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GENERATIVE ARTIFICIAL INTELLIGENCE ADOPTION AMONG SYSTEM INTEGRATION PROFESSIONALS IN THE CHINA'S GREATER BAY AREA: A UTAUT PERSPECTIVE

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Abstract

Generative artificial intelligence introduces an adoption-obsolescence paradox, a condition where technology simultaneously enhances efficiency yet threatens professionals' core skills. Based on the Unified Theory of Acceptance and Use of Technology (UTAUT), this study evaluated how performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC) predict behavioral intention (BI) and use behavior (UB) among system integration professionals in China's Greater Bay Area (GBA). Utilizing a mixed-methods design, the research analysed survey data from 319 professionals alongside qualitative insights from 50 focus group participants. The model accounted for 58.8% of BI variance and 50.9% of UB variance. High utility coexists with adoption anxiety, and a governance gap inhibits actual use. Professional capacity determines adoption intensity: role, education, and autonomy yielded significant variances, whereas age, gender, experience and company size were non-significant. Mainland professionals reported significantly higher BI ($M = 5.54$) than Hong Kong counterparts ($M = 5.12$), $t(317) = -2.53$, $p = .012$. Consequently, leaders should prioritize data privacy and human-in-the-loop policies over top-down mandates to foster sustainable innovation.

Keywords: generative artificial intelligence, system integration, Greater Bay Area, Unified Theory of Acceptance and Use of Technology, adoption-obsolescence paradox, performance expectancy, effort expectancy, social influence, facilitating conditions, professional capacity, data privacy, human-in-the-loop, governance gap, top-down mandates.

1.0 Introduction

The information technology (IT) industry faces a structural disruption as generative artificial intelligence (GenAI)—unlike prior rule-based enterprise software—autonomously executes the advanced cognitive tasks that define professional technical expertise, including software development, architectural design, and code debugging (Bommasani et al., 2021; Bubeck et al., 2023). This architectural shift produces an adoption obsolescence paradox: client-driven market mandates compel practitioners to integrate tools that simultaneously automate the competencies on which their professional value depends (Amankwah-Amoah & Appiah, 2025; Raisch & Krakowski, 2021). This sociotechnical tension is amplified within China's Greater Bay Area (GBA), a primary technological innovation hub operating under the one country, two systems framework that integrates nine Mainland cities with Hong Kong and Macau under divergent regulatory frameworks (Lin et al., 2024; Ye et al., 2021).

Although the UTAUT remains the predominant baseline framework for explaining and predicting individual technology acceptance across the information systems (IS) literature (Venkatesh et al., 2003), the IS literature remains unclear on how the model operates when agentic AI technologies simultaneously enhance efficiency and threaten professional expertise (Venkatesh, 2022). Furthermore, the specific boundary conditions that influence technology adoption intensity within high-stakes corporate environments remain undetermined.. The literature remains fragmented regarding whether adoption variance is primarily driven by an individual's professional capacity—defined by professional role, educational attainment, and professional autonomy—or by traditional demographic characteristics such as age, gender, experience, and company size (Blut et al., 2022). Finally, the cross-jurisdictional dynamics generated by the institutional duality of the GBA remain insufficiently understood, leaving it unclear whether regulatory variations alter the foundational structural mechanisms of technology adoption or merely influence adoption intensity (Venkatesh & Zhang, 2010).

1.1 Problem Statement

This study addresses the central problem of how and why system integration professionals in the GBA adopt GenAI when it directly affects their core professional competencies and values. The problem has three interconnected dimensions.

First, the UTAUT's structural pathways have not been validated within a high-stakes professional population confronting the adoption obsolescence paradox—a condition in which technology simultaneously generates operational utility and threatens the professional identity of its users. For system integration professionals, adoption carries direct career risk, as the model's original validation contexts involved low-stakes, homogeneous populations such as students and general consumers for whom no comparable professional threat existed (Blut et al., 2022; Venkatesh, 2022).

Second, the boundary conditions that govern adoption intensity within specialized professional populations remain empirically unresolved. The traditional demographics variables—age, gender, experience, and company size—were designed for low-stakes populations and are theoretically underdeveloped for specialized professional populations confronting skill substitution (Blut et al., 2022; Venkatesh, 2022). Whether professional capacity variables, specifically professional role, educational attainment, and autonomy, constitute more meaningful boundary conditions for this population has not been empirically tested.

Third, the cross-jurisdictional dynamics within the GBA remain insufficiently understood. It remains unknown whether institutional differences between Mainland and Hong Kong fundamentally alter the underlying structural mechanisms of adoption or merely influence adoption intensity (Venkatesh & Zhang, 2010).

1.2 Research Objectives

This study pursues four objectives designed to elucidate the drivers of GenAI adoption. The primary objective is to investigate the core UTAUT determinants—performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC)—as predictors of GenAI adoption among system integration professionals in the GBA. The second objective is to explore the boundary conditions of the professional context, determining whether professional capacity—specifically role, educational attainment, and autonomy—or traditional demographic variables primarily drive adoption intensity. The third objective is to assess the robustness of the UTAUT model across the distinct jurisdictions of Hong Kong and the Mainland GBA, examining whether observed variances are attributable to differences in adoption intensity rather than model structure. The fourth objective is to develop practical, evidence-based recommendations for system integration firms and organizational leaders, assisting organizations in designing GenAI adoption strategies that address both the core drivers of adoption and the professional concerns regarding skill obsolescence and loss of autonomy.

1.3 Research Questions

This study addresses this gap by examining the following four research questions (RQ1–RQ4):

Research question one (RQ1): how do performance expectancy (PE), effort expectancy (EE), and social influence (SI) predict the behavioral intention (BI) to adopt GenAI, and how do facilitating conditions (FC) and behavioral intention subsequently influence use behavior (UB) among system integration professionals in the GBA?

Research question two (RQ2): to what extent do the boundary conditions of professional capacity, specifically professional role, educational attainment, and autonomy, determine adoption intensity compared to the demographic variables, namely age, gender, professional experience, and company size?

Research question three (RQ3): what are the significant differences in the overall adoption intensity and the structural path coefficients of the GenAI adoption model between the institutional contexts of Hong Kong and the Mainland GBA?

Research question four (RQ4): what evidence-based management strategies are required to foster sustainable GenAI adoption while mitigating skill obsolescence threat among system integration professionals?

2.0 Literature Review

2.1 The GenAI Revolution in Professional Work

The IT industry is experiencing structural strain of a qualitatively different character than prior technological disruptions (Tunçalp, 2025). System integration professionals—the specialists who design, connect, and maintain complex enterprise technology systems for clients—occupy a highly demanding position within this landscape (Maddukuri, 2025). The growing complexity of digital ecosystems has made internal management untenable for most traditional organizations, driving persistent demand for external expertise (Moussa, 2013; Singh et al., 2024). Clients now actively discriminate in favor of firms that demonstrably adopt the newest tools at speed, transforming technology adoption from a strategic choice into a competitive prerequisite (Ambrozio et al., 2025; Faulconbridge et al., 2024). This reflects a broader strategic shift in the industry's business model, away from selling hours of labor and toward selling optimized digital outcomes, which compels firms to leverage automation to reduce labor costs and protect margin structures (Kohtamäki et al., 2019). Crucially, this market environment exposes system integration firms to intense external pressure: corporate clients increasingly mandate the demonstrable integration of cutting-edge computational tools as a non-negotiable procurement condition to guarantee service velocity and cost reduction (Bonin et al., 2025). Consequently, the implementation of advanced technology has shifted from an internal strategic option to a coercive market imperative necessary for institutional survival (Ambrozio et al., 2025).

The current wave of disruption is driven by the architectural transformation of artificial intelligence (AI) from discriminative to generative modeling (Ronge et al., 2025). Traditional AI architectures are fundamentally deterministic and discriminative, operating on rule-based frameworks to classify data, optimize predefined workflows, or predict outcomes based on structured historical inputs (Feuerriegel et al., 2024). In contrast, generative models utilize advanced deep learning architectures to map the underlying probability distributions of massive datasets, allowing the systems to synthesize entirely novel, contextual artifacts—ranging from complex code blocks to complete enterprise architectures—from natural language prompts (Ronge et al., 2025). These systems demonstrate distinct agentic capabilities, planning and executing multi-stage computational sequences with minimal human intervention, thereby shifting the human-machine dynamic from standard tool delegation to collaborative co-creation (Bubeck et al., 2023; Feuerriegel et al., 2024; Jäkel & Hummel, 2025).

However, this algorithmic agility introduces critical operational challenges. Generative models operate as highly opaque "black boxes" whose internal decision logic is hidden from the user, rendering them susceptible to algorithmic hallucinations—the generation of syntactically flawless yet factually incorrect or insecure outputs (Arrieta et al., 2020; Maia et al., 2025). This architectural opacity fundamentally restructures the technical specialist's core duties, shifting the locus of human labor away from original authorship and directly toward the cognitive burden of system auditing, validation, and risk management (Maia et al., 2025). Table 1 addresses these fundamental variations by presenting a comparative analysis between traditional rule-based IT systems and generative, probabilistic paradigms across key operational dimensions.

Table 1

Comparative Analysis of Traditional IT and Generative AI Paradigms

Feature	Traditional IT / AI	Generative AI (GenAI)	Source
Core Logic	Rule-Based: Executes pre-programmed rules (e.g., spam filters) based on discriminative modeling.	Generative Modeling: Synthesizes new artifacts (code, text) based on probability distributions.	(Feuerriegel et al., 2024)
Transparency	Transparent: Logic is traceable; errors are deterministic and debugging is linear.	Opaque (Black Box): Internal decision-making is hidden; prone to hallucinations requiring expert validation.	(Arrieta et al., 2020; Maia et al., 2025)
Human Role	Delegation: Humans assign specific subtasks; the system has no agency.	Co-Creation: Humans and agents interact iteratively; initiation is not limited to humans.	(Feuerriegel et al., 2024)

Impact	Augmentation: Removes routine work to support human experts.	Substitution Threat: Automates core cognitive tasks (coding, reasoning).	(Raisch & Krakowski, 2021; Bubeck et al., 2023)

Note. Sourced from Feuerriegel et al. (2024), Arrieta et al. (2020), Bubeck et al. (2023), and Raisch and Krakowski (2021).

The operational restructuring generated by these architectural changes yields concrete reconfigurations across the entire system integration technical landscape. AI integration disrupts organizational knowledge regimes by replicating domain expertise through self-learning capabilities, which redefines professional value away from the memorization of technical syntax or the manual construction of software components (Toniolo & Sobrero, 2025). Instead, professional value resides in the capacity to interpret, direct, and critically evaluate machine-generated outputs. The most prevalent application is code generation, where tools such as ChatGPT and GitHub Copilot automate the production of boilerplate code, SQL queries, and complex software methods from natural language prompts (Maia et al., 2025). This transitions the developer's role from writing syntax to reviewing logic—a shift that increases near-term productivity but introduces a substantial validation burden. Because GenAI code is produced by an opaque model, debugging machine-generated logic demands a higher order of theoretical understanding than original authorship (Maia et al., 2025).

Furthermore, GenAI's impact extends into the core integration tasks of data mapping and error handling, where algorithms automate complex schema adaptation by analysing large transaction datasets to facilitate intelligent error resolution (Maddukuri, 2025). This enables the creation of adaptive workflows capable of self-optimization in response to real-time operational data (Pingili, 2025), repositioning the integration professional's function from manual intervention to the architectural governance of self-correcting systems. Knowledge work within the integration domain is similarly affected: practitioners employ GenAI to contextualize technical solutions and benchmark internal processes against global standards (Simaremare & Edison, 2024). As generative tools automate routine configuration tasks, professional value increasingly accrues from architectural oversight and systemic reliability assurance rather than from the volume of manual work performed (Singh et al., 2024). Table 2 maps these localized structural shifts across technical domains, tracking the empirical transition of practitioners from hands-on creation tasks to high-level systemic orchestration.

Table 2

Operational Shift of System Integration: From Creation to Orchestration

Technical Domain	Traditional Creation Task	GenAI Orchestration Task	Operational Impact
Software Development	Manual writing of syntax; boilerplate coding; manual debugging.	Natural-language prompting to generate code; auditing AI-generated logic.	Shift from authoring to auditing; requires higher theoretical skill to debug opaque outputs (Maia et al., 2025).
Data Integration	Manual configuration of schema mappings and transformation rules.	Automated schema adaptation based on learned patterns from data history.	Reduced manual configuration; improved consistency in error handling (Maddukuri, 2025).

Workflow Design	Workflows manually designed and reworked when requirements change.	Adaptive workflow designs that self-optimize using real-time data.	Dynamic orchestration; reduced need for manual workflow tuning (Pingili, 2025).
Knowledge Work	Manual search and synthesis of solutions; informal benchmarking.	AI-assisted contextualization of search results and global benchmarking.	Faster problem understanding and reuse of global patterns (Simaremare & Edison, 2024; Bonin et al., 2025).
Professional Role	Hands-on configuration and routine interventions.	Architectural oversight and governance of agentic systems.	Value capture shifts from time spent to system reliability (Singh et al., 2024).

Note. Synthesized from Maia et al. (2025), Maddukuri (2025), Pingili (2025), Singh et al. (2024), and Bonin et al. (2025).

This operational restructuring generates an adoption-obsolescence paradox within the system integration profession. Standard technology acceptance frameworks fail to adequately capture this socio-technical dilemma because they are structurally underspecified for technologies that possess agentic capabilities (Venkatesh, 2022). While intense client-driven market mandates compel professionals to rapidly integrate these tools to maintain institutional competitiveness (Bonin et al., 2025), the act of deployment accelerates human capital obsolescence by automating the cognitive tasks that comprise the baseline economic value of the practitioner (Amankwah-Amoah & Appiah, 2025). This generates a deep systemic tension: practitioners who delegate core technical tasks to automated agents risk rapid professional deskilling and role degradation, whereas those who reject these tools confront immediate competitive marginalization (Raisch & Krakowski, 2021). This intersection of operational motivation and profound identity anxiety is structurally distinct from earlier waves of software adoption, as the technology operates simultaneously as an enabling agent and a substitutive threat.

2.2 UTAUT Determinants in the GenAI Context

To systematically evaluate how system integration professionals navigate these structural tensions when making adoption decisions, this study utilizes the UTAUT as its foundational framework (Venkatesh et al., 2003). Developed via the empirical synthesis of eight prominent historical technology acceptance models, the UTAUT consistently accounts for approximately 70% of the variance in behavioral intention (BI), establishing the UTAUT as the dominant standard in IS literature.

Historically, these antecedent frameworks remained bounded by critical structural constraints. The widely implemented Technology Acceptance Model (TAM) focused heavily on individual utility calculations (Davis, 1989) but lacked the social and environmental pathways required to evaluate mandatory corporate settings (Venkatesh & Davis, 2000). Concurrently, the Theory of Planned Behavior (TPB) incorporated individual control beliefs and subjective norms (Ajzen, 1991) but failed to account for the organizational variables necessary to evaluate mandatory workplace adoption settings (Venkatesh et al., 2003). To eliminate measurement redundancy and build a unified baseline, Venkatesh et al. (2003) integrated the core elements of these competing models into four parsimonious determinants: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC), as outlined in Table 3.

Table 3

Comparative Analysis of Antecedent Technology Acceptance Models.

Theory / Model	Core Constructs	Key Limitation Addressed by UTAUT
Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975)	Attitude toward Behavior; Subjective Norm.	TRA is a generalized psychological theory. UTAUT contextualized these constructs specifically for technology, converting Subjective Norm into SI.
Technology Acceptance Model (TAM) (Davis, 1989)	Perceived Usefulness; Perceived Ease of Use.	While highly effective, TAM lacked the social and organizational variables necessary for mandatory workplace settings. UTAUT integrated these constructs via PE and EE.
Motivational Model (MM) (Davis et al., 1992)	Extrinsic Motivation; Intrinsic Motivation.	MM focused heavily on psychological incentives. UTAUT incorporated Extrinsic Motivation into PE.
Theory of Planned Behavior (TPB) (Ajzen, 1991)	Attitude; Subjective Norm; Perceived Behavioral Control.	TPB extended TRA by adding control beliefs. UTAUT operationalized these constructs as SI and EE.
Combined TAM-TPB (C-TAM-TPB) (Taylor & Todd, 1995)	Constructs from both TAM and TPB.	This hybrid synthesis proved more explanatory than either framework alone.
Model of PC Utilization (MPCU) (Thompson et al., 1991)	Job-fit; Complexity; Long-term Consequences; Affect;	MPCU provided a granular view of determining factors but lacked simplicity.

	Social Factors; Facilitating Conditions.	UTAUT streamlined "Job-fit" into PE and "Complexity" into EE.
Innovation Diffusion Theory (IDT) (Moore & Benbasat, 1991)	Relative Advantage; Ease of Use; Image; Visibility; Compatibility; Results Demonstrability; Voluntariness of Use.	IDT provided a broad set of innovation characteristics. UTAUT streamlined "Relative Advantage" into PE and "Image" into SI.
Social Cognitive Theory (SCT) (Compeau & Higgins, 1995b)	Outcome Expectations (Performance and Personal); Self-efficacy; Affect; Anxiety.	SCT introduced emotional and capability constructs. UTAUT integrated outcome expectations into PE and clarified that anxiety and self-efficacy operate indirectly.

Note. Adapted from Venkatesh et al. (2003).

Because the UTAUT was originally validated using static, rule-based software applications, its core constructs must be re-contextualized to account for the unique uncertainties inherent in GenAI adoption (Venkatesh, 2022). Furthermore, due to the theoretical tensions introduced by the adoption-obsolescence paradox—where the technology introduces high utility and identity threat concurrently—the structural hypotheses in this study are formulated non-directionally. This approach utilizes two-tailed statistical testing to empirically investigate how these competing forces alter traditional technology acceptance dynamics.

PE represents the individual's cognitive calculation of whether deploying a specific technology will optimize task execution and maximize professional productivity (Venkatesh et al., 2003). Within the system integration workflow, GenAI demonstrates immediate operational utility by automating boilerplate code generation, accelerating schema mapping, and facilitating rapid information discovery (Maddukuri, 2025; Maia et al., 2025; Simaremare & Edison, 2024). Even when practitioners exhibit heightened long-term anxiety regarding skill replacement, the immediate pressure to achieve aggressive project timelines and compress delivery cycles serve as an acute survival mechanism that drives near-term utility calculations (Schmitt et al., 2024). This study tests whether this rational performance calculation remains the primary driver of BI when evaluated against the threat of professional obsolescence.

$H1_0$: PE does not affect BI of system integration professionals to adopt GenAI.

$H1_a$: PE significantly affects BI of system integration professionals to adopt GenAI.

EE captures the perceived ease of use and structural learning curve associated with a newly introduced system (Venkatesh et al., 2003). While natural language prompt interfaces are highly accessible, the actual cognitive effort required to successfully manage generative models is structurally complex. Practitioners face a continuous validation burden, requiring advanced theoretical knowledge to safely audit, debug, and secure opaque, machine-generated outputs that are prone to unpredictable hallucinations (Coutinho et al., 2024; Maia et al., 2025). This structural reality shifts human labor from linear execution to complex conceptual oversight, creating significant cognitive friction and technical debt that may distort standard ease-of-use perceptions.

$H2_0$: EE does not affect BI of system integration professionals to adopt GenAI.

$H2_a$: EE significantly affects BI of system integration professionals to adopt GenAI.

SI measures the degree to which an individual alters their BI in response to the explicit expectations of key stakeholders within their social and professional environment (Venkatesh et al., 2003). In the hyper-competitive GBA technology ecosystem, social influence transcends standard peer encouragement, manifesting as a coercive institutional pressure originating from corporate clients and organizational leaders. Because corporate clients increasingly mandate the use of AI-optimized deployment strategies as a prerequisite for contract award, practitioners are forced to utilize these tools to maintain professional legitimacy and operational viability, transforming social influence into a market survival mandate (Faulconbridge et al., 2025).

$H3_0$: SI does not affect BI of system integration professionals to adopt GenAI.

$H3_a$: SI significantly affects BI of system integration professionals to adopt GenAI.

FC represent the structural availability of organizational, technical, and institutional infrastructure required to operationalize a technology platform (Venkatesh et al., 2003). When evaluating the implementation of generative tools that handle sensitive client source code, intellectual property, and proprietary data architectures, basic technical infrastructure is insufficient. The critical facilitating condition shifts to the existence of transparent data governance frameworks addressing AI ethics, intellectual property protection, and data privacy policies (Maia et al., 2025; Ye et al., 2024). In the absence of robust institutional safeguards, data privacy apprehensions operate as a severe structural inhibitor that blocks actual usage, irrespective of individual motivation or hardware availability (Maia et al., 2025).

$H4_0$: FC does not affect UB of GenAI among system integration professionals.

$H4_a$: FC significantly affects the UB of GenAI among system integration professionals.

Finally, BI serves as the conscious cognitive formulation of a user's plan to execute a specific technology deployment, acting as the immediate baseline antecedent to actual UB (Venkatesh et al., 2003). This study evaluates the efficiency with which individual intention translates into actual daily system usage within an operating environment characterized by high cognitive anxiety and strict market compliance requirements.

$H5_0$: BI does not influence the UB of GenAI among system integration professionals.

$H5_a$: BI significantly affects the UB of GenAI among system integration professionals.

Despite the UTAUT's documented explanatory robustness, three literature gaps constrain its direct application to professional GenAI adoption. First, the literature overconcentrates on low-stakes, homogeneous populations—students and general consumers—for whom adoption carries no professional risk, creating a construct validity problem for specialized practitioners confronting skill obsolescence (Blut et al., 2022). Second, cross-cultural adoption research has relied exclusively on comparisons between different institutional regions, leaving the framework empirically untested within a dual-institutional regulatory zone

(Venkatesh & Zhang, 2010). Third, the UTAUT's reliance on traditional demographic boundary conditions—age and gender—neglects the structural and cognitive characteristics of the professional that meaningfully differentiate high-stakes technology adoption (Blut et al., 2022; Venkatesh, 2022). The present study directly addresses all three gaps.

2.3 Boundary Conditions: Professional Capacity and Institutional Duality

While the original formulation of the UTAUT relies on traditional demographic variables (such as age, gender, and experience) as primary moderating variables (Venkatesh et al., 2003), this study posits that such characteristics are theoretically insufficient for explaining adoption variance within specialized technical populations confronting a severe disruption. This study investigates professional capacity, namely professional role, education, and autonomy, that equip an individual to navigate socio-technical disruption—as a key boundary condition (Blut et al., 2022). Professional capacity is operationalized through three specialized dimensions: professional role, educational attainment, and professional autonomy.

Professional role captures the structural divergence in utility and threat calculations created by an individual's position within the corporate hierarchy (Burton-Jones & Hubona, 2005). The adoption-obsolescence paradox is experienced unevenly across the corporate architecture: strategic management professionals typically view GenAI as a powerful capacity multiplier that optimizes institutional output and compresses overhead costs without threatening their own strategic responsibilities (Raisch & Krakowski, 2021). Conversely, technical professionals experience the technology as an immediate, substitutive hazard capable of automating their core operational competencies, creating cognitive resistance among practitioners whose occupational status is tied to manual code execution (Schmitt et al., 2024).

$H6_0$: There is no significant difference in the BI to adopt GenAI between strategic management and technical professionals.

$H6_a$: There is a significant difference in the BI to adopt GenAI between strategic management and technical professionals.

Educational attainment reflects the metacognitive capabilities required to successfully navigate opaque, probabilistic computer systems (Blut et al., 2022). Professionals possessing advanced academic credentials in computer science, software engineering, or information systems possess the theoretical foundation necessary to interpret, deconstruct, and confidently audit complex algorithmic outputs (Stibe & Dinh, 2024). In contrast, practitioners lacking an advanced theoretical grounding are more likely to perceive the GenAI as an inscrutable "black box," resulting in elevated levels of technology anxiety and lower adoption confidence.

$H7_0$: There is no significant difference in the BI to adopt GenAI between professionals with advanced degrees and those with lower educational qualifications.

$H7_a$: There is a significant difference in the BI to adopt GenAI between professionals with advanced degrees and those with lower educational qualifications.

Professional autonomy evaluates the degree of agency an individual retains over the scheduling, configuration, and execution of technology within their corporate workflow. When organizational leadership compounds external client pressure by mandating internal tool usage, the result is frequently defensive resistance and a compliance mindset that suppresses genuine adoption commitment (Jussupow et al., 2022). Conversely, when technical professionals are granted the occupational autonomy to experiment with and direct tool implementation, they develop an intrinsic orientation toward the platform, viewing it as an empowering instrument for technical innovation rather than a replacement mechanism (Schmitt et al., 2024).

$H8_0$: There is no significant difference in the BI to adopt GenAI between voluntary and mandatory users.

$H8_a$: There is a significant difference in the BI to adopt GenAI between voluntary and mandatory users.

In tandem with professional capacity, macro-level institutional context operates as a critical environmental boundary condition. The GBA is characterized by profound institutional duality, wherein two entirely divergent regulatory and political frameworks govern the digital economy within a single economic zone (Lin et al., 2024). Within the Mainland GBA jurisdiction, government policy operates as a proactive, mobilizing force aimed at national AI sovereignty (Ma, 2024). The state heavily subsidizes infrastructure, provides localized computing clusters, and actively mandates the implementation of state-approved foundational models across public and private enterprise architectures (Ho, 2025). This aggressive, top-down institutional mobilization cultivates a corporate climate characterized by a high tolerance for algorithmic experimentation and strong social influence driving implementation (Zhan & Luo, 2025).

Conversely, the Hong Kong jurisdiction utilizes a common law framework that prioritizes stringent regulatory compliance, international alignment, and strict risk mitigation over state-sponsored industrial mobilization (Ho, 2025). Governed by the Personal Data Privacy Ordinance (PDPO), technology deployment in Hong Kong is heavily constrained by strict data governance boundaries, cross-border data transfer limitations, and severe corporate liability penalties (Xie et al., 2024). For system integration professionals in Hong Kong, this strict legal environment generates a persistent governance gap; while generative tools are technically accessible, the acute threat of legal liability and compliance violations functions as a severe structural inhibitor that suppresses individual usage behavior (Ye et al., 2024). Table 4 contrasts these cross-jurisdictional features, demonstrating how divergent macro-level regulatory and cultural environments fundamentally reconfigure the localized operation of the primary UTAUT determinants.

Table 4

Comparative Analysis of Institutional Contexts in the Greater Bay Area

Dimension	Mainland GBA Context	Hong Kong Context	Impact on UTAUT Determinants
System Feature	State-mobilized AI sovereignty.	Common law framework prioritizing risk mitigation.	Alters FC (access vs. restriction).
Policy vs. Regulation	Proactive government policies drive rapid industrial implementation (Ma, 2024).	Strict privacy regulations (PDPO) act as a gatekeeper for data usage (Ho, 2025).	Policy accelerates PE; regulation increases EE.
Cultural Norms	High tolerance for experimentation; adoption viewed as a righteous cause (Zhan & Luo, 2025).	Cautious, compliance-driven corporate culture focused on individual liability.	Shapes SI (enthusiastic adoption vs. coercive compliance).
Adoption Scenarios	Aggressive deployment in domestic enterprise architecture (Deloitte, 2025).	Highly restricted usage constrained by intellectual property and data borders (Ye et al., 2024).	Drives the overall intensity of BI and actual UB.

Note. Synthesized from Deloitte (2025), Ho (2025), Ma (2024), Xie et al. (2024), Ye et al. (2024), and Zhan and Luo (2025).

Despite this pronounced regulatory divergence, system integration professionals across both jurisdictions share a common technological ecosystem: they design, integrate, and deploy using the same foundational model providers, cloud-native architectures, and client-facing digital delivery stacks (Amankwah-Amoah & Appiah, 2025; Wu et al., 2024). Furthermore, the rise of cloud computing creates an AI democratization effect, allowing small firms to access the same advanced computational capabilities as large multinational enterprises, ensuring that no professional is shielded from the technological shift based purely on firm size or resources (Costa et al., 2024). This professional convergence ensures that the underlying cognitive mechanism of adoption—weighing individual utility against the skill substitution threat—remains structurally consistent across jurisdictions, justifying the application of the UTAUT model while treating institutional context as the boundary condition that influences adoption intensity rather than adoption structure (Venkatesh & Zhang, 2010).

$H9_0$: There is no significant difference in overall adoption intensity between professionals operating in the Mainland GBA and professionals in Hong Kong.

$H9_a$: There is a significant difference in overall adoption intensity between professionals operating in the Mainland GBA and professionals in Hong Kong.

$H10_0$: The structural path coefficients of the UTAUT model do not significantly differ between system integration professionals in Hong Kong and the Mainland GBA.

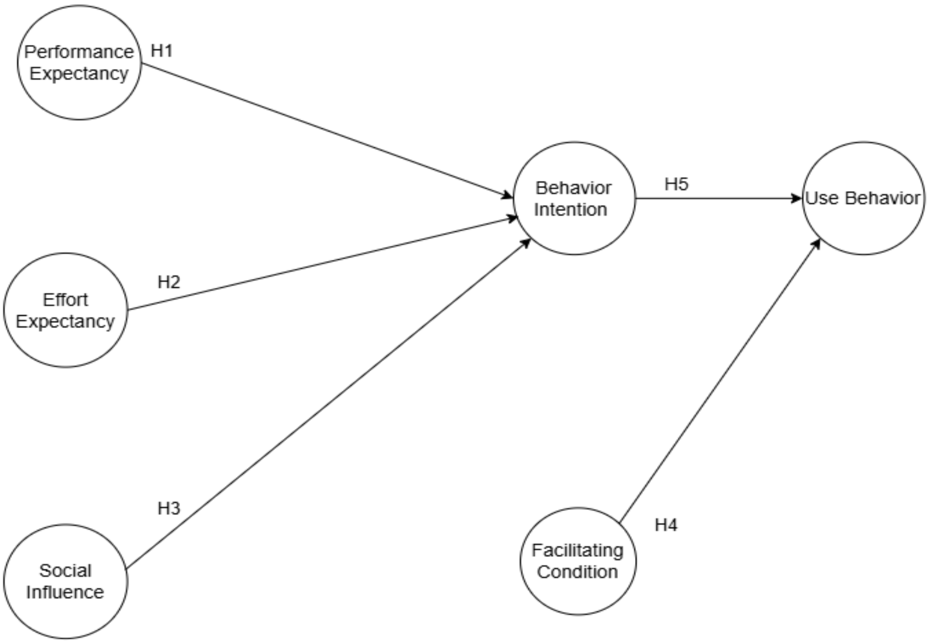
$H10_a$: The structural path coefficients of the UTAUT model significantly differ between system integration professionals in Hong Kong and the Mainland GBA.

2.4 Research Framework and Hypotheses

To systematically ground these individual and environmental boundary conditions within the mechanisms of technology acceptance, the research framework is depicted in **Error! Reference source not found.**.

Figure 1

The Research Framework of UTAUT



Professional Capacity (H6a–H8a) & Adoption Intensity (H9a): Evaluated via ANOVA and t-tests.

Cross-Regional Model Structure Variance (H10a): Evaluated via Multi-Group Analysis.

Demographic Variables (Age, Gender, Experience, and Company Size): Evaluated via ANOVA and t-tests.

To serve as a direct reference matrix for the subsequent PLS-SEM analysis, the full complement of primary structural pathways and exploratory boundary-condition hypotheses is systematically consolidated in Table 5.

Table 5

Summary of Proposed Research Hypotheses (Alternative)

UTAUT Core Hypotheses	
H1$_a$	PE significantly affects the BI to adopt GenAI.
H2$_a$	EE significantly affects the BI to adopt GenAI.

H3$_a$ SI significantly affects the BI to adopt GenAI.

H4$_a$ FC significantly affects the UB to adopt GenAI.

H5$_a$ BI significantly affects the UB to adopt GenAI.

Boundary Condition Hypotheses

H6$_a$ There is a significant difference in the BI to adopt GenAI between strategic management and technical staff.

H7$_a$ There is a significant difference in the BI to adopt GenAI between professionals with advanced degrees and those with lower educational qualifications.

H8$_a$ There is a significant difference in the BI to adopt GenAI between voluntary and mandatory users.

H9$_a$ There is a significant difference in overall adoption intensity between professionals operating in the Mainland GBA and professionals in Hong Kong.

H10$_a$ The structural path coefficients of the UTAUT model significantly differ between system integration professionals in Hong Kong and the Mainland GBA.

Note. The core structural determinants (H1a–H5a) establish the foundational adoption mechanism, while the exploratory hypotheses (H6a–H10a) replace traditional demographic factors to explain group variations.

3.0 Research Methodology

3.1 Research Paradigm and Design

The empirical investigation of GenAI adoption among system integration professionals necessitates an epistemological framework capable of capturing both quantifiable socio-technical relationships and the nuanced psychological climates that govern specialized corporate workflows. This study utilizes a post-positivist research paradigm, which acknowledges that while social realities can be measured objectively, human observation is inherently fallible and influenced by context (Creswell & Creswell, 2018).

To operationalize this paradigm within the unique institutional duality of GBA, a sequential explanatory mixed-methods design was deployed. The study was structured into two distinct, interconnected phases. Phase one implemented a cross-sectional quantitative survey to evaluate the structural hypotheses derived from the UTAUT model and to establish statistical variances across professional subgroups. Phase two sequentially conducted stratified focus groups to explain the statistical patterns identified in phase one, providing the qualitative depth necessary to interpret why specific boundary conditions emerge within the GBA context.

3.2 Sampling and Data Collection

The target population comprised system integration professionals working at firms in the GBA. For the quantitative phase, a stratified purposive sampling strategy was employed to secure regional representation proportionate to service sector economic contributions. Official statistics indicate that Hong Kong contributes approximately US$378 billion to the regional service GDP, while the relevant Mainland cities contribute approximately US$510 billion, establishing a target sampling ratio of approximately 1 to 1.35 (Hong Kong to Mainland). To control for organizational resource availability, the sample was further stratified by company size following the classification guidelines of China's Ministry of Industry and Information Technology (MIIT): small enterprises (fewer than 100 employees), medium organizations (100–299), and large corporations (300 or more).

To determine the minimum sample size required to ensure adequate statistical power for subsequent partial least squares structural equation modeling (PLS-SEM), an *a priori* power analysis was conducted. Utilizing the inverse-square-root method recommended by Hair et al. (2021), with behavioral intention as the endogenous construct receiving the maximum of three direct structural paths (PE, EE, and SI), at a 5% significance level and minimum statistical power of .80, the model required a minimum threshold of 76 valid responses. The digital data collection phase generated an initial pool of 328 completed instruments. A rigorous data screening protocol identified nine responses for exclusion: responses completed in under two minutes were flagged as insufficiently engaged (DeSimone et al., 2015), and univariate outliers with standardized Z scores exceeding ±3.29 were removed (Tabachnick & Fidell, 2007). The final valid sample size was stabilized at 319 system integration professionals, comprising 138 professionals from Hong Kong and 181 from Mainland GBA cities, thereby substantially exceeding the minimum requirements for robust structural modeling.

For the qualitative phase, a purposive stratified sampling strategy was utilized to recruit 50 system integration professionals from firms distinct from those in the survey cohort.

Participants were distributed across four stratified sessions: Hong Kong management (n = 12), Hong Kong technical staff (n = 13), Mainland GBA management (n = 12), and Mainland GBA technical staff (n = 13), yielding 24 management-level and 26 technical execution participants.

3.3 Instrumentation and Operationalization

The quantitative survey instrument was developed by adapting validated measurement scales from prominent IS literature, contextualized specifically for the specialized domain of system integration. All baseline latent constructs were operationalized using a standardized seven-point Likert scale. The measurement items for PE, EE, SI, and FC were adapted directly from the seminal framework established by Venkatesh et al. (2003). Actual UB was captured through self-reported operational frequencies, while the construct of professional autonomy was assessed using a four-item scale adapted from Moore and Benbasat (1991), rather than the standard UTAUT binary scale, allowing the study to assess autonomy as a continuous psychological state capturing the individual's sense of agency beyond mere organizational compliance.

To ensure linguistic and conceptual equivalence across both jurisdictions, the initial English instrument was subjected to a rigorous back translation procedure (Brislin, 1970) and evaluated through a pilot study involving 33 practitioners, confirming Cronbach's alpha values at or above the .70 threshold for all constructs prior to full regional distribution. The qualitative phase utilized a semi-structured focus group protocol with open-ended questions thematically aligned with the quantitative constructs to facilitate explanatory triangulation (Creswell & Creswell, 2017), specifically probing the tension between operational efficiency and skill replacement and the influence of regional regulatory environments on adoption.

All data collection procedures received institutional ethics review board approval. Informed consent was obtained electronically from every participant prior to each phase. Survey responses were decoupled from IP addresses, and all focus group transcripts were pseudonymized using alpha-numeric codes (e.g., P-HK-DIR-01) to protect participant confidentiality and prevent identification of individuals or their employers.

4.0 Research Findings

4.1 Introduction

The analytical process proceeds through a systematic sequence to ensure statistical rigor. First, data collection and response patterns are analysed to establish the quality and representativeness of the sample (4.2). Second, descriptive statistics summarize respondents' demographics and confirm adequate stratification across boundary condition categories (4.3). Third, the measurement model is assessed for reliability and validity using PLS-SEM (4.4). Finally, the structural model is evaluated to test the research hypotheses and examine specific group differences using *t*-tests, ANOVA, and Multi-Group Analysis (4.5–4.7)..

4.2 Preliminary Data Diagnostics and Non-Response Bias

The integrity of the empirical findings depends on a rigorous preliminary assessment of potential sampling biases and distributional anomalies. To evaluate non-response bias, the dataset was divided into early respondents (n = 160) and late respondents (n = 159), assuming late respondents share characteristics with non-respondents (Armstrong & Overton, 1977). Independent samples *t*-tests yielded no statistically significant differences across any core theoretical variable, confirming that non-response bias does not threaten the generalizability of the dataset. All measured latent variables exhibited absolute skewness values well below 2.0 and absolute kurtosis values significantly under 7.0, satisfying the baseline normality assumptions required for PLS-SEM.

4.3 Respondents' Demographic Information

The demographic data show that most of the workforce is male (74.9%) and highly educated, with 81.8% having at least a bachelor's degree. This high level of education is typical for the system integration sector and is important for this study, as it means participants have the theoretical background needed to assess the validation challenges associated with AI coding errors. Adequate stratification across all boundary condition categories was confirmed, as summarized in Table 6.

Table 6

Respondents' Demographic Information (n = 319)

Demographic Variable	Category	Frequency	Percentage
Gender	Male	239	74.90%
	Female	65	20.40%
	Prefer not to say	15	4.70%
Age Group	22–28 (Gen Z)	38	11.90%
	29–38 (Millennials)	125	39.20%
	39–48 (Gen X)	93	29.20%
	49+ (Baby Boomers)	49	15.40%
Professional Role	Director	54	16.90%
	Project Manager	59	18.50%
	Technical Staff	178	55.80%
	Other	28	8.80%
Experience	Junior (0–7 years)	104	32.60%
	Middle (8–11 years)	115	36.10%
	Senior (12+ years)	100	31.30%
Education	Diploma/Associate	56	17.50%
	Bachelor's Degree	185	58.00%
	Master's/Doctorate	76	23.80%
Company Size	Small (<100)	37	11.60%
	Medium (100–299)	33	10.30%
	Large (300+)	249	78.10%
Voluntariness (Autonomy)	Voluntary Users	239	74.90%
	Mandatory Users	80	25.10%

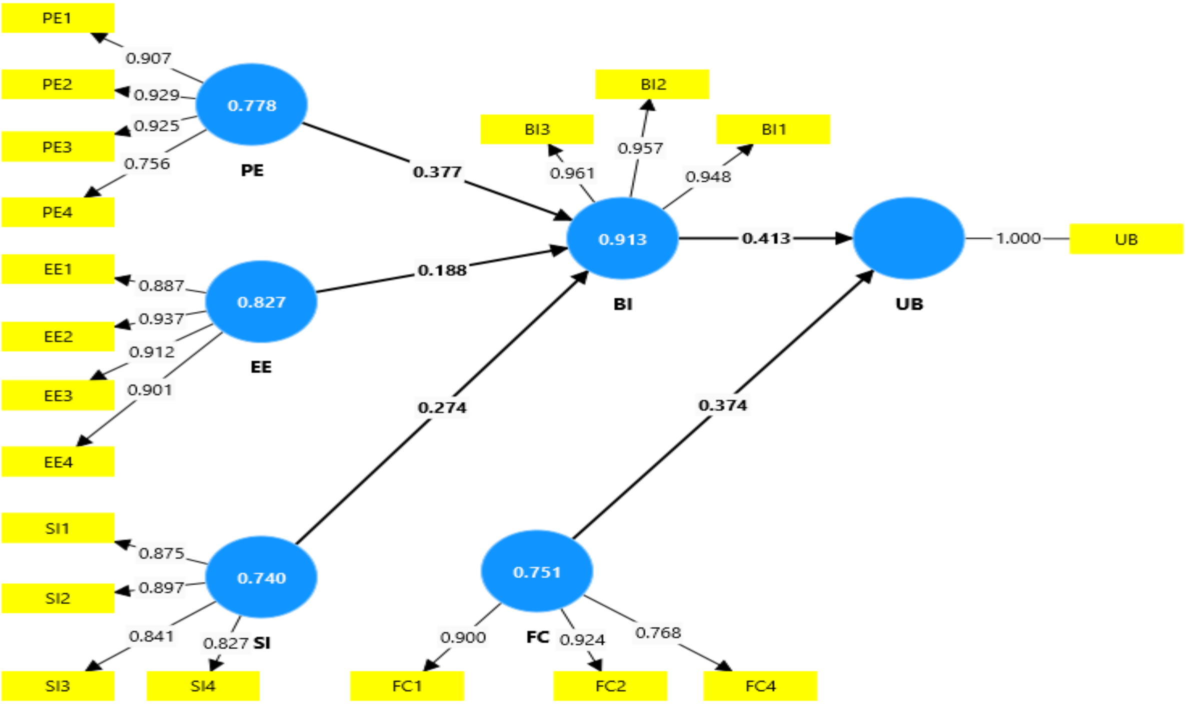
Note. The distribution confirms adequate stratification across all independent variable categories to support robust multi-way analysis of variance and boundary condition testing.

4.4 Evaluation of the Reflective Measurement Model

The assessment of the reflective measurement model required the systematic verification of indicator reliability, convergent validity, and discriminant validity. Figure 2 presents the measurement model generated by the PLS-SEM, displaying the standardized outer loadings for the indicators and the AVE values within the constructs.

Figure 2

Measurement Model Estimation via PLS Algorithm



Note. The measurement model displays standardized outer loadings for the indicators and AVE values within the constructs.

Indicator reliability was evaluated by examining the standardized outer loadings of all reflective measures against the threshold of .708. Item FC3, which measured system incompatibility within the facilitating conditions construct, exhibited a severely deficient negative loading (λ = −.587) and was subsequently deleted from the model. This deletion is theoretically justified as modern cloud-native delivery of GenAI platforms renders local system compatibility a largely irrelevant barrier (Hair et al., 2021). Following this correction, all retained indicators demonstrated standardized outer loadings ranging from .768 to .961, with all paths achieving high statistical significance ($p < .001$) and structural t-values exceeding 1.96.

Convergent validity was firmly established across all latent dimensions, with AVE metrics ranging from .726 to .913, comfortably exceeding the .50 empirical threshold. All variables achieved Cronbach's alpha values and composite reliability coefficients exceeding .835. Table 7 synthesizes the exact reliability and validity scores for each theoretical dimension.

Table 7

Convergent Validity and Internal Consistency Reliability

Construct	CA	Composite reliability (ρ_a)	Composite reliability (ρ_c)	AVE
UTAUT Constructs				
Performance Expectancy (PE)	.903	.916	.933	.778
Effort Expectancy (EE)	.930	.931	.950	.827
Social Influence (SI)	.883	.887	.919	.740
Facilitating Conditions (FC)†	.835	.884	.900	.751
Behavioral Intention (BI)	.952	.953	.969	.913

Note. Thresholds: CA > .70, ρ_c > .70, AVE > .50. †Item FC3 was removed due to a low outer loading (λ = -.587).

Discriminant validity was confirmed using two criteria. First, the Fornell-Larcker criterion was fully satisfied, as the square root of the AVE for each construct exceeded its highest inter-construct correlation. Second, all HTMT ratios remained below the conservative threshold of .90 (Henseler et al., 2015), establishing that the measurement instruments possess adequate discriminant properties for structural path modeling.

Prior to evaluating the structural model, a full inner collinearity assessment confirmed the absence of common method bias. All inner model VIF values ranged between 1.695 and 3.692, well below the critical ceiling of 5.0, demonstrating that multicollinearity does not distort the structural results.

4.5 Structural Model Estimation and Hypothesis Testing

The structural model was evaluated by implementing a bias-corrected bootstrapping procedure utilizing 5,000 empirical subsamples; a two-tailed p value below .05 was used to support the hypotheses (Hair et al., 2021). The resulting path analysis confirmed all five core hypotheses. PE emerged as the strongest structural predictor of individual BI ($\beta = .377, p < .001, f^2 = .129$), leading to the definitive rejection of the null hypothesis $H1_0$ in favor of the alternative hypothesis $H1_a$. SI ($\beta = .274, p = .004, f^2 = .065$) and EE ($\beta = .188, p = .034, f^2 = .023$) also exerted statistically significant effects on BI, confirming the alternative hypotheses $H3_a$ and $H2_a$ while rejecting their respective null counterparts. Finally, FC significantly determined actual UB ($\beta = .374, p < .001, f^2 = .168$), justifying the rejection of $H4_0$, and BI emerged as the strongest determinant of UB ($\beta = .413, p < .001, f^2 = .205$), justifying the rejection of $H5_0$.

The structural model demonstrated high explanatory power, accounting for 58.8% of the variance in BI ($R^2 = .588$) and 50.9% of the total variance in actual UB ($R^2 = .509$). A subsequent blindfolding procedure with an omission distance of 7 confirmed the strong predictive relevance of the model, yielding Q^2 values between .497 and .529. The comprehensive results of the bootstrapping and path analyses are detailed in Table 8.

Table 8

Structural Path Coefficients, Effect Size and Hypothesis Test Results

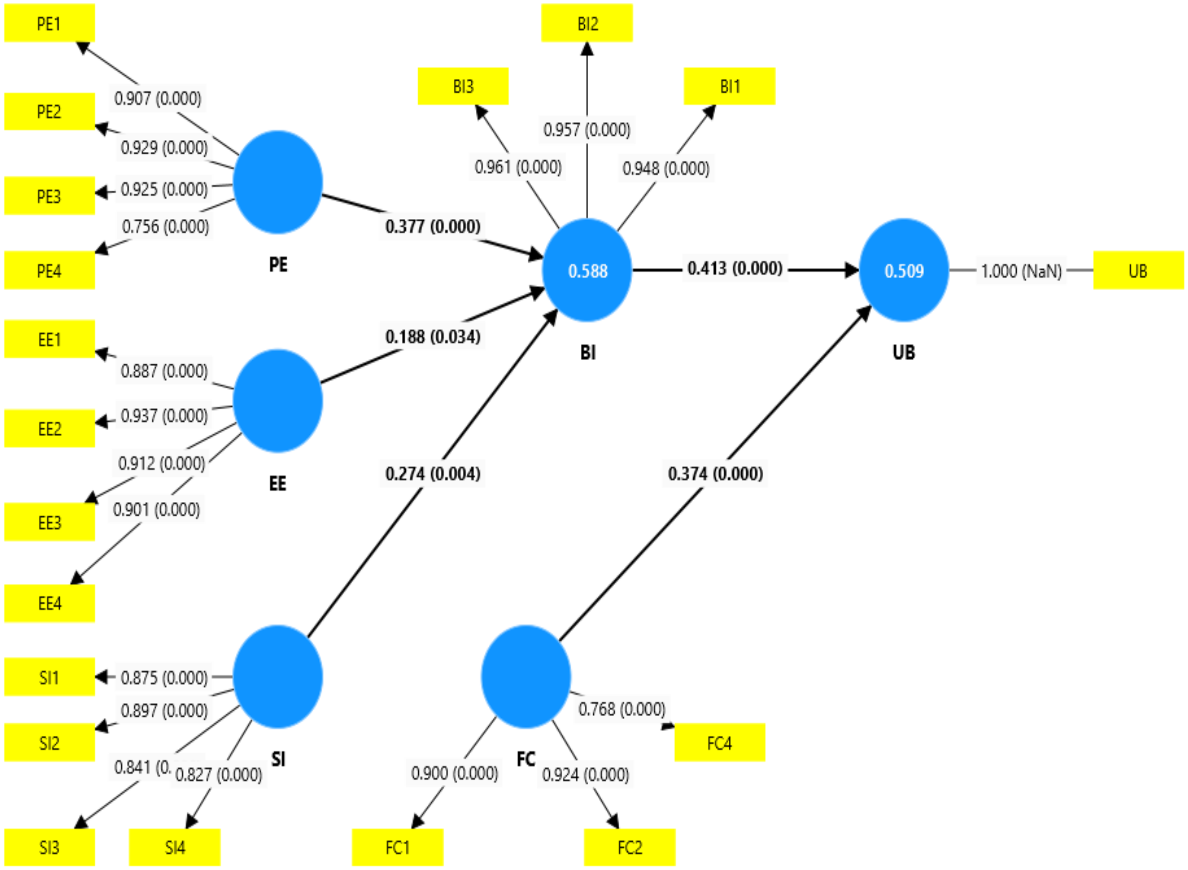
Hypothesis	Path	β	*t*-value	*p*-value	95% CI	f^2	Decision
UTAUT Relationships							
H1	PE → BI	.377	5.327	.001***	[.24, .52]	.129	Supported
H2	EE → BI	.188	2.125	.034*	[.01, .36]	.023	Supported
H3	SI → BI	.274	2.843	.004**	[.08, .46]	.065	Supported
H4	FC → UB	.374	7.375	.001***	[.28, .48]	.168	Supported
H5	BI → UB	.413	7.636	.001***	[.30, .52]	.205	Supported

Note. Significance levels are indicated as follows: $*p < .05$, $**p < .01$, $***p < .001$ (two-tailed); NS means not significant. According to Cohen (1988), effect size (f^2) is classified as small at .02, medium at .15, and large at .35.

To provide a visual schematic of these statistical relationships and path metrics, Figure 3 presents the completed structural equation model, showing the standardized path coefficients and explanatory variances achieved by the primary determinants.

Figure 3

Structural Model and Bootstrapping Results



Note. Path coefficients are displayed on the respective arrows with exact *p*-values in parentheses. All hypothesized structural paths are statistically significant at the $p < .05$ level or better (two-tailed).

4.6 Boundary Conditions: Multi-Group Analysis

To evaluate the macro-level boundary condition of institutional context, a multi-group analysis (MGA) was executed to compare Hong Kong technology practitioners against Mainland GBA specialists. Prior to MGA, the typically covers the Measurement Invariance of Composite Models (MICOM) procedure was conducted to confirm that the constructs are understood conceptually in the same way across both groups (Henseler et al., 2016), successfully establishing full measurement invariance. Compositional invariance was confirmed for all constructs, with composite correlation (*c*) values ranging from .996 to 1.000 (all $p > .05$), satisfying the threshold of $c > .95$ (Henseler et al., 2015). This confirms that any subsequent differences found are genuine contextual variations and not measurement artefacts. The subsequent MGA analysis revealed that the structural mechanisms of adoption were statistically equivalent across the regional boundary, demonstrating no significant variations in structural path coefficients between the two groups (e.g., for the BI to UB pathway, $\Delta\beta = -.051$, $p = .667$).

Consequently, the study fails to reject $H10_0$, indicating structural model stability across both jurisdictions. The precise path comparisons are outlined in Table 9.

Table 9

Multi-Group Analysis: Path Coefficient Comparison

Path	β (HKG)	β (Mainland)	$\Delta\beta$	*p*-value	Decision
Core UTAUT Relationships					
PE → BI	.405	.320	.085	.598	NS
EE → BI	.191	.168	.023	.907	NS
SI → BI	.264	.315	–.050	.804	NS
FC → UB	.258	.266	–.008	.962	NS
BI → UB	.357	.408	–.051	.667	NS

Note. β = standardized path coefficient; $\Delta\beta$ = difference in path coefficients (Hong Kong – Mainland GBA); *p*-values based on bootstrap permutations. Threshold for significance: $p < .05$ (two-tailed). Non-significant (NS) results indicate that path coefficients do not differ significantly between groups (Hair et al., 2021).

Although the structural pathways remained invariant, a subsequent series of independent-samples t tests assessing the underlying construct means revealed a highly significant cross-border divergence in overall adoption intensity. Mainland GBA professionals reported significantly higher adoption across all six constructs (see Table 10), with the divergence most pronounced in use behavior ($M = 5.24$ vs. 4.22, $t(317) = -5.97$, p

< .001, *d* = 0.67) and social influence (*d* = 0.63), and smallest in behavioral intention (*M* = 5.54 vs. 5.12, *t*(317) = −2.53, *p* = .012, *d* = 0.29). This systematic and statistically significant deviation successfully rejects the null hypothesis $H9_0$ in favor of the alternative hypothesis $H9_a$. Table 10 provides a comparative summary of these constructs mean differences between the two jurisdictions.

Table 10

Comparison of Construct Means: Hong Kong vs. Mainland GBA

Construct	Hong Kong Mean (SD)	Mainland Mean (SD)	t-value	*p*-value	Cohen's *d*
PE	4.84 (1.35)	5.35 (1.19)	-3.47	< .001	0.40
EE	4.53 (1.31)	5.16 (1.14)	-4.43	< .001	0.51
SI	4.46 (1.34)	5.24 (1.13)	-5.61	< .001	0.63
FC	3.96 (0.89)	4.38 (0.81)	-4.29	< .001	0.49
BI	5.12 (1.52)	5.54 (1.39)	-2.53	= .012	0.29
UB	4.22 (1.61)	5.24 (1.40)	-5.97	< .001	0.67

Note: Degrees of freedom *df* = 317. Significance indicates higher adoption intensity in the Mainland group. According to Cohen (1988), a Cohen's *d* value of 0.2 is considered small, 0.5 is regarded as medium, and 0.8 is classified as large.

4.7 Boundary Conditions: Professional Capacity

Regarding professional capacity boundary conditions, one-way ANOVA and independent *t*-tests established that role, education, and autonomy, significantly determine individual adoption intensity. Professional role generated significant variance, as strategic management professionals reported significantly higher BI (*M* = 5.87) than technical professionals (*M* = 5.17), *F*(3, 315) = 3.54, *p* = .015, leading to the rejection of the null hypothesis $H6_0$ in favor of

$H6_a$. Educational attainment also produced significant variation: professionals possessing advanced post-graduate degrees demonstrated higher BI (*M* = 5.70) than professionals holding diplomas (*M* = 5.07), *F*(2, 316) = 3.47, *p* = .032, rejecting the null hypothesis $H7_0$.

Professional autonomy emerged as the single most powerful differentiator within the professional context: voluntary adopters reported drastically higher BI (*M* = 5.80) than individuals operating under rigid mandatory corporate directives (*M* = 4.05), *t*(317) = 10.91, *p* < .001, rejecting the null hypothesis $H8_0$ in favor of the alternative hypothesis $H8_a$. In contrast, all traditional demographic variables have no statistically significant variances: age *F*(3, 315) = 1.68, *p* = .172; gender *t*(302) = 0.25, *p* = .806; experience *F*(2, 316) = 2.65, *p* = .072; and company size *F*(2, 316) = 1.44, *p* = .239, recording no statistical impact on technology acceptance behavior.

Table 11

Summary of Demographic Effects on GenAI Adoption Constructs

Boundary Condition	Key Result (Significant Constructs)	Theoretical Implication
Voluntariness of Use	Significant: All 6 Constructs	Suggests that Autonomy is a prerequisite for GenAI adoption.
Professional Role	Significant: All except UB	Suggests that Hierarchy of Threat Existed (Directors > Technical Staff).
Education Level	Significant: All 6 Constructs	Suggests Higher Education facilitates adoption.
Institutional Context	Significant: All except Structural Paths	Suggests Institutional Duality (Mainland intensity > Hong Kong).
Company Size	Non-Significant (Universal)	Suggests the AI Democratization Effect (Resource gap neutralized).
Age Group	Non-Significant (Universal)	Suggests Identity threat is universal across generations.
Gender	Non-Significant (Universal)	Suggests Identity threat is universal across gender.
Experience	Non-Significant (Universal)	Suggests Experience level does not predict GenAI use.

Note. $n = 319$ ($n = 304$ for gender). Significance indicates $p < .05$. All 6 Constructs refer to PE, EE, SI, FC, BI, and UB.

To synthesize these comparative findings, Table 11 contrasts the significant professional capacity variables against the non-significant traditional demographic variables. This summary visually confirms that adoption intensity in the GenAI context is dictated by professional capacity—specifically professional role, educational attainment, and professional autonomy—rather than traditional demographic variables such as age, gender, professional experience, and company size.

The non-significance of company size, *F*(2, 316) = 1.44, *p* = .239, empirically supports the AI democratization effect, suggesting that cloud-based delivery has neutralized traditional resource advantages as an adoption boundary (Costa et al., 2024).

5.0 Discussion

5.1 Triangulation and Conceptual Integration

By integrating the quantitative findings with the qualitative thematic narratives using a merging integration strategy, this study surfaces operational contradictions that challenge traditional technology acceptance assumptions (Fetters et al., 2013).

Thematic saturation was confirmed across four stratified sessions following a clear three-phase saturation pattern (Guest et al., 2006). Phase one (sessions one and two) produced six foundational codes: C1 (Adoption–Obsolescence Paradox), C3 (Governance Gap), and C4 (Market Mandate) emerged in session one; C2 (Validation Burden), C6 (Hierarchy of Threat), and C9 (Education Advantage) emerged and immediately reached redundancy in session two. Phase two (session three) produced one contextual code: C5 (Institutional Duality). Phase three (session four) produced the final two codes: C7 (Autonomy and Empowerment) and C8 (Habituated Use), both achieving immediate internal redundancy within the same session.

Inter-rater reliability was validated at κ = .895 (p < .001), classified as "almost perfect agreement" and confirming structural robustness and independence from coder bias (Landis & Koch, 1977).

5.2 Integrated Findings: Triangulation of Quantitative and Qualitative Evidence

First, PE emerged as the strongest statistical predictor of BI ($\beta = .377$, $p < .001$), yet in this professional context, PE does not merely capture utility — it captures the rational calculation by which professionals weigh immediate competitive gain against long-term career risk (Raisch & Krakowski, 2021). Consequently, this high utility perception coexists with professional anxiety, as technical professionals simultaneously recognize GenAI's functional value and fear its threat to their expert status.

This dual-edged orientation was powerfully summarized by an anchor technical professional (P-HK-TECH-04):

> *"It is a double-edged sword. It creates code instantly, which is great for meeting my project deadlines. But it scares me. If the AI is this good today, where will I be in five years? If I rely on it too much, I will forget the basics. I worry that I am slowly losing the core skills that made me an expert in the first place."*

The strong PE path ($\beta = .377$) thus coexists with the adoption–obsolescence paradox (C1), indicating that high utility frequently generates professional anxiety rather than straightforward satisfaction (Raisch & Krakowski, 2021), consistent with the elevated dispersion in BI scores (*SD* = 1.45).

Second, the validation burden and governance gap: the weakest EE path (β = .188) is explained by a validation burden (C2: Validation Burden). While the survey indicated high interface accessibility (*M* = 4.88), the qualitative data reveals that natural language simplicity masks the cognitive effort required to audit opaque, hallucination-prone outputs. Human labor shifts from original code authorship toward auditing and risk management, reducing engineers to "*code janitor[s] cleaning up the AI's mess*" (P-HK-TECH-05), where "*the AI lies confidently*" (P-HK-TECH-12), confirming that sustained validation effort heavily offsets initial ease of use (Maia et al., 2025).

Concurrently, social influence (β = .274) operates not as peer support, but as a coercive market mandate (C4: Market Mandate): "*For us, it is not a choice; it is coercive pressure. Clients in Shenzhen specifically ask, 'Is this AI-optimized?'*" (P-HK-DIR-10; Faulconbridge et al., 2025). Facilitating conditions recorded the lowest construct mean (*M* = 4.45, *SD* = 0.86), with qualitative evidence confirming a critical organizational governance gap (C3: Governance Gap) in data privacy and intellectual property frameworks rather than hardware deficiency (Ye et al., 2024): "*It feels like the Wild West... There is no clear policy from the top on what happens if an engineer accidentally leaks IP into ChatGPT.*" (P-HK-DIR-04).

Third, institutional duality: the multi-group analysis confirmed structural path invariance across jurisdictions (Henseler et al., 2016), yet macro-level institutional duality (C5: Institutional Duality) heavily dictates adoption execution intensity (Ho, 2025; Lin et al., 2024). In the Mainland GBA, state-mobilized policies act as an institutional accelerator. Guided by active state policies aimed at national AI sovereignty, technology deployment is framed as an institutional imperative and a collective "righteous cause" driven by national development goals. This mobilization logic removes hesitation, cultivates a high tolerance for algorithmic experimentation, and rewards deployment speed over caution, pulling Mainland professionals into high UB ($M = 5.24$) despite an internal corporate vacuum: *"In Hong Kong, they ask about liability first. Here, they ask 'how advanced is your AI?' first... We frame AI adoption not just as a tool, but as a righteous cause."* (P-ML-DIR-01).

Conversely, the Hong Kong jurisdiction utilizes a regulatory framework that prioritizes risk mitigation and strict compliance. Governed by the Personal Data Privacy Ordinance (PDPO), technology deployment is heavily constrained by data governance boundaries and potential liabilities. Governance ambiguity triggers intense compliance anxiety, functioning as a severe regulatory brake where practitioners deliberately suppress UB out of fear of personal or corporate liability: *"The regulatory caution in Hong Kong acts as a massive brake. We are terrified of the PDPO... We cannot risk a compliance breach just to code faster."* (P-HK-DIR-08).

Notably, mature Mainland practitioners described GenAI usage that had become reflexive rather than consciously planned (C8: Habituated Use)—"*the friction is gone... it is automatic now*" (P-ML-TECH-01)—suggesting the BI–UB structural path ($\beta = .413$) may be partially bypassed as deliberate planning dissolves into embedded professional practice (Limayem et al., 2007). Critically, this jurisdictional divergence implies that the SI path coefficient ($\beta = .274$) masks two structurally distinct mechanisms—coercive compliance in Hong Kong and national-identity mobilization in the Mainland—a boundary condition that future split-context measurement designs should address (Venkatesh & Zhang, 2010).

Fourth, professional capacity: adoption intensity is fundamentally determined by professional capacity. A distinct hierarchy of threat (C6: Hierarchy of Threat) exists: directors view GenAI as a strategy to "*scale our output without scaling our headcount*" (P-ML-DIR-07), whereas technical professionals experience the same utility as direct substitution—the "Skill Trap" (P-HK-TECH-04; Raisch & Krakowski, 2021; Schmitt et al., 2024). Advanced educational attainment (C9: Education Advantage) reduces the validation burden by providing the mathematical foundation to audit probabilistic outputs (Stibe & Dinh, 2024): lower-educated practitioners "*copy-paste and pray it works*" (P-HK-TECH-09), while post-graduates confidently audit the algorithm—"*Because I know how the model works mathematically, I am not afraid of it.*" (P-HK-TECH-11). Professional autonomy (C7: Autonomy and Empowerment) emerged as the single strongest differentiator, $t(317) = 10.91$, $p < .001$, with voluntary adopters ($M = 5.80$) reporting drastically higher BI than mandatory users ($M = 4.05$), consistent with Self-Determination Theory (Ryan & Deci, 2000): "*When I choose to use the tool, I feel empowered... But when my boss mandates it, it becomes compliance, not innovation.*" (P-ML-TECH-04).

Fifth, non-significance of traditional demographic variables: age, gender, and experience are statistically non-significant in technology acceptance outcomes, as GenAI threatens the coding task itself rather than any specific demographic group—rendering the substitutive threat universal across the workforce (Amankwah-Amoah & Appiah, 2025). The non-significance of company size empirically supports the AI democratization effect (Costa et al., 2024): cloud-based delivery neutralizes traditional resource advantages, confirming substitutive pressure operates independently of company size.

5.3 Theoretical Implications

The findings carry five theoretical implications for the IS literature on agentic technology adoption. First, the study supports the continued applicability of the UTAUT framework within the system integration context, with professionals continuing to prioritize rational utility as a primary factor when evaluating new systems (Blut et al., 2022). Second, the data provides empirical context for the adoption–obsolescence paradox (Raisch & Krakowski, 2021): the UTAUT constructs do not merely predict intention to use—they capture the psychological friction professionals experience when adoption threatens their core technical skills. Third, for cloud-delivered AI, governance readiness is a critical component of FC, with organizational policies regarding data privacy and legal liability acting as the primary facilitating conditions, rather than physical infrastructure (Venkatesh et al., 2003; Ye et al., 2024). Fourth, institutional duality (Ho, 2025) can shape adoption intensity without altering the underlying structural model (Venkatesh & Zhang, 2010). Fifth, professional capacity variables serve as more salient boundary conditions than traditional demographic factors, with age, gender, experience, and company size yielding non-significant variances, empirically supporting the AI democratization effect (Costa et al., 2024).

5.4 Practical Implications

For organizational leaders in the system integration sector, the findings suggest five actionable considerations. First, performance metrics should reward the complexity of problems solved rather than volume of output, demonstrating that GenAI supports professional growth rather than cost reduction. Second, structured reward systems should recognize professionals who apply GenAI to complex problems, thereby validating expert craftsmanship. Third, a human-in-the-loop policy should be formalized, granting professionals authority to reject or modify AI outputs, transforming verification into empowered oversight rather than compliance. Fourth, training should be differentiated by role and educational attainment: technical staff should focus on auditing AI outputs to build self-efficacy, while leadership training should address algorithmic limitations for realistic project expectations. Fifth, GBA firms should adopt region-specific strategies: Mainland leaders can leverage institutional momentum through visible performance goals, while Hong Kong management should prioritize data governance and liability protections before accelerating adoption.

5.5 Research Limitations and Future Research

Several limitations qualify these findings. First, the cross-sectional design limits the study's ability to determine whether the observed adoption anxiety is a permanent professional feature or a transitional phase and precludes causal conclusions regarding the BI-UB pathway over time (Limayem et al., 2007). Second, use behavior was measured primarily through frequency and intensity rather than deep structural usage, which may not differentiate routine compliance from innovative engagement; future research should employ multi-item behavioral measures to strengthen construct validity. Third, the sample was confined to system integration professionals within the GBA, limiting generalizability to other professions and to regions with different regulatory frameworks, such as Western countries (Venkatesh & Zhang, 2010). Furthermore, the purposive sampling method may have overrepresented individuals with strong opinions on the technology while underrepresenting the passive majority. Fourth, the reliance on self-reported data introduces potential social desirability bias, as professionals may have artificially inflated their reported adoption scores to project a technologically adept identity (Venkatesh et al., 2003). Finally, while the study identified a governance gap through individual perceptions of FC, it did not explicitly model actual organizational policies, client contracts, or government regulations as independent variables; future research would benefit from measuring the actual top-down market mandates and legal liability frameworks imposed on firms to directly quantify how these structures constrain or accelerate adoption behavior beyond individual perception.

Five directions are proposed for future research. First, longitudinal designs are needed to monitor how the adoption–obsolescence paradox develops over time. Future studies should measure professionals at 6, 12, and 18-month intervals to determine whether the observed adoption anxiety is a permanent professional feature or a transitional phase as GenAI matures. Second, experimental designs could isolate the specific triggers of adoption anxiety and establish causal evidence for the role of professional autonomy. Presenting GenAI as a subordinate assistant versus an autonomous agent to separate participant groups would allow researchers to determine the optimal level of agentic autonomy that maximizes adoption without triggering skill-substitution threat. Third, future scholarship should examine whether increasing the transparency of GenAI outputs through explainable AI (XAI) reduces the educational prerequisites for adoption, potentially allowing diploma-level professionals to adopt the technology with the same confidence as their postgraduate peers (Stibe & Dinh, 2024). Fourth, replication across other knowledge-intensive professions—such as legal, medical, and financial services—would test the boundary conditions of the adoption–obsolescence paradox beyond the system integration sector; furthermore, comparative studies in Western countries would isolate the effects of institutional duality by contrasting state-mobilized AI policy against market-driven contexts. Fifth, researchers should validate the AI democratization effect by testing the model across a wider range of organizational sizes as GenAI evolves from individual productivity tools to enterprise-wide architectural systems, determining whether the non-significance of company size persists beyond the current study's context (Costa et al., 2024).

6.0 Conclusion

The study addressed the four research questions outlined in Section 1.3 through mixed-methods research of GenAI adoption among system integration professionals in the GBA.

The study results suggest that the core UTAUT mechanism remains applicable within this high-stakes professional context. PE, EE, and SI emerged as significant predictors of BI, while FC and BI jointly predicted UB. However, the data indicates that this utility-driven adoption coexists with professional anxiety, illustrating an adoption-obsolescence paradox wherein the technology simultaneously enhances operational efficiency and threatens human expertise (Raisch & Krakowski, 2021).

The study results suggest that adoption intensity is more strongly associated with professional capacity, specifically professional role, educational attainment, and autonomy, than with traditional demographic variables such as age, gender, experience, and company size. The statistical non-significance of these demographic variables suggests that the substitutive pressure of GenAI acts as a universal professional experience, neutralized primarily by individual cognitive resources and structural empowerment.

Furthermore, the cross-jurisdictional analysis indicates that institutional duality significantly shapes adoption intensity, even as the underlying cognitive mechanism remains largely invariant across regions. The proactive, state-mobilized policy environment in the Mainland GBA appears to accelerate adoption behavior, whereas the regulatory caution prevalent in Hong Kong acts as a substantial inhibitor.

To foster sustainable technology integration, the study suggests that organizational leaders should address the existing governance gap by implementing transparent data policies and prioritizing frameworks that embed human oversight. By recognizing and mitigating the psychological friction inherent in GenAI adoption, organizations may transform the technology from a perceived career threat into a secure instrument of empowered professional practice.

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