Hult, Ringle, & Sarstedt, 2022).

The researcher first examined the Cronbach's Alpha (α) presented in Table 4.7. All constructs achieved scores exceeding the 0.70 threshold which indicates the absence of significant reliability problems.

The researcher subsequently assessed Composite Reliability (CR) which is frequently considered a more robust and accurate measure of reliability within the PLS-SEM context. The model performed excellently in this regard. As displayed in Table 4.7 all nine constructs achieved CR scores significantly higher than the 0.70 minimum including PE=0.864 and HM=0.911 as well as FC=0.911.

The internal consistency of the measurement model is fully supported given that the more robust CR measure was strong for all constructs and the Alpha scores were also acceptable.

4.3.3 Convergent Validity

Finally, convergent validity was assessed using the Average Variance Extracted (AVE). This test confirms that the items for a construct are closely related. The AVE value must be above 0.50, which means the construct explains at least half of the variance of its items (Fornell & Larcker, 1981).

The results in Table 4.7 show that all nine constructs passed this test comfortably. The AVE values ranged from a low of 0.588 (AI Anxiety) to a high of 0.774 (Hedonic Motivation), with all scores clearly above the 0.50 minimum. This confirms that all constructs have good convergent validity.

4.3.4 Discriminant Validity

The final step in assessing the measurement model involves checking for discriminant validity. This test ensures that each construct in the model is distinct and does not exhibit excessive overlap with other constructs (Hair, Hult, Ringle, & Sarstedt, 2022).

The Heterotrait-Monotrait (HTMT) ratio was selected for this research. This metric represents a modern and more accurate criterion for assessment (Hair, Hult, Ringle, & Sarstedt, 2022; Henseler et al., 2015). Two thresholds were defined for this test (Henseler et al., 2015).

The first threshold requires the value to fall below 0.85 for conceptually distinct constructs. A second and more liberal threshold below 0.90 is also acceptable for constructs that are conceptually very similar (Henseler et al., 2015). The results of the HTMT analysis are presented in Table 4.8.

Table 4.8

Discriminant Validity (Heterotrait-Monotrait Ratio - HTMT)

	AIA	BI	EE	FC	HM	PE	SI	TAI	UB
AIA									
BI	0.126								
EE	0.118	0.481							
FC	0.141	0.314	0.443						
HM	0.144	0.602	0.527	0.347					
PE	0.205	0.741	0.673	0.359	0.592				
SI	0.166	0.652	0.342	0.446	0.541	0.626			
TAI	0.090	0.290	0.435	0.555	0.376	0.361	0.294		
UB	0.122	0.898	0.553	0.390	0.679	0.775	0.583	0.360	

However, one value was found to be higher involving the pair between Behavioural Intention (BI) and Use Behaviour (UB) which yielded 0.898. This value is acceptable as BI and UB are conceptually very similar constructs where intention serves as the direct predictor of behaviour (Venkatesh et al., 2003). Therefore this 0.898 value remains below the 0.90 liberal threshold defined for such cases (Hair, Hult, Ringle, & Sarstedt, 2022; Henseler et al., 2015).

It is concluded that the research model possesses discriminant validity as all HTMT values fall within the accepted thresholds.

4.4 Structural Model Assessment

Now that the measurement model is confirmed as reliable and valid this section assesses the structural model or inner model. This constitutes the second step of the two-stage analytical approach (Hair, Hult, Ringle, & Sarstedt, 2022). The researcher evaluated the model's quality by checking two key metrics as described in Chapter 3. First collinearity was assessed using VIF and second the model's explanatory power was assessed using the R-square (R^2).

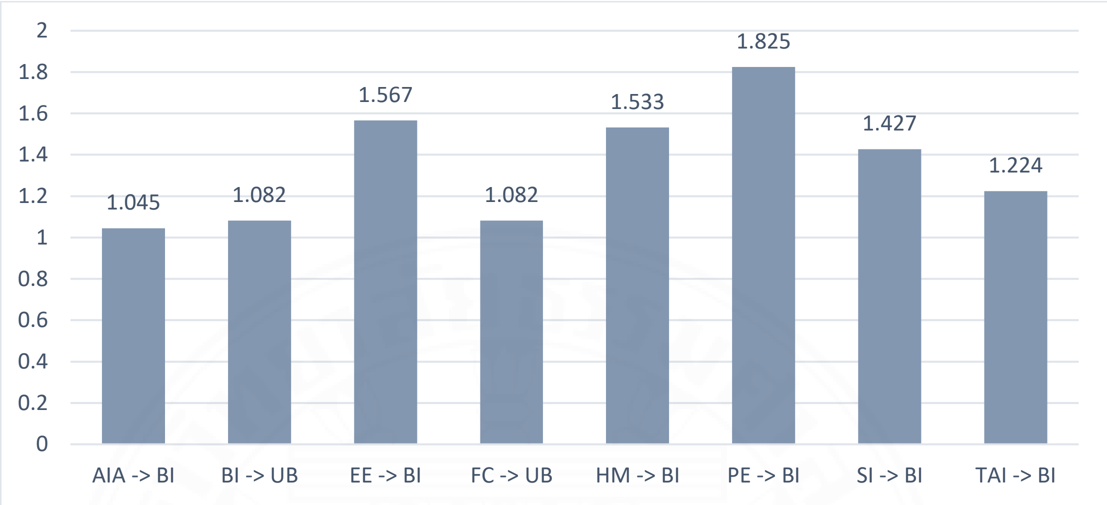
4.4.1 Collinearity Assessment

The researcher first assessed collinearity to ensure that the predictor constructs such as PE and EE do not exhibit excessive correlation with one another. This step is crucial because high correlation can destabilise the path coefficient results (Hair, Hult, Ringle, & Sarstedt, 2022). The Variance Inflation Factor or VIF was utilised for this test.

VIF values must remain below 5.0 in accordance with established guidelines (Hair, Hult, Ringle, & Sarstedt, 2022). The analysis of the inner model VIF values revealed no collinearity issues. The highest VIF value within the model was observed for the Performance Expectancy (PE) construct at 1.825. The researcher concludes that collinearity does not pose a problem for this structural model as all VIF values fall significantly below the 5.0 threshold.

Figure 4.2

Collinearity Statistics (VIF) - Inner Model



4.4.2 Explanatory Power

The second part of the assessment involved checking the model's explanatory power. This is achieved using the R-square (R^2) value which measures the proportion of variance in a dependent construct explained by its predictors (Hair, Hult, Ringle, & Sarstedt, 2022). The results of the analysis are detailed below.

For Use Behaviour (UB), the R^2 value was 0.601. For Behavioural Intention (BI), the R^2 value was 0.492.

The R^2 value for BI at 0.492 aligns closely with the 0.50 benchmark indicating a moderate level of explanatory power according to established criteria (Hair, Hult, Ringle, & Sarstedt, 2022). R^2 value for UB at 0.601 is also considered moderate as it falls above 0.50 but below 0.75. These results confirm that the proposed model is effective and possesses sufficient explanatory power for the key dependent constructs(Hair, Hult, Ringle, & Sarstedt, 2022).

Table 4.9

Results of Explanatory Power (R^2)

Endogenous Construct	R-Square (R^2)	R-Square Adjusted	Explanatory Power
Behavioural Intention (BI)	0.492	0.483	Moderate
Use Behaviour (UB)	0.601	0.598	Moderate

4.5 Hypothesis Testing Results

This section presents the results of the main hypothesis tests covering H1 to H8. The researcher analysed the structural model to test the conceptual framework.

As described in Chapter 3 the researcher used a bootstrapping procedure with 5,000 resamples to determine the statistical significance of the paths. The decision rule for supporting a hypothesis was a p-value below 0.05 (Hair, Hult, Ringle, & Sarstedt, 2022). For hypothesis H6 which predicted a negative effect the path coefficient (β) also needed to be negative for the hypothesis to be supported. The results of all hypothesis tests are summarised in Table 4.10.

Table 4.10

Summary of Hypothesis Testing Results

Hypothesis	Path	Path Coefficient (β)	P-Value	Decision
H1	PE -> BI	0.381	0.000	Supported
H2	EE -> BI	0.041	0.432	Not Supported
H3	SI -> BI	0.232	0.000	Supported
H4	HM -> BI	0.214	0.001	Supported
H5	TAI -> BI	0.009	0.818	Not Supported
H6	AIA -> BI	-0.025	0.557	Not Supported

Table 4.10

Summary of Hypothesis Testing Results (Cont.)

Hypothesis	Path	Path Coefficient (β)	P-Value	Decision
H7	FC -> UB	0.142	0.000	Supported
H8	BI -> UB	0.724	0.000	Supported

Note. $p < 0.05$

The main results of the structural model analysis are also shown visually in Figure 4.1. This figure includes the path coefficients (β) for each hypothesis and the R-square (R^2) values for the dependent constructs.

4.5.1 Factors Influencing Behavioural Intention (BI)

The analysis for hypotheses H1 to H6 which all predicted Behavioural Intention (BI) showed mixed results.

Three hypotheses were supported. Performance Expectancy (H1) was found to be the strongest positive predictor of BI (β =0.381, p=0.000). Social Influence (H3) also showed a significant positive effect (β =0.232, p=0.000) along with Hedonic Motivation (H4) (β =0.214, p=0.001).

The other three hypotheses were not supported. Effort Expectancy (H2) was found to be insignificant (β =0.041, p=0.432). Trust in AI (H5) was also not significant (β =0.009, p=0.818). Finally, AI Anxiety (H6) did not have a significant effect on BI (β =−0.025, p=0.557). Although the direction was negative as predicted the p-value was not significant.

4.5.2 Factors Influencing Use Behaviour (UB)

The results for the final two hypotheses which predicted Use Behaviour (UB) were both supported.

Facilitating Conditions (H7) was found to have a significant positive effect on UB (β =0.142, p=0.000). Behavioural Intention (H8) was found to be the strongest predictor in the entire model with a very large positive effect on UB (β =0.724, p=0.000).

4.6 Discussion of Findings

This section provides a discussion of the hypothesis testing results from Section 4.5. The objective is to interpret these findings and compare them with the literature reviewed in Chapter 2.

The overall model showed moderate explanatory power. The framework successfully explained 60.1% of the variance in Use Behaviour (UB) (R^2=0.601) and 49.2% of the variance in Behavioural Intention (BI) (R^2=0.492). These results show that the selected constructs are relevant for explaining Generative AI acceptance.

The discussion is structured in two parts comprising the supported hypotheses which show the main drivers and the unsupported hypotheses which reveal some important insights for the Thai startup context.

4.6.1 The Key Drivers of Acceptance (Supported Hypotheses)

The analysis confirmed five significant relationships involving H1, H3, H4, H7, and H8. These identify the primary factors driving the intention and actual use of Generative AI.

4.6.1.1 Utilitarian and Social Drivers of Intention

The most important finding is that Performance Expectancy (PE) was the strongest positive predictor of Behavioural Intention (H1 with β =0.381). This result strongly matches the original UTAUT model (Venkatesh et al., 2003) and other acceptance studies (Gansser & Reich, 2021; Papathomas et al., 2025; Salazar & Rivera, 2025; Sammet et al., 2024; Yakubu et al., 2025; Yunita, 2025). It suggests that Thai startup personnel are highly pragmatic. Their intention to use Generative AI is mainly driven by the belief that it will improve their performance and productivity. Besides this Social Influence (SI) (H3 with β =0.232) and Hedonic Motivation (HM) (H4 with β =0.214) were also significant positive drivers.

The significance of SI is consistent with research in other Asian contexts like South Korea (Kim et al., 2024). It suggests that the encouragement of colleagues and supervisors, as seen in the high mean scores in Table 4.4, is an important factor in this work culture.

The significance of Hedonic Motivation (HM) supports the idea that in an innovative culture such as among entrepreneurs adopting Generative AI (Gupta & Yang, 2024) the elements of fun, pleasure, and curiosity of using a creative tool are real motivators (Ali et al., 2024; Kang et al., 2025; Paudel & Acharya, 2025).

4.6.1.2 The Path from Intention to Use

As expected by theory Behavioural Intention (BI) was the most powerful predictor of actual Use Behaviour (UB) (H8 with β =0.724). This confirms the central logic of the UTAUT framework.

Also Facilitating Conditions (FC) was a significant predictor of UB (H7 with β =0.142). This shows that implementation requires the availability of necessary resources even with a strong intention. However, it is important to note from the descriptive data in Table 4.3 that organisational training denoted as FC3 was rated Neutral. This suggests that while FC is a driver the training part of it is still a gap in Thai startups.

4.6.2 Discussion of Unsupported Hypotheses

Some of the most interesting findings come from the three hypotheses that were not supported comprising H2, H5, and H6. These results help to explain important factors about this specific user group.

4.6.2.1 The Non-Significance of Effort Expectancy (H2)

The hypothesis that Effort Expectancy (EE) would positively influence BI was not supported (β =0.041, p=0.432).

The Unified Theory of Acceptance and Use of Technology (UTAUT) posits that the influence of Effort Expectancy is moderated by experience becoming non-significant after early stages of use (Venkatesh et al., 2003). For tech-savvy users who have widely adopted Generative AI ease of use is taken for granted functioning as an expected baseline or hygiene factor rather than a compelling motivator (Kang et al., 2025).

4.6.2.2 The Role of Trust and Anxiety (H5 and H6)

The other unsupported hypotheses were Trust in AI (TAI) denoted as H5 with β =0.009 and p=0.818 and AI Anxiety (AIA) denoted as H6 with β =−0.025 and p=0.557. It suggests that TAI and AIA are not significant factors for predicting intention in this context. A review of the descriptive data provides further clarity.

1) Trust: As shown in Table 4.3 TAI received the lowest mean scores in the model. Users were Neutral on key items like honesty (TAI2) and trustworthiness (TAI3) as well as data privacy (TAI5).

2) Anxiety: The descriptive data for AIA showed users were concerned about losing critical thinking skills (AIA2) and unverified results (AIA4).

These findings together suggest that personnel in Thai startups are using Generative AI even if they do not fully trust it and even if they have some anxieties about it.

This indicates a highly practical implementation. The strong drivers comprising PE, SI, and HM seem to be more important than the psychological concerns of TAI and AIA. For a startup focused on efficiency the usefulness associated with PE may outweigh the perceived risks. This behaviour also supports the Human-in-the-Loop concept mentioned in the literature (Gupta & Yang, 2024; Sammet et al., 2024; Yunita, 2025). Users must remain in the loop to verify the results themselves because they do not fully trust the output.

A further significant finding arises from the process of refining the AIA construct itself as detailed in Section 4.3. The researcher was required to delete one indicator comprising AIA1 and this action provides a deep insight.

The deletion of AIA1 which states "I am worried that generative AI may replace human jobs" was necessary because its loading was almost zero (0.034). This statistically demonstrates that job replacement anxiety represents a separate concept from functional anxiety. More importantly it suggests this type of socio-economic anxiety constitutes a non-relevant concern for this specific sample of highly skilled Thai startup personnel.

This methodological finding serves as a key insight for Chapter 5. It suggests that future research should not treat AI Anxiety as a single monolithic idea. Instead, Job Replacement Anxiety and Functional Anxiety such as the loss of skills should perhaps be measured as separate constructs to understand their distinct effects on adoption. This aligns with the multidimensional AI Anxiety Scale developed by Wang and Wang (2022), which empirically distinguishes 'job replacement' from 'learning' and 'configuration' anxieties (Wang & Wang, 2022), as well as recent frameworks classifying anxiety into anticipatory and existential dimensions (Frenkenberg & Hochman, 2025).

4.6.3 Answering the Research Questions

This discussion provides answers to the research questions from Chapter 1.

To answer Research Question 1 which asks what are the key factors that influence the behavioural intention and actual use of Generative AI among personnel in startups located in Thailand this study identified four distinct drivers. The analysis revealed that Performance Expectancy and Social Influence as well as Hedonic Motivation are the key factors influencing Behavioural Intention. Furthermore, Facilitating Conditions was identified as the key factor influencing actual Use Behaviour.

To answer Research Question 2 which asks what specific role does psychological factors such as Trust, Anxiety, and Hedonic Motivation play in shaping the acceptance of Generative AI within this startup context this study revealed a complex dynamic. Hedonic Motivation was found to play a significant and positive role in driving intention. In contrast Trust in AI and AI Anxiety played no significant role in predicting intention. This suggests that while personnel in Thai startups find the technology enjoyable and useful they are pragmatic enough to use it despite possessing low trust or underlying anxieties.

CHAPTER 5
CONCLUSIONS AND RECOMMENDATIONS

This chapter presents the summary of the study and the main conclusions drawn from the research findings. Following this the chapter discusses the implications of these findings for both theory and for founders and executives in startup companies.

5.1 Summary of the Study

The primary objective of this research was to investigate the factors that influence the acceptance and use of Generative AI among personnel in Thai startup companies. The study developed and tested a conceptual framework by extending the Unified Theory of Acceptance and Use of Technology or UTAUT model. This extended model included the four core constructs of UTAUT comprising Performance Expectancy and Effort Expectancy as well as Social Influence and Facilitating Conditions but also incorporated three psychological constructs including Hedonic Motivation (HM) and Trust in AI (TAI) as well as AI Anxiety (AIA).

A quantitative method was employed utilising a comprehensive multi-channel data collection strategy to ensure a representative sample. The questionnaire was distributed not only through online startup communities such as the True Digital Park private group but also via onsite data gathering at key industry events including the Bitkub Summit 2025 and the AI Thailand Conference 2025 and through direct professional outreach to specific companies. The final sample consisted of 343 valid responses from employees and founders within the Thai startup ecosystem. The data was analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) to test the eight hypotheses.

The results showed that the model had moderate explanatory power explaining 49.2% of the variance in Behavioural Intention (BI) and 60.1% of the variance in Use Behaviour (UB). The analysis confirmed five hypotheses. Performance Expectancy (H1) and Social Influence (H3) as well as Hedonic Motivation (H4) were all found to be significant positive drivers of Behavioural Intention. Facilitating Conditions (H7) and Behavioural Intention (H8) were both significant predictors of actual Use Behaviour.

However, three hypotheses were not supported. Effort Expectancy (H2) and Trust in AI (H5) as well as AI Anxiety (H6) were all found to have an insignificant effect on Behavioural Intention in this specific context.

5.2 Conclusions

Based on the findings summarised above this study draws two main conclusions which directly answer the research questions.

5.2.1 Conclusion 1: Acceptance is driven by practical utility and social norms as well as enjoyment

The first research question asked for the key factors influencing intention and use. The study concludes that the decision to accept and use Generative AI in Thai startups is highly pragmatic. The strongest driver is Performance Expectancy or PE meaning personnel use the technology because they believe it is useful and helps them improve their job performance.

This utilitarian driver is supported by two other factors comprising Social Influence and Hedonic Motivation. The positive opinion of colleagues and supervisors serves as a significant motivator. Furthermore, users are motivated by the enjoyment and curiosity associated with HM regarding the use of these creative tools rather than just for work tasks. Finally actual use is dependent on having the right organisational resources represented by Facilitating Conditions.

5.2.2 Conclusion 2: Pragmatic adoption can exist without high trust or low anxiety

The second research question asked about the role of psychological factors. This study concludes that their role is complex. While one psychological factor comprising Hedonic Motivation was a driver the other two involving Trust and Anxiety were not significant.

The descriptive data showed that users have low trust in AI especially regarding data privacy and honesty as seen in indicators TAI2 and TAI3 as well as TAI5. They also have functional anxieties about losing skills as indicated by AIA2 or unverified results as indicated by AIA4. However, these psychological concerns were not strong enough to stop them from forming an intention to use Generative AI.

This suggests that Thai startup personnel are highly pragmatic. They are using Generative AI even if they do not trust it because the benefits associated with PE are so high. This supports the Human-in-the-Loop concept where users know they must stay in the process to verify results because they do not fully trust the AI.

5.3 Implications of the Study

The conclusions drawn from this research possess several important implications for both academic theory and practical management within the startup sector.

5.3.1 Theoretical Implications

This research provides three main contributions to technology acceptance theory.

5.3.1.1 Contextualises the UTAUT Model

The study confirms that Performance Expectancy serves as a key driver consistent with UTAUT predictions. However, the non-significance of Effort Expectancy (H2) also supports the original theory's proposition that EE becomes less important for experienced and tech-savvy users. Ease of use represents a hygiene factor rather than a motivator for this sample.

5.3.1.2 Identifies "Pragmatic Adoption"

The findings challenge the assumption that high trust is always necessary for technology acceptance. This study proposes a model of pragmatic adoption where users proceed despite low trust and high anxiety provided that the perceived utility (PE) and social drivers (SI) remain sufficiently strong.

5.3.1.3 Refines the AI Anxiety Construct

The methodological finding from Chapter 4 constitutes a key theoretical implication. The item for job replacement anxiety denoted as AIA1 was removed because it did not measure the same concept as the other anxiety items. This strongly suggests that AI Anxiety represents a multidimensional rather than a monolithic construct. Future research must measure Socio-Economic Anxiety such as job loss as a separate construct from Functional Anxiety which includes loss of skills or erroneous results.

5.3.2 Managerial Implications

The findings provide practical guidelines for startup leaders in Thailand.

5.3.2.1 Realign Strategy and Training towards Practical Utility

This study found that Performance Expectancy or utility constitutes the strongest driver of adoption whereas Effort Expectancy or ease of use is not significant. Additionally, employees rated current training support as merely Neutral.

To address this management should shift their focus from how to use the tool to why to use it. Since basic functional training is unnecessary for this tech-savvy group resources should be redirected to Strategic Application. Leaders should organise workshops that demonstrate specific use cases where AI solves complex problems or increases productivity. By highlighting tangible benefits rather than just technical features the organisation can effectively motivate employees and fill the existing training gap with high-value content.

5.3.2.2 Foster a Learning Organisation via AI Champions

Since Social Influence drives adoption creating a supportive environment is essential. To sustain learning beyond the strategic workshops mentioned above leaders should cultivate a Learning Organisation spearheaded by designated AI Champions.

These internal influencers act as daily mentors who facilitate dynamic peer-to-peer learning. Instead of waiting for the next official training session Champions can share successful prompts and practical tips in real-time. This strategy creates a culture of continuous knowledge exchange establishing Generative AI usage as a collective professional norm.

5.3.2.3 Establish a Clear Human-in-the-Loop Policy

Although employees use Generative AI frequently the results show they still harbour anxiety about mistakes and do not fully trust the technology. To address this management should implement a clear Human-in-the-Loop policy.

This policy should define AI as a supportive helper and require that a human expert must always verify its output. This verification process provides psychological reassurance allowing employees to utilise the technology for efficiency without the fear of being held responsible for unchecked errors.

5.4 Limitations and Recommendations for Future Research

Finally, this study must be viewed in light of its limitations which in turn provide clear recommendations for future research.

5.4.1 Limitations of the Study

Although this research provides valuable insights certain limitations should be noted to understand the scope of the findings.

5.4.1.1 Sample Characteristics

The participants in this study were predominantly young comprising 92.7% Generation Y and Z and highly educated. This demographic profile is typical for the startup sector but may differ from the general workforce. Therefore, the findings particularly the non-significance of Effort Expectancy reflect the views of a tech-savvy group and may not apply to industries with lower digital literacy.

5.4.1.2 Geographical Scope

The sample was primarily based in the Bangkok Metropolitan Region accounting for 75.2%. While this distribution aligns with the fundamental characteristic of the Thai startup ecosystem where the industry is mainly located in the capital city it implies that the findings are specific to this urban context. Consequently, the results may not fully capture the perspectives or unique challenges faced by the smaller number of startups operating in regional areas.

5.4.1.3 Cross-Sectional Data

This study employed a cross-sectional design collecting data at a single point in time. Consequently, it captures a snapshot of user perceptions. It does not account for how attitudes such as trust or anxiety might evolve as users gain more experience with the technology over time.

5.4.2 Recommendations for Future Research

Based on the findings of this study, several directions for future research are proposed to expand understanding in this field.

5.4.2.1 Refine the "AI Anxiety" Construct

A key methodological finding of this study was the distinction between different types of anxiety. Future research should explicitly measure "Socio-Economic Anxiety" (e.g., fear of job replacement) and "Functional Anxiety" (e.g., fear of errors) as separate constructs. This would clarify which specific type of fear acts as a barrier to adoption in different contexts.

5.4.2.2 Conduct Comparative Studies

To broaden the applicability of the framework, future research could test this model in different sectors. Comparing these results with traditional industries (such as manufacturing or retail) or with older demographic groups would provide valuable insights into whether "Trust" and "Effort Expectancy" become significant barriers for users with lower technological proficiency.

5.4.2.3 Longitudinal Studies

To address the limitation of cross-sectional data, a longitudinal study is recommended. Tracking users over a period of 6 to 12 months would reveal how pragmatic adoption evolves. For instance, it could determine if "Trust in AI" naturally increases after prolonged use, or if "Functional Anxiety" decreases as users become more skilled.

5.4.2.4 Qualitative Investigation

Since this study found that users adopt AI despite having low trust, a qualitative study using in-depth interviews would be beneficial. This approach could explore the underlying reasons for this "pragmatic adoption" and uncover the specific strategies users employ to manage risks in their daily work.

REFERENCES

Books and Book Articles

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate Data Analysis*. Cengage. https://books.google.co.th/books?id=0R9ZswEACAAJ

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a Silver Bullet. *Journal of Marketing Theory and Practice*, 19(2), 139-152. https://doi.org/10.2753/MTP1069-6679190202

Hair, J., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2022). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM).*

Hair, J., Hult, G. T. M., Ringle, C., Sarstedt, M., Danks, N., Ray, S., & St, C. (2022). *Book Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R*. https://doi.org/10.1007/978-3-030-80519-7

Hair, J., Sarstedt, M., & Ringle, C. (2021). Partial Least Squares Structural Equation Modeling. In (pp. 1-47). https://doi.org/10.1007/978-3-319-05542-8_15-2

Yamane, T. (1967). *Statistics: An introductory analysis* (2nd ed.). Harper & Row.

Articles

Abdalla, S. Z. S. (2025). Understanding ChatGPT adoption for data analytics learning: A UTAUT perspective among social science students in Oman. *Social Sciences & Humanities Open*, 11, 101310. https://doi.org/10.1016/j.ssaho.2025.101310

Alateeg, S., Alhammadi, A., Alayed, S., & Helmi, M. (2024). Factors Influencing on Behavioral Intention to Adopt Artificial Intelligence for Startup Sustainability. *Kurdish Studies*, 12, 2924-2941.

Ali, M. S. M., Wasel, K. Z. A., & Abdelhamid, A. M. M. (2024). Generative AI and Media Content Creation: Investigating the Factors Shaping User Acceptance in the Arab Gulf States. *Journalism and Media*, 5(4), 1624-1645. https://www.mdpi.com/2673-5172/5/4/101

Aung, H. (2025). *Perceived AI Job Threat and Competency: The Role of Education in AI-Induced Job Replacement Anxiety*

Cengiz, S., & Peker, A. (2025). Generative artificial intelligence acceptance and artificial intelligence anxiety among university students: the sequential mediating role of attitudes toward artificial intelligence and literacy. *Current Psychology*, 44(9), 7991-8000. https://doi.org/10.1007/s12144-025-07433-7

Chan, C. K. Y., & Lee, K. K. W. (2023). The AI generation gap: Are Gen Z students more interested in adopting generative AI such as ChatGPT in teaching and learning than their Gen X and millennial generation teachers? *Smart Learning Environments*, 10(1), 60. https://doi.org/10.1186/s40561-023-00269-3

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

Dang, Q., & Li, G. (2025). Unveiling trust in AI: the interplay of antecedents, consequences, and cultural dynamics. *AI & SOCIETY*. https://doi.org/10.1007/s00146-025-02477-6

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

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, 18(1), 39-50. https://doi.org/10.1177/002224378101800104

Frenkenberg, A., & Hochman, G. (2025). It’s Scary to Use It, It’s Scary to Refuse It: The Psychological Dimensions of AI Adoption—Anxiety, Motives, and Dependency. *Systems*, 13(2), 82. https://www.mdpi.com/2079-8954/13/2/82

Gansser, O. A., & Reich, C. S. (2021). A new acceptance model for artificial intelligence with extensions to UTAUT2: An empirical study in three segments of application. *Technology in Society*, 65, 101535. https://doi.org/10.1016/j.techsoc.2021.101535

Gupta, V., & Yang, H. (2024). Study protocol for factors influencing the adoption of ChatGPT technology by startups: Perceptions and attitudes of entrepreneurs. *PLOS ONE*, 19(2), e0298427. https://doi.org/10.1371/journal.pone.0298427

Hatos, A. (2025). Anxiety in the Age of AI: Constructing a Tool to Assess Public Perceptions. *BRAIN. Broad Research in Artificial Intelligence and Neuroscience*, 16, 415. https://doi.org/10.70594/brain/16.S1/32

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

Jiang, W., Li, D., & Liu, C. (2025). Understanding dimensions of trust in AI through quantitative cognition: Implications for human-AI collaboration. *PLOS ONE*, 20(7), e0326558. https://doi.org/10.1371/journal.pone.0326558

Kang, S., Choi, Y., & Kim, B.-Y. (2025). Impact of generative AI service adoption intent on user attitudes: Focusing on the Unified Theory of Acceptance and Use of Technology. *International Journal of Innovative Research and Scientific Studies*, 8, 2021-2033. https://doi.org/10.53894/ijirss.v8i1.4874

Kaya, F., Aydin, F., Schepman, A., Rodway, P., Yetişensoy, O., & Demir Kaya, M. (2024). The Roles of Personality Traits, AI Anxiety, and Demographic Factors in Attitudes toward Artificial Intelligence. *International Journal of Human–Computer Interaction*, 40(2), 497-514. https://doi.org/10.1080/10447318.2022.2151730

Khong-khai, S., & Wu, H.-Y. (2018). Analysis of critical success factors of startups in Thailand. *Indian Journal of Public Health Research & Development*, 9, 1262. https://doi.org/10.5958/0976-5506.2018.01630.3

Kim, Y., Blazquez, V., & Oh, T. (2024). Determinants of Generative AI System Adoption and Usage Behavior in Korean Companies: Applying the UTAUT Model. *Behavioral Sciences*, 14(11), 1035. https://www.mdpi.com/2076-328X/14/11/1035

Kraivichien, N., & Pruetipibultham, O. (2024). Determinants of New Venture Survival: A Case Study of Startups in Thailand. *ABAC Journal*, 44, 148-164.

Lemay, D., Basnet, R., & Doleck, T. (2020). Fearing the Robot Apocalypse: Correlates of AI Anxiety. *International Journal of Learning Analytics and Artificial Intelligence for Education (iJAI)*, 2, 24. https://doi.org/10.3991/ijai.v2i2.16759

Mirbabaie, M., Brünker, F., Möllmann Frick, N. R. J., & Stieglitz, S. (2022). The rise of artificial intelligence – understanding the AI identity threat at the workplace. *Electronic Markets*, 32(1), 73-99. https://doi.org/10.1007/s12525-021-00496-x

Mohamed, M. G., Goktas, P., Khalaf, S. A., Kucukkaya, A., Al-Faouri, I., Seleem, E. A. E. S., Ibraheem, A., Abdelhafez, A. M., Abdullah, S. O., Zaki, H. N., & Nashwan, A. J. (2025). Generative artificial intelligence acceptance, anxiety, and behavioral intention in the middle east: a TAM-based structural equation modelling approach. *BMC Nursing*, 24(1), 703. https://doi.org/10.1186/s12912-025-03436-8

Nititham, S., & Phillips, R. (2024). The Importance of Entrepreneurship Education for Startup Creation in Thailand. 10, 991-998. https://doi.org/10.4995/HEAd24.2024.17014

Noerman, T., Riyadi, Yuliaji, E. S., & Natasha, C. A. M. (2025). The impacts of social influence and hedonic motivation on experience and continuance intention of using AI in SMEs' HRM. *Cogent Business & Management*, 12(1), 2542422. https://doi.org/10.1080/23311975.2025.2542422

Noonpakdee, W. (2024). User Adoption of Generative AI for Government Information Services in Thailand. *Rajapark Journal*, 18(60), 1 - 20. https://so05.tci-thaijo.org/index.php/RJPJ/article/view/274204

Papathomas, A., Konteos, G., & Avlogiaris, G. (2025). Behavioral Drivers of AI Adoption in Banking in a Semi-Mature Digital Economy: A TAM and UTAUT-2 Analysis of Stakeholder Perspectives. *Information*, 16(2), 137. https://www.mdpi.com/2078-2489/16/2/137

Paudel, S., & Acharya, N. (2025). Factors Affecting Behavioral Intention to Use ChatGPT: Mediating Role of Attitude. *Journal of Service Innovation and Sustainable Development*, 5, 143-162. https://doi.org/10.33168/SISD.2024.0209

Peemanee, J., Sukprasert, A., & Wongsahai, E. (2023). The effects of network and innovation capabilities on performance of startup businesses in Thailand. 21, 1-13.

Rana, M. M., Siddiqee, M. S., Sakib, M. N., & Ahamed, M. R. (2024). Assessing AI adoption in developing country academia: A trust and privacy-augmented UTAUT framework. *Heliyon*, 10(18). https://doi.org/10.1016/j.heliyon.2024.e37569

Rizomyliotis, I., Konstantoulaki, K., Battisti, E., & Do, B. (2025). Start-Up Employees Adoption of AI Technology for Innovation Ecosystems: An In-Depth Exploration. *R&D Management*, *n/a*(n/a). https://doi.org/10.1111/radm.12769

Salazar, L., & Rivera, L. (2025). A Systematic Review of Factors Influencing the Acceptance Of Artificial Intelligence Devices. *Advances in Artificial Intelligence and Machine Learning*, 05, 3954-3974. https://doi.org/10.54364/AAIML.2025.52223

Salih, L., Tarhini, A., & Acikgoz, F. (2025). AI-Enabled Service Continuance: Roles of Trust and Privacy Risk AI-Enabled Service Continuance: Roles of Trust and Privacy Risk. *Journal of Computer Information Systems*, 1-16. https://doi.org/10.1080/08874417.2025.2452544

Sammet, F., Gillig, H., & Foo, M. (2024). How do Startups use AI? A Q-methodology approach to understanding adoption patterns. *European Conference on Innovation and Entrepreneurship*, 19, 950-959. https://doi.org/10.34190/ecie.19.1.2611

Sri-ar-sa, O., & Rassameethes, B. (2025). Factors influencing the acceptance of generative AI technology usage in the work performance of state enterprise employees in Bangkok. *Procedia of Multidisciplinary Research, 3*(7), 91.

Strzelecki, A., Cicha, K., Rizun, M., & Rutecka, P. (2024). Acceptance and use of ChatGPT in the academic community. *Education and Information Technologies*, 29, 22943-22968. https://doi.org/10.1007/s10639-024-12765-1

Tanantong, T., & Wongras, P. (2024). A UTAUT-Based Framework for Analyzing Users' Intention to Adopt Artificial Intelligence in Human Resource Recruitment: A Case Study of Thailand. *Systems*, 12(1), 28.

Thanapongpopn, A., Ratananopdonsakul, R., & Chanpord, W. (2021). Key Success Factors and Framework of Fundraising for Early-Stage Startups in Thailand. *Academy of Strategic Management Journal*, 20, 2021.

Thanyawatpornkul, R. (2024). Harnessing artificial intelligence for sustainable development in emerging markets: Exploring opportunities and challenges in Thailand. *European Journal of Sustainable Development Research*, 8, em0273. https://doi.org/10.29333/ejosdr/15435

Thawesaengskulthai, N., Chatmarathong, A., & Koiwanit, J. (2024). Impact and policy supporting Thailand innovation driven enterprise: orchestrating university innovation and entrepreneurship ecosystem with public and private stakeholders. *Journal of Innovation and Entrepreneurship*, 13(1), 16. https://doi.org/10.1186/s13731-024-00371-x

Turner, R., & Carlson, L. (2003). Indexes of Item-Objective Congruence for Multidimensional Items. *International Journal of Testing*, 3, 163-171. https://doi.org/10.1207/S15327574IJT0302_5

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

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

Wang, Y.-Y., & Wang, Y.-S. (2022). Development and validation of an artificial intelligence anxiety scale: an initial application in predicting motivated learning behavior. *Interactive Learning Environments*, 30(4), 619-634. https://doi.org/10.1080/10494820.2019.1674887

Yakubu, M. N., David, N., & Abubakar, N. H. (2025). Students' behavioural intention to use content generative AI for learning and research: A UTAUT theoretical perspective. *Education and Information Technologies*, 30(13), 17969-17994. https://doi.org/10.1007/s10639-025-13441-8

Electronic Media

Juasrikul, S., & Vandenberg, P. (2022). *Thailand's Evolving Ecosystem Support for Technology Startups*. http://dx.doi.org/10.22617/TCS220314-2

https://www.adb.org

Mayer, H., Yee, L., Chui, M., & Roberts, R. (2025). *Superagency in the workplace: Empowering people to unlock AI's full potential*. McKinsey & Company.

Singh, M., & Rana, A. (2024). *Generative AI outlook 2025: Assessing opportunities and disruptions in an evolving trillion-dollar-plus market.* Bloomberg Intelligence.

StartupBlink. (2025). *Global Startup Ecosystem Index* 2025.

Other Materials (Theses, Dissertations, Unpublished Work)

Ayeni, F., Ngufor, A., Gani, E., & Mbarika, V. (2024). Adoption of generative AI (Gen-AI) in Sub-Saharan Africa: Extension of the UTAUT model. *MWAIS 2024 Proceedings*, 31. https://aisel.aisnet.org/mwais2024/31

Navarattanapaiboon, N. (2024). ChatGPT usage behavior among employees from different generations at a consulting firm in the Bangkok area [Independent study, Thammasat University]. Thammasat University Digital Collections. https://digital.library.tu.ac.th/

Bakumenko, S. (2024). *AI Generated vs. Traditional: Investigating Age Group Differences in the Perception of Art* [Master's thesis, DiVA. http://urn.kb.se/resolve?urn=urn:nbn:se:lnu:diva-130299

Söderberg, P., & Stenmark, M. (2025). *Growing With AI : Insights from a Swedish AI Startup on Internal AI Adoption – A Case Study* [Master's thesis, DiVA. http://urn.kb.se/resolve?urn=urn:nbn:se:uu:diva-562494

Teerawongsathorn, J. (2023). *Understanding the influence factors on the acceptance and use of ChatGPT in Bangkok: A study based on the Technology Acceptance Model* [Thematic paper, Mahidol University]. CMMU Digital Archive. https://archive.cm.mahidol.ac.th/handle/123456789/5280

Yunita, P. (2025). *Employees' perceptions of AI technology adoption in Swedish tech organizations* [Master's thesis, Linnæus University]. https://lnu.diva-portal.org/smash/record.jsf?pid=diva2%3A1977950&dswid=-2732

APPENDICES

APPENDIX A
ONLINE QUESTIONNAIRES (ENGLISH VERSION)

Questionnaire for a research study on: Factors Influencing the Acceptance and Use of Generative Artificial intelligence in Thai Startup companies

Part 1: Introduction and Consent

Dear Participant,

Thank you for dedicating your valuable time to participate in this research survey. This questionnaire forms part of an independent study for the Master of Business Administration (MBA) programme in Business Innovation at Thammasat University. The objective of this study is to investigate the various factors that influence the adoption and use of Generative AI technologies among personnel in Thai startup companies.

Please be assured that all information you provide will be kept strictly confidential and will only be used for aggregate analysis for academic purposes. No personal data will be disclosed under any circumstances. The researcher, therefore, kindly requests your honest responses to ensure the accuracy and integrity of the research findings.

As a token of our appreciation for your cooperation, all participants who fully complete this survey will receive a THB 100 Starbucks Card (Digital Code).

Please note: To ensure data quality and prevent duplicate entries, the Digital Code will be sent to your email following a brief data quality check by the researcher (typically within 24-48 hours).

Your email address will be treated with the utmost confidentiality and will be permanently deleted immediately after the research is concluded. Receiving the Starbucks Card is entirely optional. If you wish to participate in the research but prefer not to receive the token, you may proceed with the questionnaire and simply skip the contact information section at the end.

This questionnaire is expected to take approximately 3-5 minutes to complete. Should you have any questions, please do not hesitate to contact the researcher: Mr. Kittisak Kanokbusabarn

Email: kittisak.kan@dome.tu.ac.th

Telephone: 090-960-0671

Participant Requirements

This survey is intended for participants who meet the following two criteria:

1) You are an employee or entrepreneur in a startup company located in Thailand.

2) You have used Generative AI (e.g., ChatGPT, Gemini, Midjourney) at least once.

Please proceed only if you meet both of the requirements above.

Confirmation of Understanding and Consent

To proceed, please first confirm that you have read and understood the information provided about this study.

☐ I confirm that I have read and understood the Participant Information for this research.

Please select one of the following options:

☐ I agree to participate. (Continue)

☐ I do not wish to participate. (End the survey)

Part 2: Demographic and Contextual Information

Instructions: Please select only one option that best describes you.

1. In which industry does your startup primarily operate?

☐ FinTech

☐ HealthTech / MedTech

☐ EdTech

☐ E-commerce & Marketplace

☐ Logistics & Supply Chain

☐ FoodTech / AgriTech

☐ SaaS (Software as a Service) / Enterprise Tech

☐ Tech Consulting / Innovation Service

☐ AI / Big Data / Deep Tech

☐ Other (Please specify): ....

2. Where is your company or organisation located?

☐ Bangkok Metropolitan Region

☐ Other regions

3. How would you describe your gender?

☐ Male

☐ Female

☐ LGBTQ+

☐ Prefer not to say

4. Please select your age range.

☐ 18–28 years old

☐ 29–44 years old

☐ 45–60 years old

☐ 61 years or older

5. What is your highest level of education?

☐ Below Bachelor’s Degree

☐ Bachelor’s Degree

☐ Master’s Degree

☐ Doctoral Degree (PhD or equivalent)

6. What is your current job position (or equivalent)?

- ☐ Founder / Co-founder
- ☐ Senior Executive
- ☐ Manager or equivalent
- ☐ Supervisor or equivalent
- ☐ Officer / Staff or equivalent

7. How many years of work experience do you have in the startup sector?

- ☐ 0–3 years
- ☐ 4–5 years
- ☐ 6–10 years
- ☐ 11–15 years
- ☐ More than 15 years

8. How many employees are in your organisation?

- ☐ 25 or fewer
- ☐ 26–50
- ☐ 51–200
- ☐ 201–500
- ☐ More than 500

9. How frequently do you use Generative AI?

- ☐ Daily
- ☐ Several times a week (but not daily)
- ☐ Once a week
- ☐ 1-3 times a month
- ☐ Less than once a month

10. Which Generative AI services do you use regularly? (You may select more than one)

- ☐ ChatGPT

☐ Gemini

☐ Claude

☐ Perplexity

☐ Microsoft Copilot

☐ Grok

☐ Midjourney

☐ GitHub Copilot

☐ Other (Please specify): ....

11. What is your subscription plan for your primary Generative AI?

☐ Free plan

☐ Premium or Pro plan

☐ Team or Enterprise plan

☐ Pay-as-you-go plan (API services)

☐ Other (Please specify): ....

Part 3: Measurement of Constructs

This section contains statements regarding your opinions and experiences about the acceptance and use of Generative AI in your work.

Instructions: For each statement below, please indicate your level of agreement based on your personal experiences and perceptions.

The scale is defined as follows:

5 = Strongly Agree

4 = Agree

3 = Neutral

2 = Disagree

1 = Strongly Disagree

Questions	Levels of agreement				
	1	2	3	4	5
Performance Expectancy					
PE1: I believe generative AI provides me with useful information and services.					
PE2: Using generative AI helps me boost my productivity on tasks (e.g., by saving time or improving the quality of my work).					
PE3: I think generative AI assists me in solving complex problems.					
PE4: Generative AI helps me develop new ideas.					
Effort Expectancy					
EE1: I find generative AI to be simple and easy to use.					
EE2: The features of generative AI are easy for me to operate and control.					
EE3: It would not be difficult for me to become highly skilled at using generative AI.					
EE4: I can adapt how I use Generative AI to suit different types of tasks.					
Social Influence					
SI1: My supervisor or colleagues encourage me to use generative AI systems.					
SI2: My colleagues generally have a positive opinion about using generative AI.					
SI3: My organisation has a policy or guidelines that encourage employees to use Generative AI.					
Facilitating Conditions					

Questions	Levels of agreement				
	1	2	3	4	5
FC1: My company provides the necessary resources and technical infrastructure (e.g., computers, budget, software) for using Generative AI.					
FC2: There is sufficient support from AI experts in my organisation for using generative AI.					
FC3: My company offers adequate training for the use of generative AI.					
FC4: My company has appropriate measures in place to ensure data security for the use of Generative AI.					
Hedonic Motivation					
HM1: I find using Generative AI to be enjoyable and fun.					
HM2: Generative AI helps me satisfy my curiosity.					
HM3: Generative AI makes me feel excited to constantly learn new things.					
Trust in AI					
TAI1: I trust that generative AI is designed to help users, not for the personal gain of the developer.					
TAI2: I believe generative AI is honest and does not misuse information or its advantages over users.					
TAI3: Generative AI seems to be trustworthy.					
TAI4: I have some understanding of how Generative AI reasons to produce its results.					
TAI5: I believe that Generative AI will not disclose my information without permission.					
AI Anxiety					
AIA1: I am worried that generative AI may replace human jobs.					

Questions	Levels of agreement				
	1	2	3	4	5
AIA2: I fear that using generative AI too much will make me dependent on it and cause me to lose some of my critical thinking skills.					
AIA3: I am concerned that generative AI might get out of control and not function properly.					
AIA4: I feel unconfident when I have to rely on results generated by Generative AI without verification.					
Behavioural Intention					
BI1: I am willing to use generative AI.					
BI2: I plan to use generative AI to improve my work performance.					
BI3: I intend to continue using generative AI in the future.					
BI4: I intend to recommend that my colleagues use Generative AI.					
Use Behaviour					
UB1: I personally use generative AI.					
UB2: I use generative AI to explore new ways of working.					
UB3: I use generative AI applications on various devices that I own.					
UB4: I use Generative AI to assist in strategic decision-making or work planning.					
UB5: I apply the output from Generative AI in work that has an organisational impact.					

Additional Comments and Contact Information (Optional)

1. Do you have any other comments or useful information you wish to share for this research? (Optional)

....

2. Email address (Optional, for the guaranteed THB 100 Starbucks Card)

Instructions:

1. Please provide your email address if you wish to receive the THB 100 Starbucks Card (Digital Code).

2. The code will be sent within 24-48 hours following a data quality check by the researcher to prevent duplicate entries. If you prefer not to receive the token, you may leave this field blank.

3. Your information will be treated with the utmost confidentiality and will be permanently deleted once the research is concluded and the token has been delivered

....

APPENDIX B
ONLINE QUESTIONNAIRES (THAI VERSION)

แบบสอบถามเพื่องานวิจัยเรื่อง: ปัจจัยที่มีอิทธิพลต่อการยอมรับและการใช้งาน Generative AI ในสตาร์ทอัพไทย

เรียน ผู้เข้าร่วมการวิจัย

ขอขอบพระคุณเป็นอย่างสูงที่ท่านสละเวลาอันมีค่าเพื่อเข้าร่วมการตอบแบบสอบถามฉบับนี้ แบบสอบถามนี้เป็นส่วนหนึ่งของการค้นคว้าอิสระ หลักสูตรบริหารธุรกิจมหาบัณฑิต สาขาวิชานวัตกรรมทางธุรกิจ มหาวิทยาลัยธรรมศาสตร์ โดยมีวัตถุประสงค์เพื่อศึกษาปัจจัยต่าง ๆ ที่มีอิทธิพลต่อการยอมรับและการใช้เทคโนโลยี Generative AI ของบุคลากรในบริษัทสตาร์ทอัพของประเทศไทย

ข้อมูลที่ได้รับจากท่านจะถูกเก็บรักษาเป็นความลับอย่างเคร่งครัด และจะถูกนำไปใช้เพื่อการวิเคราะห์ในภาพรวมสำหรับวัตถุประสงค์ทางการศึกษาเท่านั้น จะไม่มีการเปิดเผยข้อมูลส่วนบุคคลของผู้ตอบแบบสอบถามไม่ว่ากรณีใด ๆ ทั้งสิ้น ผู้วิจัยจึงใคร่ขอความอนุเคราะห์จากท่านในการตอบแบบสอบถามตามความเป็นจริง เพื่อให้ได้ผลการวิจัยที่ถูกต้องและสมบูรณ์ที่สุด

และเพื่อเป็นการแสดงความขอบคุณสำหรับความร่วมมือของท่าน ผู้ที่ตอบแบบสอบถามฉบับสมบูรณ์ทุกท่าน จะได้รับ Starbucks Card (Digital Code) มูลค่า 100 บาท ในการนี้ ผู้วิจัยจึงใคร่ขอความอนุเคราะห์ท่านในการให้ข้อมูลอีเมลสำหรับติดต่อกลับในส่วนท้ายของแบบสอบถาม

หมายเหตุ: เพื่อรักษาคุณภาพของงานวิจัยและป้องกันการตอบซ้ำ Digital Code จะถูกจัดส่งให้ท่านทางอีเมล หลังจากที่ผู้วิจัยได้ตรวจสอบความสมบูรณ์ของข้อมูล (Data Quality Check) เรียบร้อยแล้ว (โดยทั่วไปใช้เวลา 24-48 ชั่วโมง)

อีเมลของท่านจะถูกเก็บรักษาเป็นความลับสูงสุด และจะถูกทำลายทิ้งทันทีหลังจากที่การวิจัยเสร็จสิ้นและได้จัดส่งของสมนาคุณเรียบร้อยแล้ว ทั้งนี้ การรับ Starbucks Card เป็นไปตามความสมัครใจ หากท่านประสงค์เข้าร่วมการวิจัยแต่ไม่ประสงค์รับของสมนาคุณ ท่านสามารถดำเนินการตอบแบบสอบถามต่อได้ทันที โดยไม่ต้องกรอกข้อมูลสำหรับติดต่อกลับในส่วนท้ายครับ

แบบสอบถามนี้คาดว่าจะใช้เวลาในการตอบประมาณ 3-5 นาที

หากท่านมีข้อสงสัยใด ๆ ท่านสามารถติดต่อผู้วิจัยได้ที่ นายกิตติศักดิ์ กนกบุษบาล

อีเมล: kittisak.kan@dome.tu.ac.th
โทรศัพท์: 090-960-0671

ข้อกำหนดสำหรับผู้เข้าร่วมการวิจัย

แบบสอบถามนี้จัดทำขึ้นสำหรับผู้เข้าร่วมที่มีคุณสมบัติตรงตามข้อกำหนด 2 ข้อดังต่อไปนี้:

1) ท่านเป็นพนักงานหรือผู้ประกอบการในบริษัทสตาร์ทอัพที่ตั้งอยู่ในประเทศไทย

2) ท่านเคยมีประสบการณ์ใช้งาน Generative AI (เช่น ChatGPT, Gemini, Midjourney) มาแล้วอย่างน้อย 1 ครั้ง

โปรดดำเนินการต่อเฉพาะเมื่อท่านมีคุณสมบัติตรงตามข้อกำหนดทั้งสองข้อข้างต้น

การยืนยันความเข้าใจและให้ความยินยอม

เพื่อดำเนินการต่อ โปรดยืนยันว่าท่านได้อ่านและเข้าใจข้อมูลเกี่ยวกับการวิจัยทั้งหมดแล้ว

☐ ข้าพเจ้ายืนยันว่าได้อ่านและเข้าใจคำชี้แจงผู้เข้าร่วมการวิจัยฉบับนี้โดยละเอียดแล้ว

โปรดเลือกหนึ่งตัวเลือกจากด้านล่างนี้

☐ ข้าพเจ้ายินดีเข้าร่วมการวิจัย (ดำเนินการต่อ)

☐ ข้าพเจ้าไม่ประสงค์เข้าร่วมการวิจัย (สิ้นสุดการทำแบบสอบถาม)

ส่วนที่ 2: ข้อมูลด้านประชากรศาสตร์และบริบท

คำชี้แจง: กรุณาเลือกคำตอบที่ตรงกับท่านมากที่สุดเพียงข้อเดียว

1. ธุรกิจสตาร์ทอัพของท่านอยู่ในอุตสาหกรรมใดเป็นหลัก

☐ FinTech (เทคโนโลยีทางด้านการเงิน)

☐ HealthTech / MedTech (เทคโนโลยีด้านสุขภาพและการแพทย์)

☐ EdTech (เทคโนโลยีด้านการศึกษา)

☐ E-commerce & Marketplace (อีคอมเมิร์ซและตลาดกลางออนไลน์)

☐ Logistics & Supply Chain (โลจิสติกส์และโซ่อุปทาน)

☐ FoodTech / AgriTech (เทคโนโลยีด้านอาหารและการเกษตร)

☐ SaaS (Software as a Service) / Enterprise Tech (เทคโนโลยีและโซลูชั่นสำหรับองค์กร)

☐ Tech Consulting / Innovation Service (ที่ปรึกษาด้านเทคโนโลยี / บริการนวัตกรรม)

☐ AI / Big Data / Deep Tech (ปัญญาประดิษฐ์และข้อมูลขนาดใหญ่)

☐ อื่น ๆ (โปรดระบุ): ....

2. บริษัทหรือองค์กรของท่านตั้งอยู่ในพื้นที่ใด

☐ กรุงเทพมหานครและปริมณฑล

☐ พื้นที่อื่น ๆ

3. กรุณาระบุเพศของท่าน

☐ ชาย

☐ หญิง

☐ LGBTQ+

☐ ไม่ประสงค์ระบุ

4. กรุณาเลือกช่วงอายุของท่าน

☐ 18–28 ปี

☐ 29–44 ปี

☐ 45–60 ปี

☐ 61 ปีขึ้นไป

5. กรุณาระบุระดับการศึกษาสูงสุดของท่าน

☐ ต่ำกว่าปริญญาตรี

☐ ปริญญาตรี

☐ ปริญญาโท

☐ ปริญญาเอก (หรือเทียบเท่า)

6. ตำแหน่งงานปัจจุบันของท่านคืออะไร

☐ เจ้าของกิจการ / ผู้ร่วมก่อตั้ง

☐ ผู้บริหารระดับสูง

☐ ผู้จัดการ หรือเทียบเท่า

☐ เจ้าหน้าที่ / พนักงานระดับปฏิบัติการ หรือเทียบเท่า

7. ท่านมีประสบการณ์ทำงานทั้งหมดกี่ปี

☐ 0–3 ปี

☐ 3–5 ปี

☐ 5–10 ปี

☐ 10–15 ปี

☐ มากกว่า 15 ปี

8. องค์กรของท่านมีพนักงานจำนวนเท่าใด

☐ 25 คน หรือน้อยกว่า

☐ 26–50 คน

☐ 51–200 คน

☐ 201–500 คน

☐ มากกว่า 500 คน

9. ท่านใช้งานบริการ Generative AI บ่อยเพียงใด

☐ ทุกวัน

☐ หลายครั้งต่อสัปดาห์ (แต่ไม่ทุกวัน)

☐ สัปดาห์ละครั้ง

☐ เดือนละ 1-3 ครั้ง

☐ น้อยกว่าเดือนละครั้ง

10. โดยปกติท่านใช้บริการ Generative AI ใดบ้างเป็นประจำ (เลือกได้มากกว่า 1 ข้อ)

☐ ChatGPT

☐ Gemini

☐ Claude

☐ Perplexity

☐ Microsoft Copilot

☐ Grok

☐ Midjourney

☐ GitHub Copilot

☐ อื่น ๆ (โปรดระบุ): ....

11. ท่านใช้แผนการสมัครสมาชิก (Subscription Plan) รูปแบบใดสำหรับบริการ Generative AI หลักของท่าน

☐ แผนบริการฟรี (Free plan)

☐ แผนพรีเมียมหรือโปร (Premium or Pro plan)

☐ แผนสำหรับทีมหรือองค์กร (Team or Enterprise plan)

☐ แผนจ่ายตามการใช้งานจริง (Pay-as-you-go plan / API services)

☐ อื่น ๆ (โปรดระบุ): ....

ส่วนที่ 3: คำถามเพื่อวัดผลตัวแปรในกรอบการวิจัย (Measurement of Constructs)

ในส่วนนี้เป็นคำถามเกี่ยวกับความคิดเห็นและประสบการณ์ของท่านต่อการยอมรับและการใช้งาน Generative AI ในการทำงานของท่าน

คำชี้แจง: กรุณาเลือกระดับความเห็นด้วยของท่านในแต่ละข้อความต่อไปนี้ โดยอิงจากประสบการณ์และความคิดเห็นส่วนตัวของท่านมากที่สุด

เกณฑ์การให้คะแนน:

5 = เห็นด้วยอย่างยิ่ง

4 = เห็นด้วย

3 = เฉย ๆ

2 = ไม่เห็นด้วย

1 = ไม่เห็นด้วยอย่างยิ่ง

คำถาม	ระดับความเห็นด้วย				
	1	2	3	4	5
ความคาดหวังด้านประสิทธิภาพ					
PE1: ฉันเชื่อว่า Generative AI ให้ข้อมูลและบริการที่เป็นประโยชน์แก่ฉัน					
PE2: การใช้ Generative AI ช่วยให้ฉันทำงานได้มีประสิทธิภาพมากขึ้น (เช่น ลดระยะเวลาในการทำงาน หรือปรับปรุงคุณภาพของผลงาน)					
PE3: ฉันคิดว่า Generative AI ช่วยฉันในการแก้ปัญหาที่ซับซ้อนได้					
PE4: Generative AI ช่วยให้ฉันพัฒนาแนวคิดใหม่ ๆ ได้					
ความคาดหวังด้านความพยายามในการใช้งาน					
EE1: ฉันคิดว่า Generative AI นั้นเรียบง่ายและใช้งานสะดวก					
EE2: ฟีเจอร์ต่าง ๆ ของ Generative AI ง่ายต่อการใช้งานและควบคุมสำหรับฉัน					
EE3: คงไม่ยากสำหรับฉันที่จะใช้งาน Generative AI ได้อย่างเชี่ยวชาญ					
EE4: ฉันสามารถปรับวิธีการใช้ Generative AI ให้เหมาะกับงานประเภทต่าง ๆ ได้					
อิทธิพลทางสังคม					
SI1: หัวหน้างานหรือเพื่อนร่วมงานของฉันสนับสนุนให้ฉันใช้ระบบ Generative AI					
SI2: โดยทั่วไปแล้ว เพื่อนร่วมงานของฉันมีความเห็นเชิงบวกต่อการใช้ Generative AI					
SI3: องค์กรของฉันมีนโยบายหรือแนวทางที่สนับสนุนให้พนักงานใช้ Generative AI					
สภาวะแวดล้อมที่เอื้ออำนวย					
FC1: บริษัทของฉันมีทรัพยากรและโครงสร้างพื้นฐานทางเทคนิคที่จำเป็น (เช่น คอมพิวเตอร์, งบประมาณ, ซอฟต์แวร์) สำหรับการใช้งาน Generative AI					

คำถาม	ระดับความเห็นด้วย				
	1	2	3	4	5
FC2: องค์กรของฉันมีการสนับสนุนจากผู้เชี่ยวชาญด้าน AI ที่เพียงพอสำหรับการใช้งาน Generative AI					
FC3: บริษัทของฉันมีการจัดอบรมที่เพียงพอสำหรับการใช้งาน Generative AI					
FC4: บริษัทของฉันมีมาตรการที่เหมาะสมในการดูแลความปลอดภัยของข้อมูลสำหรับการใช้ Generative AI					
แรงจูงใจด้านความพึงพอใจ					
HM1: ฉันรู้สึกเพลิดเพลินและสนุกกับการใช้ Generative AI					
HM2: Generative AI ช่วยตอบสนองความอยากรู้อยากเห็นของฉัน					
HM3: Generative AI ทำให้ฉันรู้สึกตื่นเต้นที่จะเรียนรู้สิ่งใหม่ ๆ อยู่เสมอ					
ความไว้วางใจใน AI					
TAI1: ฉันเชื่อมั่นว่า Generative AI ถูกออกแบบมาเพื่อช่วยเหลือผู้ใช้ ไม่ใช่เพื่อประโยชน์ส่วนตนของผู้พัฒนา					
TAI2: ฉันเชื่อว่า Generative AI มีความซื่อสัตย์ และไม่นำข้อมูลหรือความได้เปรียบไปใช้ในทางที่ผิด					
TAI3: Generative AI ดูเป็นสิ่งที่น่าไว้วางใจได้					
TAI4: ฉันเข้าใจในระดับหนึ่งว่า Generative AI ใช้เหตุผลอย่างไรในการสร้างผลลัพธ์					
TAI5: ฉันเชื่อว่า Generative AI จะไม่เปิดเผยข้อมูลของฉันโดยไม่ได้รับอนุญาต					
ความวิตกกังวลเกี่ยวกับ AI					
AIA1: ฉันกังวลว่า Generative AI อาจเข้ามาแทนที่การทำงานของมนุษย์					
AIA2: ฉันกลัวว่าการใช้ Generative AI มากเกินไปจะทำให้ฉันต้องพึ่งพามัน และทำให้ทักษะการคิดวิเคราะห์ของฉันลดลง					

คำถาม	ระดับความเห็นด้วย				
	1	2	3	4	5
AIA3: ฉันกังวลว่า Generative AI อาจทำงานผิดพลาดหรืออยู่นอกเหนือการควบคุม					
AIA4: ฉันรู้สึกไม่มั่นใจเมื่อต้องพึ่งพาผลลัพธ์ที่ Generative AI สร้างขึ้นโดยไม่มีการตรวจสอบ					
ความตั้งใจเชิงพฤติกรรม					
BI1: ฉันเต็มใจที่จะใช้ Generative AI					
BI2: ฉันวางแผนที่จะใช้ Generative AI เพื่อปรับปรุงประสิทธิภาพการทำงานของฉัน					
BI3: ฉันตั้งใจจะใช้ Generative AI ต่อไปในอนาคต					
BI4: ฉันตั้งใจจะแนะนำให้เพื่อนร่วมงานของฉันใช้ Generative AI ด้วย					
พฤติกรรมการใช้งาน					
UB1: ฉันใช้งาน Generative AI เป็นการส่วนตัว					
UB2: ฉันใช้ Generative AI เพื่อสำรวจหาวิธีการทำงานในรูปแบบใหม่ ๆ					
UB3: ฉันใช้งานแอปพลิเคชัน Generative AI บนอุปกรณ์ต่าง ๆ ที่ฉันเป็นเจ้าของ					
UB4: ฉันใช้ Generative AI เพื่อช่วยในการตัดสินใจเชิงกลยุทธ์หรือการวางแผนงาน					
UB5: ฉันนำผลลัพธ์จาก Generative AI ไปใช้จริงในงานที่มีผลต่อองค์กร					

ข้อเสนอแนะเพิ่มเติมและข้อมูลสำหรับติดต่อกลับ (ตอบตามความสมัครใจ)

1. ท่านมีความคิดเห็นหรือข้อเสนอแนะอื่น ๆ ที่เป็นประโยชน์ต่องานวิจัยนี้หรือไม่

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2. ที่อยู่อีเมล (ตอบตามความสมัครใจ เพื่อรับบัตร Starbucks Card 100 บาท)

คำชี้แจง:

1. กรุณากรอกอีเมลหากท่านประสงค์รับ Starbucks Card (Digital Code) มูลค่า 100 บาท

2. โค้ดจะถูกจัดส่งภายใน 24-48 ชม. หลังจากการตรวจสอบความสมบูรณ์ของข้อมูลโดยผู้วิจัย เพื่อป้องกันการตอบซ้ำ หากท่านไม่ประสงค์รับของสมนาคุณ สามารถเว้นว่างในส่วนนี้ได้
3. ข้อมูลของท่านจะถูกเก็บเป็นความลับสูงสุดและจะถูกทำลายทิ้งทันทีหลังสิ้นสุดการวิจัยและส่งมอบของสมนาคุณแล้ว

....

BIOGRAPHY

Name	Kittisak Kanokbusabarn
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