

## Article

# Generative AI Adoption in Local Government: A PLS-SEM and fsQCA Study of Vietnamese Civil Servants

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## Abstract

Generative artificial intelligence (GenAI) is widely considered to hold transformative potential for public administration, but its adoption in local governments remains uneven, weakly institutionalized, and shaped by informal employee experimentation. This study advances the literature by examining GenAI adoption during a rare moment of institutional restructuring in Vietnam, where the 2025 administrative reform abolished the district tier and shifted responsibilities to ward- and commune-level government. To address the unique dynamic of GenAI adoption, this research extended the Unified Theory of Acceptance and Use of Technology (UTAUT) by integrating trust in technology, perceived risk, technological awareness, and perceived organizational support. Survey data were collected from 302 civil servants across eight post-merger ward- and commune-level administrative units in a transitioning Vietnamese province. The study employs a dual-methodological approach, integrating Partial Least Squares Structural Equation Modeling (PLS-SEM) with fuzzy-set Qualitative Comparative Analysis (fsQCA) to evaluate both net effects of individual variables and the underlying causal complexity. The PLS-SEM results show that performance expectancy, social influence, technological awareness, and perceived risk are positively associated with GenAI adoption intention, while effort expectancy and trust in technology operate indirectly through performance expectancy rather than exerting a direct effect. This suggests that, in the context of local government reform, trust matters primarily when it strengthens employees' belief that GenAI can improve work performance. Perceived organizational support attenuates the positive relationship between perceived risk and adoption intention, suggesting a buffering role in reducing risk-driven experimentation under institutional uncertainty toward more structured use. The fsQCA findings reveal causal asymmetry and equifinality: adoption intention emerges through multiple pathways anchored in perceived usefulness, social influence, and facilitating conditions, whereas non-adoption is associated with low awareness and weak organizational support. The study contributes to public administration, digital governance and technology acceptance research by showing how GenAI adoption is shaped not only by individual perceptions, but also by institutional change.



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**Keywords:** generative artificial intelligence; local government; UTAUT; PLS-SEM; fsQCA; Vietnam; relevance anxiety; digital transformation

## 1. Introduction

Digital advancements form the core of contemporary public sector modernization, profoundly altering how governments organize internal operations, execute public services, and interact with the public (T. T. Nguyen et al., 2020). Among these technologies, generative artificial intelligence (GenAI) has recently attracted considerable attention because of its capacity to produce text, summarize information, support decision-making, assist service design, and automate routine administrative tasks (Bright et al., 2024; Chun & Noveck, 2025; Ababneh et al., 2020; Carrasco et al., 2023; Budai et al., 2023).

Unlike conventional public-sector information systems, which are usually designed around predefined procedures and stable organizational workflows, GenAI is conversational, probabilistic, and highly adaptable. These characteristics make it potentially useful for public organizations facing heavy workloads and increasing pressure to improve administrative responsiveness. At the same time, they introduce new concerns related to accuracy, accountability, data security, professional judgment, and the reliability of AI-generated outputs (Mergel et al., 2023; van Noordt & Misuraca, 2022).

The problem is particularly acute at the local-government level. Local governments are often the closest administrative interface between the state and citizens, and they are responsible for translating national digital-transformation agendas into everyday service delivery. However, they frequently operate with limited financial resources, uneven technical infrastructure, fragmented datasets, and insufficient specialized training. These constraints are especially visible in emerging economies, where digital-government ambitions often advance faster than local administrative capacity (Prachumrasee et al., 2025; Setthasuravich et al., 2024). As a result, GenAI adoption in local government may not occur through formal, organization-wide implementation. Instead, it may emerge through informal, uneven, and individually initiated experimentation by public employees (Nguyen Duy et al., 2026). This creates a governance dilemma: GenAI may help local civil servants cope with growing administrative demands, but its use may also remain weakly institutionalized, inconsistently governed, and insufficiently aligned with public-sector accountability requirements.

Beyond resource and infrastructure limitations, GenAI adoption in local government is also sharpened by organizational inertia and the culture of resistance to change. Public-sector organizations are often embedded in hierarchical authority structures, bureaucratic cultures, and rule-bound procedures that can inhibit the adoption of new knowledge practices and generate inertia (Ashok et al., 2021). In the case of GenAI, this inertia may be intensified because the technology challenges established administrative routines, professional judgment, and accountability arrangements. As Madan and Ashok (2023) suggest, AI adoption in public administration requires attention not only to technological capabilities but also to the organizational and contextual conditions through which AI is implemented and diffused. Therefore, informal and uneven GenAI experimentation among local civil servants should be understood not merely as a capacity gap, but as a manifestation of broader organizational change dynamics in the public sector.

This problem is particularly salient in Global South contexts, where transformative technologies are often promoted as instruments for accelerating public-sector modernization, improving service delivery and closing administrative capacity gaps. However, the adoption of such technologies does not occur on a level institutional playing field. Calzada and Eizaguirre (2025) argue that technological capabilities alone cannot bridge socio-political gaps and that innovation should be mission-oriented, context-aware, and equity-driven. In Global South settings, AI may support digital justice, service provision, and employment, but it may also reinforce dependency and inequality where infrastructures and governance remain weak. This perspective is especially relevant to local government, where national digital transformation ambitions are translated into frontline

administrative practices under conditions of limited resources, uneven technical capacity and changing institutional mandates.

Against this broader Global South backdrop, Vietnam provides a highly relevant empirical setting for examining this problem. In 2025, the country implemented one of the most significant reforms of its sub-national administrative system in recent decades. Following Resolution No. 60-NQ/TW, Decision No. 759/QĐ-TTg, and Resolution No. 202/2025/QH15, Vietnam moved from a three-tier administrative structure, consisting of province, district, and commune, to a two-tier model, consisting of province and commune, with effect from 1 July 2025 ([Communist Party of Vietnam, 2025](#); [Prime Minister of Vietnam, 2025](#); [National Assembly of Vietnam, 2025](#)). This reform reduced the number of provincial-level units from 63 to 34, abolished the district tier, and consolidated approximately 10,000 commune-level units into 3193 wards, communes, and special zones. The former Binh Duong Province, which provides the empirical setting of this study, was merged into Ho Chi Minh City as part of this restructuring.

This institutional restructuring has directly altered the responsibilities of commune-level public employees. A substantial share of administrative functions previously handled by district authorities has been redistributed, with many responsibilities moving downward to ward and commune-level units. These local offices now manage a broader portfolio of services, including education, primary healthcare, land administration, construction permitting, environmental management, and agricultural support. At the same time, they must adjust to new institutional routines, reorganized personnel structures, and expanded administrative workloads. Between July and November 2025, the newly restructured localities processed 21.8 million administrative records, of which 13.4 million were submitted online at the commune level ([Communist Party of Vietnam, 2025](#); [Government of Vietnam, 2025](#)). This sharp increase in digital and administrative workload creates strong incentives for local civil servants to seek tools that can improve efficiency and reduce task burdens.

This reform agenda also intersects with Vietnam's wider digital-transformation and AI strategies. The National Digital Transformation Program, the National Strategy on Artificial Intelligence Development to 2030 ([Prime Minister of Vietnam, 2020](#); [Government of Vietnam, 2021](#)), and Resolution No. 57-NQ/TW on science, technology, innovation, and digital transformation all emphasize the modernization of public administration through digital technologies ([Communist Party of Vietnam, 2024](#)). However, dedicated guidance for GenAI use at the commune level remains limited. Training opportunities are unevenly distributed, institutional rules remain underdeveloped, and the technical infrastructure available to local offices varies across regions United Nations Development Programme ([UNDP, 2025](#)). In this context, civil servants may encounter and use widely available GenAI tools, such as ChatGPT, Claude, Microsoft Copilot, or Gemini, without formal organizational support or clear accountability frameworks. GenAI adoption thus becomes not only a matter of technological acceptance, but also a question of local administrative capacity, institutional readiness, and public-sector risk governance.

The central problem addressed in this study is therefore the structural mismatch faced by local civil servants in post-reform Vietnam. On one side, they experience expanded workloads, stronger pressure to digitize public services, and rising expectations for administrative efficiency. On the other side, they face limited formal infrastructure, scarce role-specific training, ambiguous rules for AI-generated outputs, and unresolved concerns about privacy, hallucination, bias, and professional displacement. This creates a dual-risk situation: using GenAI may expose employees to operational, ethical, and accountability risks, but non-use may also appear risky when employees perceive it as a threat to their professional competence, legitimacy or future relevance. We refer to this latter concern as relevance anxiety. In this study, relevance anxiety denotes employees' concern that

failing to engage with GenAI may reduce their professional value in a rapidly digitizing administrative environment. Under these conditions, GenAI adoption may be driven not only by perceived usefulness and peer encouragement, but also by anxiety about remaining professionally relevant in a rapidly changing administrative environment (Nguyen Duy et al., 2026). Such adoption may occur even when employees are aware of risks, precisely because non-use may appear more professionally risky than experimenting with it.

Although research on AI in government has grown rapidly, much of the literature remains focused on macro-level issues, such as ethical principles, regulatory frameworks, data governance, and national AI strategies. Less is known about how individual public employees, especially those working in local-government units in emerging economies, form intentions to adopt or resist GenAI (Sun & Medaglia, 2019). Existing technology-adoption studies have often relied on variance-based models such as the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). While UTAUT is useful for explaining the adoption of stable and organization-sanctioned technologies, GenAI presents a more complex case. Its low entry barriers allow employees to adopt it outside formal organizational channels. Its probabilistic outputs generate uncertainty about trust and accountability. Its association with automation and job displacement may transform perceived risk from a deterrent into a motivational pressure. These features suggest that GenAI adoption in local government may not follow a simple linear logic.

Building on these premises, this study contends that fully understanding GenAI adoption necessitates both net-effect and configurational analytical approaches. Specifically, Partial Least Squares Structural Equation Modeling (PLS-SEM) isolates the individual, technological, and organizational variables driving adoption intention, whereas fuzzy-set Qualitative Comparative Analysis (fsQCA) uncovers the complex configurations of conditions driving both adoption and non-adoption. This dual approach is appropriate because adoption and resistance may be asymmetric: the conditions that encourage GenAI adoption may not simply be the opposite of those that produce non-adoption.

Given this context, the current research seeks to answer two primary questions:

**RQ1.** *Which individual, technological, and organizational factors influence local government employees' intention to adopt GenAI?*

**RQ2.** *What combinations of individual, technological, and organizational conditions lead to GenAI adoption intention and non-adoption intention?*

By answering these questions, the study contributes to the literature on AI adoption, local digital governance, and public-sector technology acceptance. It clarifies how GenAI adoption emerges under conditions of institutional restructuring, administrative workload pressure, uneven organizational support, and relevance anxiety. The study also advances adoption theory by showing why established constructs such as perceived risk, trust, facilitating conditions, and organizational support may operate differently when public employees encounter autonomous and informally accessible AI tools. In particular, it introduces relevance anxiety as a theoretical lens for explaining why perceived risk may coexist with stronger adoption intention when employees view non-use as a threat to professional relevance. Finally, by situating the analysis in Vietnam's 2025 local-government restructuring, the study offers empirical insight into how local public organizations in emerging economies respond to simultaneous technological and institutional transformations.

The remainder of the study is organized as follows. Section 2 presents the theoretical background and develops the hypotheses. Section 3 describes the research methodology. Section 4 presents the analysis and results. Section 5 discusses the main findings, contributions, and limitations. Section 6 concludes the study.

## 2. Theoretical Background and Hypothesis Development

### 2.1. UTAUT and GenAI Adoption in the Public Sector

The Unified Theory of Acceptance and Use of Technology (UTAUT) provides a suitable baseline framework for this research because it offers a theoretically established and empirically robust explanation of behavioral intention and actual technology utilization (Venkatesh et al., 2003). Compared with earlier models such as TAM and TRA, UTAUT offers higher explanatory capacity, explaining as much as 69% of variance in usage intention, whereas earlier frameworks account for roughly 40% (Kijasanayotin et al., 2009; Venkatesh et al., 2003, 2012), making UTAUT particularly valuable for investigating GenAI adoption, in which employees' use is likely shaped by performance expectations, social influence, and organizational support within a socio-technical environment (Gao et al., 2026). Because of its flexibility, scholars frequently extend this model within public-sector environments to investigate employee acceptance of various information systems and digital platforms (Al Sayegh et al., 2023). This study follows that logic by using UTAUT as a foundational model rather than as a complete explanation model for examining how technology acceptance mechanisms shift when the focal technology is autonomous, generative, probabilistic, informally accessible, and requires users to rely on algorithmic reasoning processes that are only partially transparent.

This distinction is important because GenAI differs from the stable and organization-sanctioned systems for which UTAUT has often been used. The accessibility of commercial GenAI like ChatGPT and Microsoft Copilot enables public employees to adopt these technologies independently of formal organizational approval or infrastructure (van Noordt & Tangi, 2023; Tangi et al., 2025; Bick et al., 2024; Desouza, 2021). These features directly challenge several key assumptions embedded in UTAUT, particularly those related to facilitating conditions, managerial control, and stable system artifacts. Thus, this study used UTAUT as a baseline framework, showing how established acceptance mechanisms shift when AI adoption is autonomous, informal, and shaped by trust, risk, awareness, and organizational support.

### 2.2. Extending UTAUT: Trust, Perceived Risk, Organizational Support, and Awareness

To account for these dynamics, this study extends the UTAUT framework by integrating perceived organizational support theory (Eisenberger et al., 1986), trust in technology (Lankton et al., 2015), perceived risk (Featherman & Pavlou, 2003), and technological awareness (Parasuraman & Colby, 2015). These constructs capture the institutional safety net provided by organizations, employees' confidence in the reliability and integrity of GenAI systems, the uncertainty associated with autonomous GenAI outputs, and the cognitive readiness that shapes technology engagement, respectively. Together, they reflect the distinctive institutional context of public-sector organizations in emerging economies, in which formal infrastructure is often limited, accountability pressures are high, and individual cognitive and motivational factors play a central role in shaping technology behavior.

Recent scholarship on automation anxiety and AI-related professional displacement further suggests that perceived risk should not be assumed to operate uniformly as an inhibitor in the GenAI context (Brougham & Haar, 2018; Frey & Osborne, 2017; Vrontis et al., 2022). As Ashok (2024) notes, automation can generate efficiencies by reducing repetitive tasks and cost drivers, while also creating tensions around job security, skill development, and protecting citizens from algorithmic harm. In this study, these tensions are understood as concrete sources of perceived risk: employees may view GenAI not only as a tool that improves efficiency, but also as a technology that could alter role expectations, require new competencies, and expose organizations and citizens to unintended algorithmic consequences. When employees perceive that their professional standing or future relevance

depends on engagement with new technologies, risk perceptions may motivate rather than deter adoption, a phenomenon that we hereafter refer to as relevance anxiety. The present study draws on this emerging literature to formulate competing predictions about the role of perceived risk and treats the resulting coefficient as a theoretically meaningful empirical question rather than a settled one.

## 2.3. Hypothesis Development

### 2.3.1. Performance Expectancy

Performance expectancy denotes the degree to which individuals believe that utilizing technology (here, GenAI) will improve their job outcomes (Venkatesh et al., 2003). In public-sector contexts, government employees are often burdened with high volumes of routine administrative, drafting, and analytical tasks. Prior research identifies performance expectancy as a primary driver of adoption for AI tools (Jain et al., 2022), e-tax filing systems (Alibraheem et al., 2019), and public-sector AI (Alkaabi et al., 2026; Mercuri et al., 2026). When employees perceive GenAI as improving efficiency, analytical quality, or service delivery, their intention to use the technology increases (Brynjolfsson et al., 2023). Mercuri et al. (2026) conducted a study of 1060 public-sector employees from Italy and Spain to identify their intention to use GenAI. The study finds that perceived usefulness/performance expectancy consistently emerges as a stronger predictor of adoption intention than ease of use, aligning with previous research using TAM and UTAUT models. More recently, the findings of Salah et al. (2026) provide empirical support for the role of performance expectancy in GenAI adoption intention, showing that perceived usefulness and observable performance benefits significantly enhance users' continued intention to use GenAI. Therefore:

**H1.** *Performance expectancy positively affects intention to adopt GenAI.*

### 2.3.2. Effort Expectancy

Effort expectancy concerns perceived ease of use (Venkatesh et al., 2003). The existing literature yields contradictory results regarding the influence of effort expectancy on public-sector AI adoption. Some studies highlight ease of use as a primary driver, while others report non-significant effects in bureaucratic and resource-constrained contexts (Alibraheem et al., 2019). For government employees facing high bureaucratic workloads, the intuitive nature of GenAI, and in particular, its natural-language interaction, may reduce technical barriers to entry, and foster a greater willingness to engage with the technology (Alkaabi et al., 2026). Supporting this argument, Mercuri et al. (2026) found that perceived ease of use significantly and positively influences public employees' intention to adopt GenAI in Italy and Spain, indicating that public employees are more likely to embrace GenAI when they perceive it as easy to learn, understand, and use. Therefore:

**H2.** *Effort expectancy positively affects government employees' intention to adopt GenAI.*

In addition to its direct effects, effort expectancy is theorized to influence performance expectancy. When a technology is perceived as easy to use, users expend less cognitive effort on system interaction and can focus more effectively on task execution, thereby increasing perceived usefulness (Davis, 1989; Venkatesh et al., 2003). Recent studies in the GenAI context provide strong support for this relationship. Hernández-Tamurejo et al. (2026) found that perceived ease of use significantly increases the perceived usefulness of GenAI, while Smutny and Sudzina (2026) report a strong positive effect of effort expectancy on performance expectancy in the use of ChatGPT. In addition, Alkaabi et al. (2026) showed that perceived ease of use enhances perceived usefulness among public-sector employees

adopting AI technologies, suggesting that employees are more likely to recognize the performance benefits of AI when it is easy to learn and operate. As a result, they are more likely to perceive the tool as a practical enhancer of job performance. Therefore:

**H3.** *Effort expectancy positively affects government employees' performance expectancy in the adoption of GenAI.*

### 2.3.3. Social Influence

Social influence captures the employee's perception that key individuals, including colleagues and management, explicitly endorse the utilization of targeted technological tools (Venkatesh et al., 2003). In hierarchical bureaucracies, leadership signals and peer behaviors strongly shape employees' adoption decisions. Empirical evidence from emerging economies supports this view: Jain et al. (2022) found social influence to be the strongest predictor of AI adoption in Indian social-development organizations. Social influence also plays a critical role in shaping employees' attitudes toward AI use (Distor et al., 2021). Similarly, Rodriguez Müller et al. (2025) reported that institutional pressure and managerial perceptions play an important role in AI adoption within local government, highlighting the influence of organizational and social environments on technology acceptance. More recently, Blaique et al. (2026) presented that social influence significantly enhances government employees' optimism and innovativeness toward ChatGPT adoption, highlighting the importance of managerial support and peer encouragement in fostering positive perceptions of GenAI. Therefore:

**H4.** *Social influence positively affects government employees' intention to adopt GenAI.*

Beyond its direct impact, social influence may also shape performance expectancy. Exposure to positive experiences and endorsements from peers or supervisors can lead employees to internalize beliefs about the usefulness of GenAI systems (Venkatesh & Davis, 2000; Wu et al., 2025). Supporting this view, Blaique et al. (2026) found that social influence enhanced government employees' optimism toward ChatGPT adoption. Therefore, if department heads or colleagues demonstrate how GenAI improves their work processes, employees are more likely to perceive performance benefits. Therefore:

**H5.** *Social influence positively affects government employees' performance expectancy in the adoption of GenAI.*

### 2.3.4. Facilitating Conditions

Facilitating conditions reflect the perceived readiness of organizational and technical support structures to enable successful technology integration (Venkatesh et al., 2003). Evidence from public sectors in emerging economies remains inconclusive. While some studies report significant effects (Rana et al., 2024; Alibraheem et al., 2019), others find non-significant effects in resource-constrained settings such as cloud-computing adoption in Indonesian local governments (Salam & Ali, 2020). Given that GenAI deployment requires secure networks, data-governance frameworks, and targeted training, facilitating conditions are highly instrumental in driving technological adoption intention. Consistent with this view, Nguyen Duy et al. (2026) found that the absence of implementation plans, financial resources, system integration, and structured training prevented GenAI from progressing beyond informal and voluntary use in Vietnamese local government. The authors further argued that these institutional capacity constraints limited the formal institutionalization of GenAI and placed the burden of adoption on individual employees.

Thus, it is suggested that employees are more likely to embrace emerging technologies when adequate resources, assistance, and infrastructure are available. Therefore:

**H6.** *Facilitating conditions positively affect government employees' intention to adopt GenAI.*

### 2.3.5. Technological Awareness

Technological awareness encompasses understanding of a technology's capabilities, functions, and benefits, and is closely related to the cognitive dimension of technology readiness (Parasuraman & Colby, 2015). The recent empirical literature highlights awareness as a consistent predictor of technology adoption intention across domains (Masa'deh et al., 2023; Shahzad et al., 2024). In the complex context of GenAI, higher levels of awareness reduce uncertainty and cognitive ambiguity in risk-averse public-sector environments. Employees who are more knowledgeable about GenAI applications are better positioned to integrate these tools into daily administrative workflows. Supporting this view, Tangi et al. (2025) found that public managers with higher levels of GenAI awareness were more likely to use the technology, while insufficient knowledge and awareness were among the most significant barriers to adoption. Therefore:

**H7.** *Technological awareness positively affects government employees' intention to adopt GenAI.*

### 2.3.6. Perceived Risk

Perceived risk encompasses concerns about privacy, performance errors, job displacement, and algorithmic opacity. These concerns are amplified in public administration due to accountability demands (Khaksar et al., 2021) and to GenAI-specific risks such as data-security vulnerabilities (Mahusin et al., 2024; Yigitcanlar et al., 2024), algorithmic bias, and the inherent lack of transparency or "hallucinations" in outputs (Sobrino-García, 2021; Mercuri et al., 2026). Recent evidence from the public sector suggests that concerns regarding output reliability, transparency, fairness and accountability reduce employee confidence in GenAI and can create hesitation toward its implementation (Mercuri et al., 2026). When government employees perceive that using GenAI could threaten their professional standing or lead to severe policy errors, their willingness to integrate the technology may diminish, consistent with prior technology-adoption studies (Majrashi, 2024).

However, a competing perspective grounded in the automation-anxiety and relevance-anxiety literatures suggests that risk perceptions related to professional displacement may instead motivate engagement with GenAI, as employees seek to maintain their professional relevance in an environment of rapid technological change (Brougham & Haar, 2018; Frey & Osborne, 2017; Vrontis et al., 2022). The present study follows the dominant deterrence-based framing in formulating its hypothesis and treats any opposite-signed result as an empirically meaningful basis for theoretical refinement. Therefore:

**H8.** *Perceived risk negatively affects government employees' intention to adopt GenAI.*

### 2.3.7. Perceived Organizational Support

Perceived organizational support represents the employee's belief that organizational leadership provides the requisite structural resources, training, and encouragement for technology adoption (Eisenberger et al., 1986; M. Nguyen et al., 2023). Within the public sector, strong organizational support from top management is essential to overcome bureaucratic inertia. Leadership's ability to allocate resources, provide targeted GenAI training, and foster a positive environment for learning and experimentation significantly drives innovation adoption (Jeyaraj et al., 2023; Neumann et al., 2024; Maragno et al., 2023). Moreover, Cho et al. (2025) discovered that organizational support significantly

increased AI chatbot adoption among Korean government employees and strengthened the translation of trust into actual use. Similarly, Omonov and Ahn (2025) demonstrated that organizational readiness, encompassing institutional resources, digital capabilities, and support mechanisms, positively influenced public employees' intention to adopt AI chatbots in public administration. When public agencies proactively build technological readiness and demonstrate a clear, top-down commitment to integrating GenAI, employees feel empowered and motivated to engage with the technology. Therefore:

**H9.** *Perceived organizational support positively affects government employees' intention to adopt GenAI.*

Beyond its direct impact, organizational support is expected to act as a psychological buffer against workplace stressors and uncertainties (Eisenberger et al., 1986). Previous studies indicate that robust institutional backing effectively mitigates the adverse impact of risk perception on technological integration (Featherman & Pavlou, 2003). This role is particularly important in public sector GenAI adoption, where concerns regarding data security, regulatory ambiguity, and accountability often discourage use. Nguyen Duy et al. (2026) presented that the absence of organizational guidance, training, and accountability mechanisms heightened employees' perception of risk, whereas organizational support facilitated GenAI adoption. When public-sector leaders offer clear operational guidelines, comprehensive training, and a non-punitive environment for early experimentation, employee anxiety is substantially reduced (Chen & Zhou, 2022). Consistent with this view, a supportive organizational environment has been found to enhance employees' willingness to adopt and use AI technology (Cho et al., 2025). Therefore:

**H10.** *Perceived organizational support moderates the relationship between perceived risk and the intention to adopt GenAI, such that the negative effect of perceived risk on intention is weaker when perceived organizational support is high.*

### 2.3.8. Trust in Technology

Trust in technology refers to the user's belief in the reliability, accuracy, and security of a system (Lankton et al., 2015). Prior studies show that trust facilitates the acceptance of conversational and autonomous AI systems (Gillath et al., 2021; Calhoun et al., 2019). In workplace contexts, trust has been identified as a critical determinant of AI adoption. For example, Cho et al. (2025) found that government employees who exhibited higher levels of trust in AI chatbot responses were significantly more likely to adopt and use AI chatbots in their work, highlighting trust as a key driver of AI technology adoption in the public sector. In government organizations, where data sensitivity and accountability are paramount, employees must trust that GenAI handles information responsibly and produces reliable outputs (Salam & Ali, 2020). Therefore:

**H11.** *Trust in technology positively affects government employees' intention to adopt GenAI.*

In addition, trust is theorized to influence performance expectancy. When employees trust GenAI outputs, they are more likely to integrate the technology into work processes without extensive verification, thereby enhancing perceived usefulness (Lankton et al., 2015; Choung et al., 2023; Hmoud & Várallyai, 2020). Wang et al. (2025) argue that trust is a fundamental driver of AI acceptance because it reduces uncertainty and increases users' confidence in the reliability, transparency, and credibility of AI systems, suggesting that it is perceived as a collaborator that complements employees' expertise, enhances task efficacy and supports the achievement of professional goals. Consistent with this view,

Marimon et al. (2025) found that trust in GenAI enhances work engagement and ultimately improves workplace performance. Their findings suggest that trusted GenAI systems are more likely to be perceived as valuable tools for accomplishing work and improving productivity. Therefore:

**H12.** *Trust in technology positively affects government employees' performance expectancy regarding GenAI.*

Figure 1 presents the conceptual model of the study. The model depicts the hypothesized structural relationships among UTAUT constructs, including performance expectancy, effort expectancy, social influence and facilitating conditions, and the extended constructs comprising trust in technology, perceived risk, technological awareness and perceived organizational support, as well as the focal outcome representing intention to adopt GenAI. Direct effects are illustrated using solid arrows, while dashed arrows signify indirect effects mediated by performance expectancy. The moderation effect of perceived organizational support on the perceived-risk-to-intention relationship is represented by an arrow pointing to the path between perceived risk and intention.

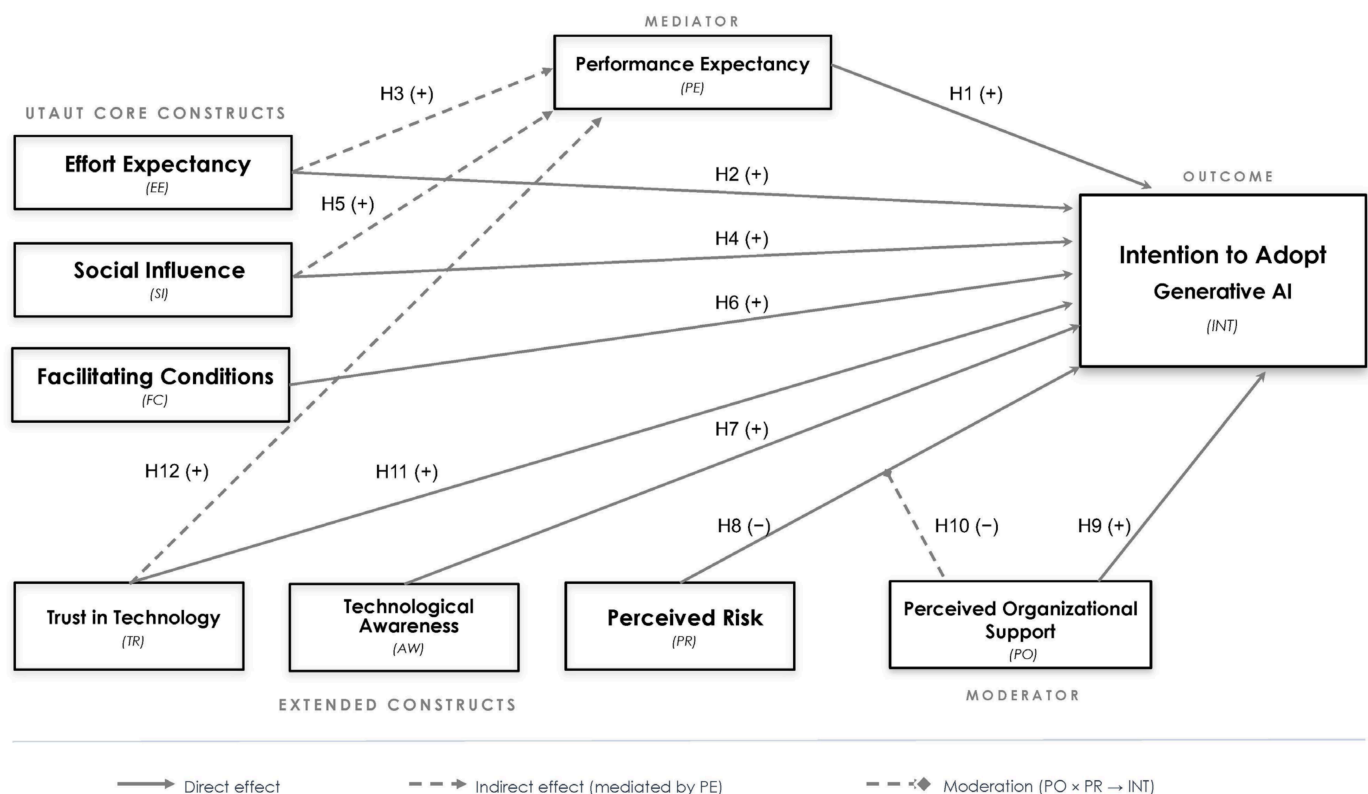


**Figure 1.** Conceptual model.

### 3. Research Methodology

This study implements a quantitative design centered on a dual-analytical methodology, combining Partial Least Squares Structural Equation Modeling (PLS-SEM) and fuzzy-set Qualitative Comparative Analysis (fsQCA), as shown in Figure 2. By synthesizing these methodologies, the research captures both individual net effects, which present the average linear impact of each antecedent on intention, and the configurational causal complexity, which illustrates how combinations of conditions jointly produce adoption or non-adoption. While PLS-SEM identifies the relative strength and significance of explanatory factors under the assumption of symmetric, linear relationships, fsQCA complements this analysis by

revealing multiple equifinal pathways leading to adoption and non-adoption outcomes (Pappas & Woodside, 2021; Hair et al., 2022; Liu et al., 2017).

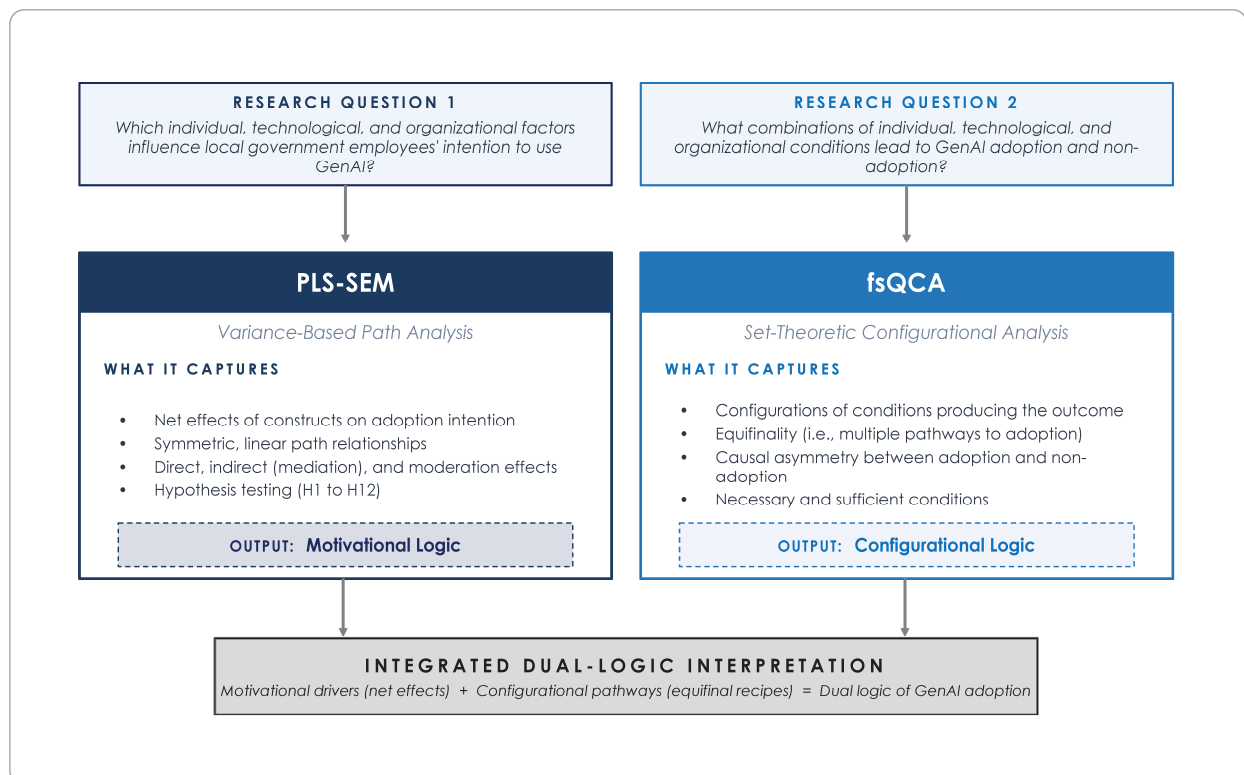


**Figure 2.** Methodological framework.

### 3.1. Measurement Instrument

A structured, closed-ended questionnaire was designed to collect primary quantitative data from local government employees. The instrument consists of two sections: the first captures demographic information, while the second measures the constructs in the proposed conceptual framework. All measurement items were assessed using a six-point Likert scale, ranging from “1 = strongly disagree” to “6 = strongly agree”. The use of a six-point scale minimizes central-tendency bias and improves response discrimination.

The measurement instruments utilized in this study were drawn from previously validated scales published in established reputable academic journals and were contextualized to reflect GenAI adoption and the public-sector setting. The items were translated into Vietnamese and back-translated by two bilingual researchers to ensure semantic equivalence. The core UTAUT constructs of intention to adopt GenAI (INT), performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC) were measured following Venkatesh et al. (2003). In particular, perceived organizational support (PO) for GenAI adoption was measured using two items adapted from Kim and Kankanhalli (2009), capturing organizational support for employee learning and work-process changes during technology adoption; trust in technology (TR) items were adapted from Kaplan and Haenlein (2019); the awareness (AW) scale was adapted from Parasuraman and Colby (2015). Finally, perceived risk (PR) was measured using the scale developed by Gerlich (2023), and was modeled as a unidimensional construct reflecting overall concerns regarding GenAI, including privacy, job displacement, and general uncertainty. Table 1 summarizes the measurement items.

**Table 1.** Measurement items.

| Construct               | Code | Measurement Item                                                                                              | Source                       |
|-------------------------|------|---------------------------------------------------------------------------------------------------------------|------------------------------|
| Performance Expectancy  | PE1  | Generative AI will help me be more productive.                                                                | Venkatesh et al. (2003)      |
|                         | PE2  | The adoption of generative AI will help public organizations deliver services in a better way.                |                              |
|                         | PE3  | The application of generative AI will improve the quality and efficiency of services in public organizations. |                              |
| Effort Expectancy       | EE1  | I am confident that I can use generative AI applications proficiently.                                        | Venkatesh et al. (2003)      |
|                         | EE2  | I feel that systems or services with generative AI integration are easy to use.                               |                              |
|                         | EE3  | I find it quite simple to learn how to use generative AI.                                                     |                              |
| Social Influence        | SI1  | The leader of my unit encourages me to use generative AI at work.                                             | Venkatesh et al. (2003)      |
|                         | SI2  | My colleagues encourage me to use generative AI at work.                                                      |                              |
|                         | SI3  | Overall, my department has a positive view of using generative AI to improve public services.                 |                              |
| Facilitating Conditions | FC1  | I believe I will have all the resources I need to use generative AI at work.                                  | Venkatesh et al. (2003)      |
|                         | FC2  | I am provided with the necessary knowledge, guidance, and training to use generative AI.                      |                              |
|                         | FC3  | I will get support from colleagues or experts for the use of generative AI at work.                           |                              |
| Trust in Technology     | TR1  | I think generative AI is easy to understand and provides logical output.                                      | Kaplan and Haenlein (2019)   |
|                         | TR2  | I believe that the results from generative AI are objective and unbiased.                                     |                              |
|                         | TR3  | I think the results from generative AI are unlikely to be mistaken.                                           |                              |
| Awareness               | AW1  | I am familiar with the functions and applications of generative AI in my field.                               | Parasuraman and Colby (2015) |
|                         | AW2  | I have knowledge and understanding of how generative AI works, its applications, and its benefits.            |                              |
|                         | AW3  | I can quickly recall information about generative AI that I have received or heard.                           |                              |

Table 1. Cont.

| Construct                        | Code | Measurement Item                                                                                          | Source                     |
|----------------------------------|------|-----------------------------------------------------------------------------------------------------------|----------------------------|
| Perceived Risk                   | PR1  | The use of generative AI may affect privacy, as information I provide may be used without my knowledge.   | Gerlich (2023)             |
|                                  | PR2  | The development of generative AI may lead to some job positions being replaced.                           |                            |
|                                  | PR3  | Overall, I believe that the use of generative AI still entails hidden risks.                              |                            |
| Perceived Organizational Support | PO1  | My agency helps me learn how to apply generative AI to my work.                                           | Kim and Kankanhalli (2009) |
|                                  | PO2  | My agency provides the necessary support so that I can change the way I work when adopting generative AI. |                            |
| Intention to Adopt GenAI         | INT1 | I support the application of generative AI in public organizations.                                       | Venkatesh et al. (2003)    |
|                                  | INT2 | I will regularly use generative AI in my work in the future.                                              |                            |
|                                  | INT3 | I will enthusiastically encourage others to use generative AI at work.                                    |                            |

To secure content validity and contextual relevance, the measurement scales were evaluated by one public-administration scholar and one experienced public officer. A pilot study was then conducted with 40 respondents. The results of the pilot confirmed that the reliability of all constructs was satisfactory for subsequent quantitative analysis.

### 3.2. Sampling and Empirical Setting

A multi-stage sampling strategy was employed to ensure coverage of diverse local-government contexts within a single transitioning Vietnamese province (i.e., the former Binh Duong Province, which has since been administratively merged into Ho Chi Minh City). In the first stage, survey sites were selected using stratified purposive sampling based on the province's three "dynamic spatial zones": (1) urban reconstruction and transit-oriented development zones, (2) innovation-driven and smart-city zones, and (3) ecological urban-industrial-service zones. Eight ward- and commune-level local government units were selected, all of which were post-merger administrative units. This sampling design enables an examination of GenAI adoption within reorganized bureaucratic settings, where new institutional routines and personnel arrangements are still being established (Patton, 2015).

In the second stage, respondents were selected using convenience sampling within each site, due to access constraints. Eligible respondents were civil servants currently working in the selected People's Committees who handled administrative work involving information technology. Although the second-stage sampling is non-probabilistic, the multi-stage geographic stratification in the first stage helps to enhance contextual diversity across spatial zones. Generalization claims, however, are deliberately confined to the surveyed transitional province; broader national inference would require complementary samples from other regions.

Sample-size adequacy was assessed against established standards for structural equation modeling. Following Bentler and Chou (1987), who recommend a minimum of five observations per estimated parameter, and the Yamane (1967) sampling formula, the mini-

minimum required sample was estimated at 286 respondents. This threshold also exceeds the commonly recommended minimum of 200 cases for SEM analysis (Hoyle & Gottfredson, 2015; Kline, 2011). The achieved sample of 302 respondents therefore satisfies the relevant power requirements.

### 3.3. Data Collection and Ethical Considerations

Ethical approval for the study was obtained from the Khon Kaen University Ethics Committee for Human Research (Approval No. HE683189). Approval was sought from Khon Kaen University because the lead researchers are affiliated with that institution; in addition, local research permissions were obtained from the relevant Vietnamese ward and commune-level People's Committees, and from the corresponding provincial-level administrative authorities, prior to data collection. Before the survey, all respondents were briefed on the study's purpose, the voluntary nature of participation, and the preservation of confidentiality, after which they provided explicit informed consent. The study design deliberately excluded personally identifiable information, ensuring that all participant responses were fully anonymized before any data analysis occurred.

Data collection was conducted in July 2025, following a period of administrative restructuring. Survey questionnaires were distributed in paper form directly to local-government offices. A total of 400 questionnaires were distributed, and 302 valid responses were secured after filtering out incomplete or inconsistent entries, resulting in a 75.5% effective response rate. The distribution by site is reported in Table 2. Response rates ranged from 62% to 96% across sites. While we cannot fully rule out non-response bias, the relatively high overall response rate and the diversity of zones covered mitigate this concern. Demographic profiles by site did not reveal systematic differences in age, gender, or education that would suggest substantial self-selection.

**Table 2.** Survey distribution across sampled units.

| No.   | Unit   | Zone | Surveys Sent | Valid Responses | Response Rate |
|-------|--------|------|--------------|-----------------|---------------|
| 1     | Unit A | 3    | 50           | 36              | 72%           |
| 2     | Unit B | 2    | 50           | 36              | 72%           |
| 3     | Unit C | 3    | 50           | 35              | 70%           |
| 4     | Unit D | 2    | 50           | 42              | 84%           |
| 5     | Unit E | 2    | 50           | 48              | 96%           |
| 6     | Unit F | 2    | 50           | 42              | 84%           |
| 7     | Unit G | 1    | 50           | 31              | 62%           |
| 8     | Unit H | 1    | 50           | 32              | 64%           |
| Total |        |      | 400          | 302             | 75.5%         |

The demographic profile in Table 3 reflects the workforce composition of local government units in the surveyed province. The majority of respondents are between 25 and 44 years old, with a slight overrepresentation of male respondents (52.3% vs. 44.0% female). The vast majority hold a bachelor's degree (85.8%), with 11.9% holding a master's degree. The sample is heavily skewed toward staff-level positions (97.4%), with only 2.6% ( $n = 8$ ) in leadership roles. Inferences regarding leadership perceptions are therefore not feasible from this sample, and the practical implications focus on staff-level adoption dynamics.

**Table 3.** Sample demographics.

| Demographic | Category          | n   | %    |
|-------------|-------------------|-----|------|
| Gender      | Female            | 133 | 44.0 |
|             | Male              | 158 | 52.3 |
|             | Prefer not to say | 11  | 3.6  |
| Age         | 20–24             | 11  | 3.6  |
|             | 25–29             | 52  | 17.2 |
|             | 30–34             | 52  | 17.2 |
|             | 35–39             | 97  | 32.1 |
|             | 40–44             | 61  | 20.2 |
|             | 45–49             | 15  | 5.0  |
|             | 50–54             | 10  | 3.3  |
|             | ≥55               | 4   | 1.3  |
| Position    | Leader            | 8   | 2.6  |
|             | Staff             | 294 | 97.4 |
| Education   | College           | 6   | 2.0  |
|             | Bachelor's        | 259 | 85.8 |
|             | Master's          | 36  | 11.9 |
|             | Doctorate         | 1   | 0.3  |

### 3.4. Analytical Approach

This study adopted a dual-analytical framework combining Partial Least Squares Structural Equation Modeling (PLS-SEM) and fuzzy-set Qualitative Comparative Analysis (fsQCA) to capture both the net effects and configurational complexity of GenAI adoption among local government employees. PLS-SEM estimates the direct, indirect, and moderating relationships among latent constructs, while fsQCA identifies alternative combinations of technological, individual, and organizational conditions that are sufficient for adoption and non-adoption. This complementary design is consistent with recent AI public-administration research that uses mixed analytical approaches to explain both statistical relationships and contextual mechanisms of AI use (Madan & Ashok, 2025).

PLS-SEM was selected because the study extends an established technology acceptance framework and tests a complex model involving multiple reflective constructs, mediation through performance expectancy, and moderation by perceived organizational support. The method is appropriate for prediction-oriented research and for assessing measurement quality and structural relationships in theory-extending models (Hair et al., 2022). The analysis was performed in SmartPLS 4 using a bootstrap procedure with 5000 resamples for inference. Although the data has a nested structure (i.e., 302 employees within eight units), the present analysis estimates the model under the standard assumption of independent observations. We acknowledge this limitation in Section 5.4, where we discuss multilevel structure and the implications for standard-error estimates.

Complementing the PLS-SEM analysis, this study implements fsQCA by capturing the asymmetric combinations of conditions that drive or inhibit GenAI adoption. This is important because the conditions associated with adoption are not necessarily the inverse of those associated with non-adoption. Therefore, this approach is particularly appropriate for identifying equifinal pathways and conjunctural effects in local-government settings (Fiss, 2011; Pappas & Woodside, 2021; Ragin, 2008; Rasoolimanesh et al., 2021).

For the fsQCA analysis, construct scores were calculated as the average of their respective measurement items and were then calibrated into fuzzy-set membership scores using theoretically grounded anchors. Using the calibrate function in fsQCA 4.1, three qualitative anchors were defined: full membership (0.95) at 5.5 (i.e., respondents who consistently selected the highest options); the crossover point (0.5) at 3.5 (i.e., the mathematical mid-

point between “slightly disagree” and “slightly agree”); and full non-membership (0.05) at 1.5 (i.e., respondents who consistently selected the lowest options). These anchors are theory-driven and anchored to the Likert metric, which is consistent with set-theoretic methodological principles (Ragin, 2008).

Following Pappas and Woodside (2021) and Greckhamer et al. (2018), the fsQCA procedure proceeded in three steps: (1) construction of the truth table; (2) necessity analysis using a consistency threshold of 0.90; and (3) sufficiency analysis using a consistency threshold of 0.80 and a frequency threshold consistent with sample size. The intermediate solution is reported in this paper, with assumptions about peripheral conditions guided by the directional expectations in the conceptual model.

#### 4. Analysis and Results

The following section reports the empirical evidence obtained through the sequential application of PLS-SEM and fsQCA analyses. Prior to hypothesis testing, the measurement model and potential common method bias considerations are reported, followed by structural model results, mediation and moderation analyses, and the fsQCA findings.

##### 4.1. Measurement Model

The reflective measurement model was verified through the assessment of indicator reliability, internal consistency reliability, convergent validity, and discriminant validity (Hair et al., 2022). Table 4 presents strong internal consistency for all constructs, with Cronbach’s alpha and composite reliability (CR) exceeding the minimum required value of 0.70 (Hair et al., 2022; Bryman & Bell, 2015). Convergent validity was confirmed, as all indicator loadings exceeded 0.70 and were statistically significant at  $p < 0.01$ . However, because some items’ loadings were close to 0.95, additional checks were conducted to assess potential indicator redundancy and multicollinearity, as suggested by Hair et al. (2022). The outer VIF values ranged from 1.414 to 4.730, which are below the recommended threshold of 5.00. Therefore, indicator-level multicollinearity was not considered problematic.

**Table 4.** Summary of the reflective measurement model.

| Construct               | Item | Loading | AVE   | CR    | Cronbach $\alpha$ | Outer VIF |
|-------------------------|------|---------|-------|-------|-------------------|-----------|
| Intention to Adopt      | INT1 | 0.938   | 0.880 | 0.956 | 0.932             | 3.961     |
|                         | INT2 | 0.928   |       |       |                   | 3.408     |
|                         | INT3 | 0.948   |       |       |                   | 4.404     |
| Performance Expectancy  | PE1  | 0.901   | 0.858 | 0.948 | 0.917             | 2.549     |
|                         | PE2  | 0.940   |       |       |                   | 4.187     |
|                         | PE3  | 0.938   |       |       |                   | 4.222     |
| Facilitating Conditions | FC1  | 0.914   | 0.852 | 0.945 | 0.913             | 2.823     |
|                         | FC2  | 0.920   |       |       |                   | 3.218     |
|                         | FC3  | 0.935   |       |       |                   | 3.559     |
| Awareness               | AW1  | 0.921   | 0.872 | 0.953 | 0.927             | 3.345     |
|                         | AW2  | 0.944   |       |       |                   | 3.956     |
|                         | AW3  | 0.937   |       |       |                   | 3.633     |
| Effort Expectancy       | EE1  | 0.925   | 0.879 | 0.956 | 0.931             | 3.330     |
|                         | EE2  | 0.949   |       |       |                   | 4.447     |
|                         | EE3  | 0.939   |       |       |                   | 4.018     |

Table 4. Cont.

| Construct                        | Item | Loading | AVE   | CR    | Cronbach $\alpha$ | Outer VIF |
|----------------------------------|------|---------|-------|-------|-------------------|-----------|
| Perceived Organizational Support | PO1  | 0.936   | 0.884 | 0.938 | 0.869             | 2.437     |
|                                  | PO2  | 0.944   |       |       |                   | 2.437     |
| Perceived Risk                   | PR1  | 0.852   | 0.671 | 0.859 | 0.761             | 1.772     |
|                                  | PR2  | 0.882   |       |       |                   | 1.601     |
|                                  | PR3  | 0.714   |       |       |                   | 1.414     |
| Social Influence                 | SI1  | 0.923   | 0.874 | 0.954 | 0.928             | 3.406     |
|                                  | SI2  | 0.953   |       |       |                   | 4.730     |
|                                  | SI3  | 0.929   |       |       |                   | 3.543     |
| Trust in Technology              | TR1  | 0.903   | 0.745 | 0.897 | 0.832             | 2.198     |
|                                  | TR2  | 0.919   |       |       |                   | 2.508     |
|                                  | TR3  | 0.759   |       |       |                   | 1.629     |

In addition, the average variance extracted (AVE) values for all constructs were above the minimum criterion of 0.50, indicating that each construct explains more than half of the variance of its indicators. Discriminant validity was assessed using both the Fornell–Larcker criterion (Fornell & Larcker, 1981) and the Heterotrait–Monotrait (HTMT) ratio, with all HTMT values below the conservative threshold of 0.85 (Henseler et al., 2016). Although some CR values slightly exceeded the 0.95 threshold, the AVE and HTMT results confirmed acceptable convergent and discriminant validity (Table 5).

Table 5. Combined Fornell–Larcker and HTMT Criterion Matrix.

|     | AW           | EE           | FC           | INT          | PO           | PR           | PE           | SI           | TR           |
|-----|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|
| AW  | <b>0.934</b> | 0.731        | 0.735        | 0.614        | 0.744        | 0.393        | 0.471        | 0.605        | 0.667        |
| EE  | 0.678        | <b>0.938</b> | 0.732        | 0.620        | 0.611        | 0.437        | 0.670        | 0.676        | 0.652        |
| FC  | 0.677        | 0.675        | <b>0.923</b> | 0.635        | 0.688        | 0.329        | 0.566        | 0.748        | 0.704        |
| INT | 0.572        | 0.578        | 0.586        | <b>0.938</b> | 0.587        | 0.523        | 0.634        | 0.636        | 0.586        |
| PO  | 0.666        | 0.549        | 0.613        | 0.529        | <b>0.940</b> | 0.360        | 0.403        | 0.682        | 0.607        |
| PR  | 0.332        | 0.378        | 0.299        | 0.462        | 0.290        | <b>0.819</b> | 0.357        | 0.375        | 0.527        |
| PE  | 0.436        | 0.620        | 0.519        | 0.586        | 0.361        | 0.328        | <b>0.926</b> | 0.502        | 0.523        |
| SI  | 0.562        | 0.629        | 0.690        | 0.592        | 0.612        | 0.329        | 0.464        | <b>0.935</b> | 0.642        |
| TR  | 0.583        | 0.577        | 0.619        | 0.538        | 0.517        | 0.445        | 0.474        | 0.582        | <b>0.863</b> |

Note: Diagonals (**bold**) represent the square root of the AVE; lower triangle values represent latent variable correlations; upper triangle values represent HTMT ratios.

We note that the perceived risk (PR) construct displays the lowest reflective indicator loading (PR3 = 0.714), the lowest AVE (0.671), and the lowest Cronbach's alpha (0.761) of all constructs. These values nonetheless exceed accepted thresholds. Because the three PR items span theoretically distinct facets (i.e., privacy [PR1], professional displacement [PR2], and general residual risk [PR3]), the interpretation of any PR-related coefficient is qualified accordingly in Section 5. The perceived organizational support (PO) construct is operationalized with two items, which is below the conventional three-item minimum for reflective constructs. We retain this construct because its composite reliability and AVE meet thresholds, and we explicitly acknowledge this constraint in the Section 5.4.

#### 4.2. Common Method Bias Considerations

Because the data are cross-sectional and self-reported through a single instrument and respondent group, common method bias (CMB) could in principle inflate observed

associations. During the questionnaire design phase, we implemented multiple procedural controls specifically engineered to mitigate CMB: participants received explicit assurance regarding data anonymity, and strict confidentiality was guaranteed to all respondents; item ordering was randomized so that dependent and independent constructs were not contiguous; and clear, plain-language item wording was used to reduce ambiguity (Podsakoff et al., 2003). Statistically, all inner Variance Inflation Factor (VIF) values were below 5, with no value exceeding 3.3, which is the more conservative threshold recommended by Kock (2015) for full-collinearity assessment of method effects. The pattern of null direct effects observed for several constructs (e.g., facilitating conditions, perceived organizational support, and trust) is also inconsistent with severe method-effect inflation, which would tend to produce a uniform pattern of inflated correlations.

#### 4.3. Structural Model and Hypothesis Testing

The structural model was assessed using collinearity diagnostics, explanatory power, predictive relevance, and supplementary fit indicators. All inner-model VIF values were below 5, indicating no collinearity concerns. The model exhibited moderate explanatory power, explaining 55.0% of the variance in the intention to adopt GenAI ( $R^2 = 0.550$ ) and 40.1% of the variance in performance expectancy ( $R^2 = 0.401$ ). Predictive relevance was confirmed through the Stone–Geisser  $Q^2$  statistic, with values of 0.479 and 0.337, respectively, indicating strong predictive capability (Hair et al., 2022).

Although PLS-SEM prioritizes predictive accuracy over global model fit, the Standardized Root Mean Square Residual (SRMR) was examined as a supplementary fit indicator. The model achieved an SRMR value of 0.047, meeting the recommended 0.08 benchmark for adequate model fit. Conversely, the Normed Fit Index (NFI) was 0.840, falling short of the conventional 0.90 threshold (Bentler & Bonett, 1980). We interpret this value cautiously: NFI is known to be sensitive to model complexity in PLS-SEM contexts, and is generally considered a less reliable fit index for PLS than for covariance-based SEM. Overall, the results provide a robust basis for hypothesis testing.

To evaluate the structural model, path coefficients,  $t$ -values, and  $p$ -values were derived employing a 5000-resample bootstrapping procedure. Table 6 reports the standardized path estimates and hypothesis testing outcomes for the main direct effects.

**Table 6.** Results of structural model and hypothesis testing.

| H   | Relationship         | Sign | $\beta$ | $t$   | $p$       | Outcome                                         |
|-----|----------------------|------|---------|-------|-----------|-------------------------------------------------|
| H1  | PE $\rightarrow$ INT | (+)  | 0.269   | 3.963 | <0.001 ** | Supported                                       |
| H2  | EE $\rightarrow$ INT | (+)  | −0.027  | 0.289 | 0.772     | Rejected                                        |
| H3  | EE $\rightarrow$ PE  | (+)  | 0.491   | 6.390 | <0.001 ** | Supported                                       |
| H4  | SI $\rightarrow$ INT | (+)  | 0.186   | 2.613 | 0.009 **  | Supported                                       |
| H5  | SI $\rightarrow$ PE  | (+)  | 0.067   | 0.923 | 0.356     | Rejected                                        |
| H6  | FC $\rightarrow$ INT | (+)  | 0.079   | 1.067 | 0.286     | Rejected                                        |
| H7  | AW $\rightarrow$ INT | (+)  | 0.155   | 2.133 | 0.033 *   | Supported                                       |
| H8  | PR $\rightarrow$ INT | (−)  | 0.158   | 3.065 | 0.002 **  | Rejected<br>(significant in opposite direction) |
| H9  | PO $\rightarrow$ INT | (+)  | 0.104   | 1.599 | 0.110     | Rejected                                        |
| H11 | TR $\rightarrow$ INT | (+)  | 0.033   | 0.490 | 0.624     | Rejected                                        |
| H12 | TR $\rightarrow$ PE  | (+)  | 0.151   | 2.065 | 0.039 *   | Supported                                       |

Note. \*  $p < 0.05$ ; \*\*  $p < 0.01$ . Path coefficients are standardized estimates from a PLS-SEM bootstrap with 5000 resamples. H8 was formulated as a directional negative hypothesis; the observed coefficient is significant in the opposite direction (i.e., positive), and H8 is therefore rejected on directional grounds. H10 (i.e., the moderation hypothesis) is reported separately in Section 4.5.

## Main Effects

Performance expectancy (PE) serves as a potent positive predictor of local-government employees' intention to adopt GenAI ( $\beta = 0.269$ ,  $t = 3.963$ ,  $p < 0.001$ ), supporting H1. This confirms that perceived improvements in work efficiency and effectiveness are the most influential motivational driver of GenAI adoption.

In contrast, effort expectancy (EE) is not a significant direct effect predictor of adoption intention ( $\beta = -0.027$ ,  $t = 0.289$ ,  $p = 0.772$ ), which consequently leaves H2 unsupported. This suggests that effort expectancy alone does not directly motivate public employees to engage with GenAI. However, effort expectancy positively and significantly influences performance expectancy ( $\beta = 0.491$ ,  $t = 6.390$ ,  $p < 0.001$ ), supporting H3. This result implies that ease of interaction with GenAI enhances employees' perception of its usefulness, thereby indirectly shaping adoption intention.

Social influence (SI) is significantly and positively associated with employees' adoption intention ( $\beta = 0.186$ ,  $t = 2.613$ ,  $p = 0.009$ ), confirming the relationship hypothesized in H4. This highlights the legitimizing role of supervisors, peers, and departmental norms in shaping employees' willingness to use GenAI. However, social influence does not significantly affect performance expectancy ( $\beta = 0.067$ ,  $t = 0.923$ ,  $p = 0.356$ ), causing the rejection of H5. This suggests that while social cues encourage use, they do not necessarily enhance perceptions of GenAI's instrumental value.

Facilitating conditions (FC) exhibit a positive but statistically non-significant relationship with the intention to use GenAI ( $\beta = 0.079$ ,  $t = 1.067$ ,  $p = 0.286$ ), resulting in the rejection of H6. Likewise, perceived organizational support (PO) fails to demonstrate a significant direct effect on intention ( $\beta = 0.104$ ,  $t = 1.599$ ,  $p = 0.110$ ); hence, H9 is also unsupported. These findings indicate that institutional resources and support, while important, do not directly motivate adoption when examined through a linear, net-effect lens. The configurational analysis below provides a more nuanced view of their role.

Technological awareness (AW) positively and significantly affects adoption intention ( $\beta = 0.155$ ,  $t = 2.133$ ,  $p = 0.033$ ), supporting H7. These results suggest that greater familiarity with GenAI applications and functions enhances employees' readiness to engage with the technology.

Contrary to conventional technology-acceptance assumptions, perceived risk (PR) shows a positive and statistically significant association with adoption intention ( $\beta = 0.158$ ,  $t = 3.065$ ,  $p = 0.002$ ). Because H8 was formulated as a directional negative hypothesis, the observed coefficient is significant in the opposite direction. H8 is therefore rejected on directional grounds, and the unexpected positive association is treated as a substantively important empirical finding that requires careful theoretical interpretation. We return to this finding in Section 5.1.4, where we consider three competing interpretations (i.e., risk-driven motivation or "relevance anxiety", reverse causality, and cognitive-consistency effects).

Finally, the statistical analysis reveals that trust in GenAI (TR) fails to significantly influence behavioral intention ( $\beta = 0.033$ ,  $t = 0.490$ ,  $p = 0.624$ ), resulting in the rejection of H11. However, trust significantly and positively affects performance expectancy ( $\beta = 0.151$ ,  $t = 2.065$ ,  $p = 0.039$ ), supporting H12. This pattern suggests that trust in GenAI shapes perceptions of utility rather than directly triggering adoption intention.

Overall, the PLS-SEM results indicate that performance expectancy, social influence, technological awareness, and (unexpectedly) perceived risk have direct effects on the adoption intention of local-government employees in the surveyed province, while effort expectancy and trust influence intention indirectly through performance expectancy.

#### 4.4. Mediation Analysis

To further confirm the indirect pathways through performance expectancy, mediation analyses were executed utilizing a 5000-resample bootstrapping procedure (Table 7). The results demonstrate that performance expectancy exerts a significant mediating role between effort expectancy and adoption intention ( $\beta = 0.132$ ,  $t = 2.960$ ,  $p = 0.003$ ), indicating an indirect-only mediation pattern, given that the direct EE-INT path is non-significant. In contrast, performance expectancy does not mediate the relationship between social influence and intention ( $\beta = 0.018$ ,  $t = 0.856$ ,  $p = 0.392$ ), nor between trust and intention ( $\beta = 0.041$ ,  $t = 1.817$ ,  $p = 0.069$ ). These results suggest that social influence operates directly on intention, while trust primarily shapes perceptions of utility rather than behavioral commitment.

**Table 7.** Mediation analysis results.

| Indirect Path                         | $\beta$ | $t$   | $p$   | Decision                 |
|---------------------------------------|---------|-------|-------|--------------------------|
| EE $\rightarrow$ PE $\rightarrow$ INT | 0.132   | 2.960 | 0.003 | Mediated (indirect-only) |
| SI $\rightarrow$ PE $\rightarrow$ INT | 0.018   | 0.856 | 0.392 | Not mediated             |
| TR $\rightarrow$ PE $\rightarrow$ INT | 0.041   | 1.817 | 0.069 | Not mediated             |

#### 4.5. Moderation Analysis

To examine whether the organizational context shapes the effect of risk perceptions on adoption intention, a moderation analysis was conducted. As shown in Table 8, the interaction term between perceived organizational support and perceived risk is statistically significant ( $\beta = -0.082$ ,  $t = 2.243$ ,  $p = 0.025$ ), supporting H10. The negative sign indicates that the positive PR-INT slope is attenuated at higher levels of perceived organizational support. In effect, when employees feel institutionally supported, the motivational pressure associated with perceived risk is buffered, suggesting that organizational support alters how employees interpret and respond to GenAI-related uncertainties. The simple-slopes pattern is illustrated in Figure 3. We note that the effect size of the interaction is modest in practical terms; we therefore present this as a directional and theoretically interpretable buffering effect rather than a large practical effect.

**Table 8.** Moderation effect testing result.

| Interaction                      | $\beta$ | $p$   | Result        |
|----------------------------------|---------|-------|---------------|
| PO $\times$ PR $\rightarrow$ INT | −0.082  | 0.025 | H10 supported |

#### 4.6. fsQCA Results

##### 4.6.1. Necessity Analysis

Prior to conducting the standard truth-table analysis for sufficiency, we conducted an analysis of necessary conditions to determine whether any individual antecedent is a prerequisite for the outcome. Adhering to established fsQCA protocols (Schneider & Wagemann, 2012), a stringent consistency threshold of 0.90 was adopted to safeguard against the inclusion of trivial necessary conditions. The analysis was conducted for both the presence of intention (INT) and the negation of intention ( $\sim$ INT). The results are summarized in Table 9.

Based on the necessity analysis, performance expectancy (PE) and social influence (SI) approach the standard benchmark for necessity regarding intention presence, with consistency scores of 0.936 and 0.912, respectively. This implies that without perceiving the technology as useful, and without social endorsement, the formation of adoption intention is unlikely. The analysis of non-intention reveals that the absence of awareness ( $\sim$ AW) and the absence of perceived organizational support ( $\sim$ PO) meet the necessity

threshold for resistance, with consistency scores of 0.946 and 0.936, respectively. We interpret this asymmetry cautiously: both consistencies sit only modestly above 0.90, and the corresponding coverage values are around 0.50. Following [Schneider and Wagemann \(2012\)](#), we therefore avoid strong claims of “trivial necessity” and treat these as suggestive evidence of an enabling-baseline role for awareness and organizational support, rather than as deterministic prerequisites of resistance.

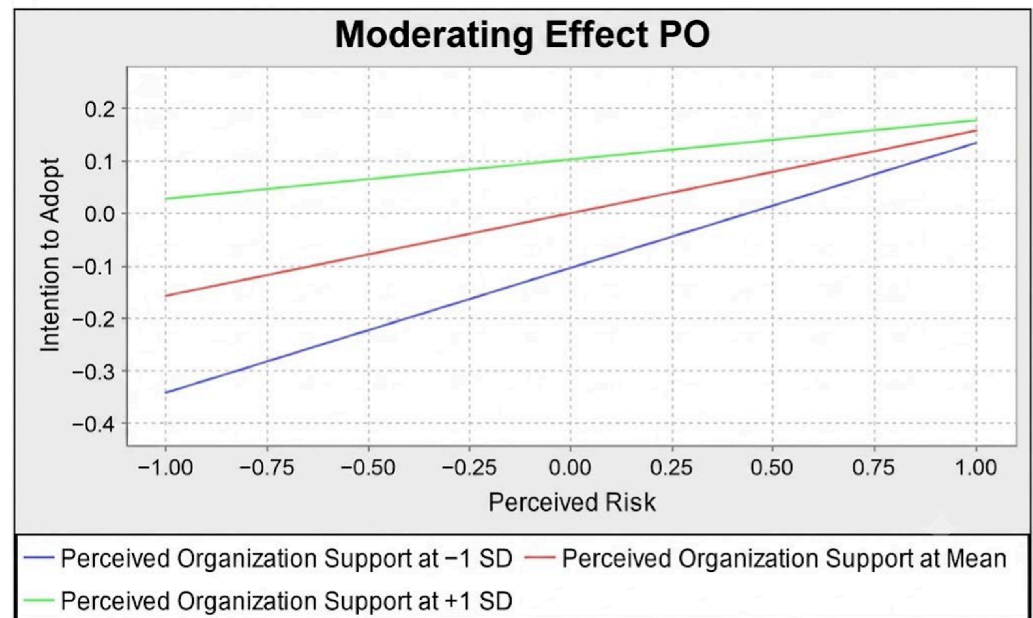


**Figure 3.** Interaction of perceived organizational support on the relationship between perceived risk and adoption intention. Note. The simple-slopes plot is drawn at  $\pm 1$  standard deviation from the mean of perceived organizational support. The positive slope from perceived risk to intention is steeper at low levels of organizational support and is attenuated at high levels.

**Table 9.** Analysis of necessary conditions.

| Condition | INT—<br>Consistency | INT—<br>Coverage | ~INT—<br>Consistency | ~INT—<br>Coverage |
|-----------|---------------------|------------------|----------------------|-------------------|
| PE        | 0.936               | 0.939            | 0.862                | 0.204             |
| ~PE       | 0.206               | 0.864            | 0.741                | 0.732             |
| EE        | 0.876               | 0.961            | 0.816                | 0.211             |
| ~EE       | 0.280               | 0.866            | 0.847                | 0.618             |
| SI        | 0.912               | 0.951            | 0.827                | 0.203             |
| ~SI       | 0.235               | 0.852            | 0.799                | 0.682             |
| FC        | 0.869               | 0.965            | 0.786                | 0.206             |
| ~FC       | 0.285               | 0.849            | 0.865                | 0.609             |
| TR        | 0.829               | 0.961            | 0.819                | 0.224             |
| ~TR       | 0.331               | 0.886            | 0.856                | 0.541             |
| PR        | 0.898               | 0.939            | 0.854                | 0.211             |
| ~PR       | 0.246               | 0.877            | 0.754                | 0.635             |
| AW        | 0.801               | 0.984            | 0.757                | 0.220             |
| ~AW       | 0.365               | 0.864            | 0.946                | 0.529             |
| PO        | 0.836               | 0.982            | 0.761                | 0.211             |
| ~PO       | 0.329               | 0.854            | 0.936                | 0.574             |

Note. “~” denotes the logical negation NOT (i.e., the absence of a condition). Coverage values around 0.50 should be interpreted cautiously, particularly for the necessity claims involving negated conditions.

Importantly, the necessity pattern highlights causal asymmetry: the conditions that approach necessity for adoption are not the simple inverse of those approaching necessity for non-adoption. This is an empirically meaningful indication that linear, symmetric models can mask important configurational structure.

#### 4.6.2. Sufficiency Analysis

A truth-table analysis was conducted to identify configurations of conditions sufficient to produce both adoption intention (INT) and non-adoption ( $\sim$ INT). The intermediate solution is reported, as it balances theoretical parsimony with empirical relevance. Table 10 summarizes the resulting configurations, distinguishing core and peripheral conditions using the Fiss (2011) convention.

**Table 10.** Configurations for the intention (and non-intention) to adopt GenAI.

| Condition            | Configurations for INT |       |       |       | Configurations for $\sim$ INT |       |
|----------------------|------------------------|-------|-------|-------|-------------------------------|-------|
|                      | 1                      | 2     | 3     | 4     | 5                             | 6     |
| PE                   | ●                      | ●     | ●     | ●     | ⊗                             |       |
| FC                   | ●                      | ●     | ●     | ●     | ⊗                             | ⊗     |
| SI                   | ●                      | ●     | ●     | ●     | ⊗                             | ⊗     |
| EE                   | •                      | •     | •     |       | ⊗                             | ⊗     |
| TR                   | •                      | •     |       | •     | ⊗                             | ⊗     |
| PR                   | •                      |       | •     | •     |                               | •     |
| AW                   |                        | •     | •     | •     | ⊗                             | ⊗     |
| PO                   |                        | •     | •     | •     | ⊗                             | ⊗     |
| Raw coverage         | 0.698                  | 0.647 | 0.651 | 0.635 | 0.617                         | 0.605 |
| Unique coverage      | 0.070                  | 0.020 | 0.024 | 0.008 | 0.062                         | 0.050 |
| Consistency          | 0.989                  | 0.992 | 0.995 | 0.995 | 0.917                         | 0.845 |
| Solution coverage    |                        | 0.742 |       |       | 0.667                         |       |
| Solution consistency |                        | 0.987 |       |       | 0.857                         |       |

Note. Symbols follow Fiss (2011): large filled circles (●) denote the presence of a core condition; small filled circles (•) denote the presence of a peripheral condition; large crossed circles (⊗) denote the absence of a core condition; small crossed circles (⊗) denote the absence of a peripheral condition; blank cells indicate “do not care”.

To examine whether the fsQCA findings were sensitive to calibration choice, calibration robustness checks were conducted after the main sufficiency analysis (Table 11). The baseline calibration used anchors of 5.5, 3.5, and 1.5. Two alternative calibrations were then applied by slightly shifting the full-membership and full non-membership anchors. Specifically, the alternative calibrations used anchors of 5.25/3.5/1.75 and 5.75/3.5/1.25. Calibration-threshold robustness testing evaluates whether QCA solutions change when calibration thresholds are perturbed.

**Table 11.** Results of the calibration robustness tests.

| Model for INT | Calibration Anchors | Solution Coverage | Solution Consistency | Assessment    |
|---------------|---------------------|-------------------|----------------------|---------------|
| Baseline      | 5.5/3.5/1.5         | 0.742             | 0.987                | Main solution |
| Robustness 1  | 5.25/3.5/1.75       | 0.743             | 0.986                | Stable        |
| Robustness 2  | 5.75/3.5/1.25       | 0.769             | 0.980                | Stable        |

The sufficiency analysis was rerun using the same set of eight conditions and the same frequency cutoff of 5. Across the three calibration models, the main causal configurations for INT remained substantially stable. Solution consistency remained high, ranging from 0.980 to 0.987, while solution coverage ranged from 0.742 to 0.769. The results indicate that the fsQCA findings are not driven by a single calibration specification.

As supplementary evidence, the analysis was also repeated for the absence of behavioral intention. The main configuration involving the joint absence of PE, EE, SI, FC, TR, AW, and PO appeared consistently across calibration models, supporting the asymmetric interpretation of the findings.

#### 4.6.3. Configurations Leading to Intention

The fsQCA results identify four distinct configurations (Configurations 1–4) that are sufficient for adoption intention. The overall solution demonstrates high consistency (0.987) and substantial coverage (0.742). Across all four configurations, it is shown that performance expectancy, social influence, and facilitating conditions are core conditions, underscoring their central role in enabling GenAI adoption. The peripheral conditions vary across configurations, revealing multiple equifinal pathways to the same outcome. For interpretive clarity, we label the four configurations as follows.

Configuration 1 (the “Pragmatist” pathway) shows that the joint presence of performance expectancy, effort expectancy, social influence, facilitating conditions, trust, and perceived risk constitutes a sufficient causal recipe for adoption intention, regardless of awareness and organizational support. This pathway reflects a pragmatically driven adoption logic, in which perceived utility and social cues outweigh institutional considerations.

Configuration 2 (the “Institutionally Supported” pathway) demonstrates that when technological awareness and perceived organizational support are both present, adoption intention can occur regardless of perceived risk, provided that trust in GenAI is high.

Configuration 3 (the “Risk-Engaged” pathway) shows that with strong awareness and organizational support, perceived risk can substitute for trust as a motivating condition. This is consistent with the interpretation that risk perceptions can motivate engagement when employees feel institutionally supported.

Configuration 4 (the “Fully Embedded” pathway) indicates that adoption intention can emerge from a comprehensive combination of institutional, cognitive, and motivational conditions, regardless of effort expectancy, which suggests that the ease of use of GenAI is no longer essential once other enablers are firmly in place.

#### 4.6.4. Configurations Leading to Non-Intention

The fsQCA results identify two configurations (Configurations 5 and 6) sufficient for non-adoption intention. The solution exhibits an overall consistency of 0.857 and coverage of 0.667, indicating a reasonable explanation of resistance behavior. Both configurations are characterized by the core absence of effort expectancy, social influence, facilitating conditions, trust, awareness, and organizational support. Configuration 5 additionally includes the peripheral condition absence of performance expectancy, whereas Configuration 6 indicates that resistance can occur even when perceived risk is present, with performance expectancy being irrelevant (a “do-not-care” condition). The lower consistency of Configuration 6 (0.845) suggests that it should be interpreted with appropriate caution. Figure 4 summarizes the dual logics of GenAI adoption identified in the study.

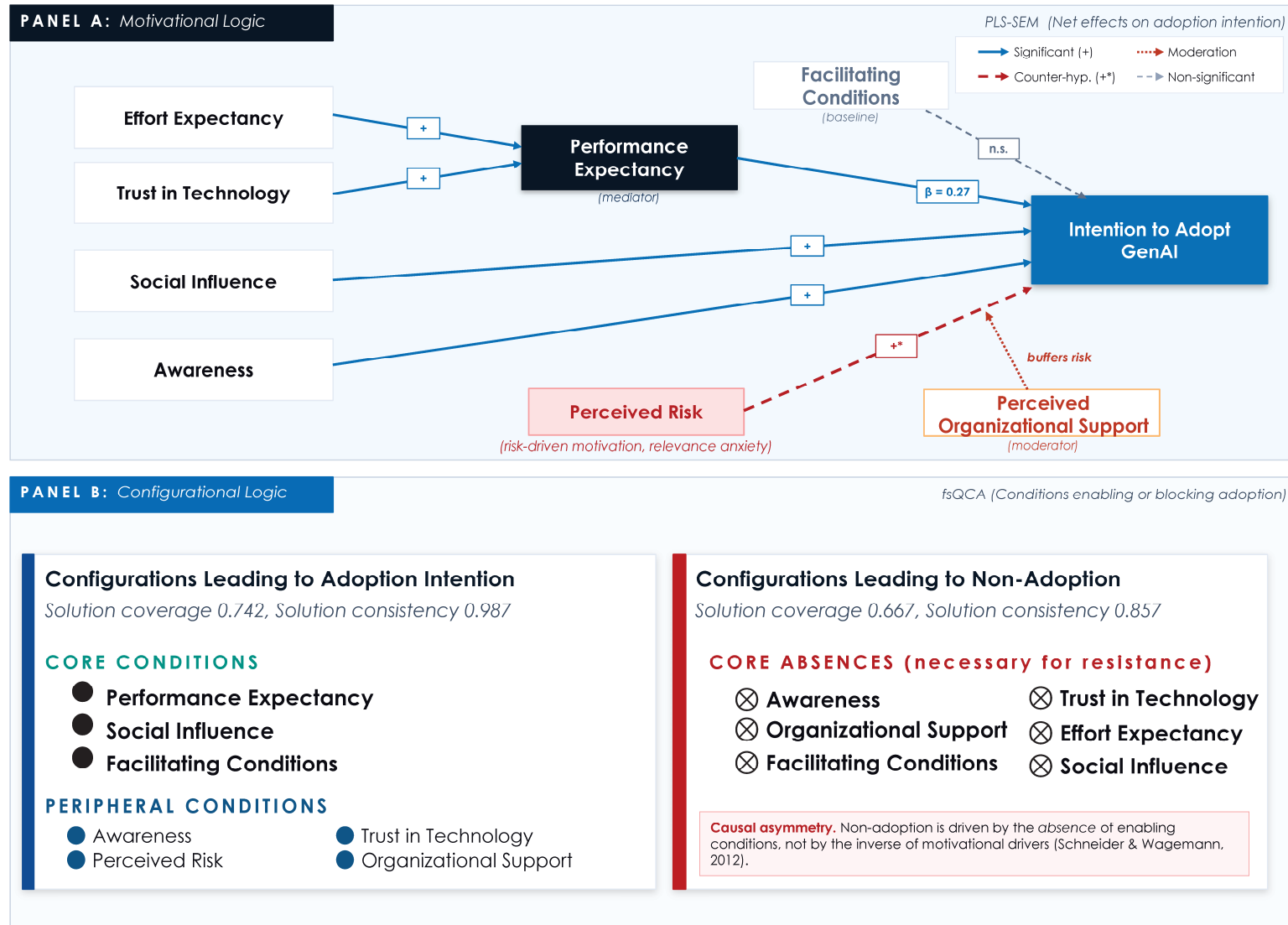


Figure 4. Dual-logic model of GenAI adoption in local government.

## 5. Discussion

### 5.1. Main Findings

By deploying a complementary PLS-SEM and fsQCA framework, this research investigates the determinants of GenAI adoption among local government employees, focusing on the unique context of a transitioning province in Vietnam. The findings reveal that GenAI adoption in public bureaucracy does not follow a single linear logic. Instead, it emerges from a combination of motivational drivers, institutional conditions, and configurational dynamics, reflecting both formal and informal pathways of technology use.

#### 5.1.1. Performance Expectancy as the Primary Motivational Driver

Across both the PLS-SEM and fsQCA approaches, performance expectancy emerges as the most robust and consistent driver of GenAI adoption. In the PLS-SEM analysis, performance expectancy exhibits the strongest net effect on intention ( $\beta = 0.269, p < 0.001$ ), and in the fsQCA results it plays the role of a core condition in four adoption-producing configurations (i.e., Configurations 1–4). This aligns with established meta-analyses of UTAUT and the broader technology-acceptance literature that identifies perceived utility as the primary driver of adoption (Ahn & Chen, 2022; Chatterjee et al., 2023; Dwivedi et al., 2019; Venkatesh et al., 2003). This convergence underscores that government employees are primarily motivated to engage with GenAI when they clearly perceive its capacity to improve efficiency, task quality, and administrative effectiveness.

The configurational analysis also reveals an important nuance: performance expectancy alone is not sufficient to produce adoption. High perceived usefulness must coexist with social endorsement and basic facilitating conditions. This finding reflects the unique constraints of public bureaucracy, where technological value must be both useful and legitimate to influence behavior.

#### 5.1.2. The Enduring Institutional Role of Social Influence

Social influence plays a critical legitimizing role in GenAI adoption. The PLS-SEM results confirm a positive and significant relationship between social influence and intention ( $\beta = 0.186, p = 0.009$ ), and the fsQCA identifies social influence as a core condition across all high-adoption configurations. In hierarchical administrative contexts, social cues reduce normative uncertainty and signal the acceptability of experimenting with a technology that remains institutionally ambiguous. Consequently, the decision to adopt GenAI transcends individual agency, operating instead as a socially embedded process governed by collective institutional expectation and informal authorization.

#### 5.1.3. Effort Expectancy and Trust as Indirect Enablers

Contrary to traditional UTAUT assumptions, the study finds that effort expectancy does not directly influence the intention to adopt GenAI ( $\beta = -0.027, p = 0.772$ ). Instead, effort expectancy positively affects performance expectancy ( $\beta = 0.491, p < 0.001$ ), which in turn influences adoption intention through a significant indirect path ( $\beta = 0.132, p = 0.003$ ). This indicates that ease of use contributes to adoption indirectly by enhancing perceptions of usefulness, rather than acting as an independent motivator.

A similar pattern is observed for trust in GenAI. The PLS-SEM results show that trust does not exert a significant direct effect on intention but positively influences performance expectancy ( $\beta = 0.151, p = 0.039$ ). The fsQCA results show that trust functions as a peripheral condition that varies across configurations (e.g., present in Configurations 1, 2, and 4; absent or “do not care” in Configuration 3). Trust therefore appears to enhance employees’ confidence in GenAI outputs and thereby strengthens perceived performance benefits, but it does not by itself trigger adoption intention.

#### 5.1.4. Perceived Risk and the Moderating Role of Organizational Support

The most theoretically intriguing finding concerns perceived risk. While H8 hypothesized a negative effect, the PLS-SEM results reveal a positive and significant relationship between perceived risk and adoption intention ( $\beta = 0.158, p = 0.002$ ). This is consistent with the emerging literature suggesting that risk perceptions related to professional displacement and AI-related obsolescence can motivate (rather than deter) engagement with new technologies (Brougham & Haar, 2018; Frey & Osborne, 2017; Vrontis et al., 2022). We refer to this mechanism as relevance anxiety, defined as the perception that engagement with GenAI is necessary to maintain professional legitimacy and future employability. The fsQCA results provide complementary configurational evidence, as perceived risk appears as a peripheral condition in three of four adoption configurations (i.e., Configurations 1, 3, and 4).

We treat the relevance-anxiety framing as one plausible interpretation of this finding and explicitly consider two competing accounts that the cross-sectional design cannot adjudicate. First, the positive PR-INT association may reflect reverse causality: employees who are already actively using GenAI may develop sharper, more articulated perceptions of its risks, so that the observed correlation reflects a downstream sense-making process rather than an upstream motivational mechanism. Second, the positive coefficient may reflect a cognitive-consistency effect, in which respondents who have committed to using GenAI rationalize their commitment by acknowledging its risks. The current perceived-risk scale also combines privacy, professional-displacement, and general-risk items, which limits our ability to attribute the positive coefficient specifically to the relevance-anxiety mechanism. Disentangling these three accounts will require longitudinal or panel data, item-level decomposition of perceived risk, and ideally, a measured-marker variable approach to common method bias. We take these alternative interpretations seriously and treat the relevance-anxiety framing as a theoretically promising hypothesis that warrants further testing, rather than as a definitive causal claim.

The moderation analysis adds further nuance. Perceived organizational support significantly attenuates the positive PR-INT slope ( $\beta = -0.082, p = 0.025$ ). Substantively, this finding suggests that organizational support acts as an insulation mechanism, absorbing the motivational pressure of perceived risk and steering engagement toward more structured, less risk-driven use, suggesting that organizational support functions as a psychological buffer in the sense of Eisenberger et al. (1986). The effect size is modest in practical terms, and we therefore frame the result as a directionally meaningful buffering relationship rather than a large practical effect.

#### 5.1.5. Facilitating Conditions and Organizational Support as Enabling Baseline Conditions

Facilitating conditions and perceived organizational support do not demonstrate statistically significant direct effects on adoption intention in the PLS-SEM model. However, the fsQCA results reveal that the absence of these conditions is a defining feature of non-adoption configurations, and the absence of organizational support approaches the necessity threshold for resistance. We interpret this finding using the language of necessary-but-not-sufficient conditions: facilitating conditions and organizational support function as enabling baseline conditions, the presence of which does not actively motivate adoption, but the absence of which substantially raises the probability of resistance.

In earlier framings of similar findings in the public-administration and IS literature, scholars have invoked an analogy to Herzberg's motivator-hygiene framework (Herzberg et al., 1959). We use this analogy cautiously here. The original Herzbergian distinction was developed in the context of job satisfaction, not technology adoption, and the conceptual mechanisms differ in important ways. We therefore frame the finding primarily in set-

theoretic terms (i.e., necessary-but-not-sufficient conditions) and treat the hygiene-factor analogy as a heuristic device for communicating the asymmetric role of these conditions, rather than as a direct theoretical transposition.

#### 5.1.6. Informal and Individualized Adoption Pathways

The fsQCA analysis also reveals that GenAI adoption often occurs under conditions in which employees rely on individual resources, peer support, and personal initiative, particularly in contexts where formal institutional arrangements remain limited. These patterns reflect the informal and evolving nature of GenAI use in local government, where adoption often precedes formal institutionalization. Such findings challenge traditional top-down models of public-sector digital transformation, and align with emerging scholarship on shadow AI use that emphasizes bottom-up capability development and employee-led experimentation (Nguyen Duy et al., 2026; Tangi et al., 2025; van Noordt & Tangi, 2023).

#### 5.1.7. Awareness and Adoption Readiness

Awareness of GenAI technology has a significant and positive effect on intention to adopt in the PLS-SEM analysis ( $\beta = 0.155$ ,  $p = 0.033$ ), and the fsQCA shows that its absence approaches necessity for non-adoption. This asymmetry indicates that awareness facilitates readiness to adopt but is not required in every adoption pathway. Awareness shapes how GenAI is adopted, rather than simply whether it is adopted.

In Configuration 1 (i.e., the “Pragmatist” pathway), awareness is irrelevant (“do not care”). Employees in this pathway adopt GenAI primarily because they follow the institutional push and recognize the tool’s utility, even without deep cognitive familiarity with the technology. In contrast, Configurations 2, 3, and 4 (i.e., the “Institutionally Supported”, “Risk-Engaged”, and “Fully Embedded” pathways) all feature awareness as a peripheral condition combined with perceived organizational support. In these pathways, awareness functions as a cognitive enabler that allows employees to navigate the policy vacuum and to make informed use of GenAI tools. This pattern suggests that awareness distinguishes compliance-oriented adoption from more exploratory and self-directed engagement.

### 5.2. Theoretical Implications

This study advances public-sector technology-adoption research by offering a dual-logic explanation of GenAI adoption that integrates variance-based and configurational perspectives. By combining PLS-SEM with fsQCA, it moves beyond linear assumptions and shows that adoption is shaped by motivational drivers and conditional mechanisms operating simultaneously. The contribution unfolds along four lines.

First, the dual-logic model itself demonstrates that net effects and configurational pathways capture distinct but complementary dimensions of behavior. While PLS-SEM identifies performance expectancy and social influence as dominant predictors, fsQCA reveals multiple equifinal configurations leading to the same outcome, challenging the UTAUT assumption of a single dominant pathway and extending prior combined-method work (Liu et al., 2017; Pappas & Woodside, 2021) to the autonomous-AI context.

Second, the study refines acceptance theory by showing that perceived usefulness is necessary but not sufficient: performance expectancy produces adoption only when paired with social endorsement and minimal facilitating infrastructure, reflecting the constrained discretion and high accountability of public bureaucracy.

Third, it reconceptualizes trust and risk. Trust operates as an antecedent of performance expectancy rather than a direct driver of intention, while perceived risk shows a positive association with intention, contrary to the deterrence view. This introduces relevance anxiety (i.e., the pressure to engage with GenAI to preserve professional standing) as a theoretically meaningful mechanism. We emphasize, however, that the cross-sectional

design cannot confirm causality, and that reverse-causality and cognitive-consistency interpretations remain consistent with the data.

Fourth, the study reframes facilitating conditions and organizational support as enabling baseline conditions: non-significant as direct effects, but necessary-but-not-sufficient conditions for preventing resistance, thereby reconciling weak regression coefficients with strong configurational necessity. Relatedly, it positions informal “shadow” adoption as an intrinsic feature of bureaucratic digital transformation rather than deviant behavior, aligning with calls to theorize AI capability development as an employee-driven process.

### 5.3. Practical Implications

PLS-SEM identifies performance expectancy as the strongest net-effect determinant of the intention to adopt GenAI, while fsQCA additionally identifies facilitating conditions as a core condition in every adoption configuration. Public-sector managers should therefore prioritize the selection of GenAI tools that solve specific, painful problems for employees (e.g., summarizing long reports, drafting routine emails, generating templated administrative documents) over generic deployments that lack tangible benefits. Concurrently, managers should ensure that facilitating conditions are in place: stable internet, compatible hardware, and licensed access to mainstream GenAI tools, so that employees do not face technical friction as a barrier to use.

A second implication concerns the role of organizational support in moderating the effects of perceived risk. The configurations show that high perceived risk does not necessarily inhibit adoption, but only when perceived organizational support is also present (i.e., Configurations 3 and 4). Conversely, the absence of perceived organizational support consistently emerges as a precursor of resistance. Public agencies should therefore provide an explicit psychological safety net for experimentation, including clear written guidance that the organization sanctions and supports the use of GenAI for permitted task categories, a dedicated technical helpdesk to respond to operational queries, and risk-sharing protocols in which the organization assumes responsibility for sanctioned use. This allows cautious employees to engage with the technology without fear of punitive consequences for inadvertent errors.

Third, management should actively cultivate social influence to normalize the use of GenAI within the public sector. Because social influence emerged as a core condition in the dominant adoption configurations, the visibility of GenAI usage is critical. This can be achieved by identifying early adopters who match the profile of the “Pragmatist” configuration (i.e., Configuration 1: high-efficiency focus and high trust) and empowering them as internal champions to share success stories. Leadership endorsement must move beyond verbal encouragement to visible use; when department heads and managers actively use GenAI in meetings and decision support, it signals to the wider workforce that the technology is a legitimate and valued tool for public service.

Fourth, training strategies must be differentiated to address the distinct user profiles identified in the configurational analysis. A one-size-fits-all approach is inappropriate, given that the fsQCA results reveal qualitatively different recipes for adoption. For the “Pragmatist” group (i.e., Configuration 1), training should focus on efficiency and practical “how-to” techniques to maximize effort expectancy and rapid time-to-value. Practical workshops could demonstrate how GenAI can summarize lengthy policy documents, draft routine correspondence, generate meeting minutes, and automate repetitive administrative tasks, thereby maximizing perceived usefulness and reducing effort. For the “Institutionally Supported” and “Risk-Engaged” groups (i.e., Configurations 2 and 3), training should prioritize awareness and trust building, focusing on data privacy, ethics, and the underlying mechanisms of GenAI. Example activities may include case-based exercises on handling

sensitive data, guidance on privacy and confidentiality requirements, demonstrations of human verification procedures, and discussion of ethical risks such as bias and hallucination. For the “Fully Embedded” group (i.e., Configuration 4), training can move beyond basic competence to advanced use cases and prompt-engineering workshops, collaborative problem-solving sessions, and project-based learning that explores more sophisticated applications such as policy analysis support, scenario generation, and knowledge management. Tailoring educational programs in this way addresses the specific psychological and functional needs of diverse employee groups.

Finally, the analysis of non-intention indicates that resistance is often driven by a generalized deficit of environmental factors, specifically the absence of organizational support and awareness, which together approach the necessity threshold for resistance. Before pushing for adoption, public agencies should therefore ensure that these enabling baselines are in place. Pushing a complex technology on a workforce that feels unsupported and uneducated about the risks is likely to trigger the resistance configurations identified in this study. By proactively filling the knowledge void and demonstrating institutional backing, organizations can dismantle the structural barriers that lead to GenAI rejection, ensuring that even risk-averse employees are receptive to the technology.

#### 5.4. Limitations and Future Research

This study has several limitations that frame the interpretation of the findings and define avenues for future research.

The first concerns empirical scope. The data were collected from a single transitioning Vietnamese province (i.e., the former Binh Duong Province, now part of Ho Chi Minh City), so although the multi-stage stratification across three “dynamic spatial zones” enhances within-province diversity, the findings cannot be generalized to Vietnam as a whole or to other emerging economies. Future studies should test the model in other provinces and institutional settings, including healthcare, education, and central government.

A second set of limitations relates to the study’s cross-sectional, single-source design, restricting causal inference and leaving open the possibility of common method bias. While procedural remedies and a full-collinearity check (Kock, 2015) were applied, no marker-variable or Harman’s single-factor diagnostic was implemented, and longitudinal or multi-source data would strengthen causal claims, particularly for the counter-hypothesized positive perceived-risk-to-intention relationship.

Third, measurement constraints qualify two focal constructs: the perceived-risk scale blends privacy, displacement, and general-risk facets, which limits attribution of the positive association to the relevance-anxiety mechanism, and the organizational-support scale comprises only two items. Future work should decompose perceived risk into facet-specific subscales and adopt the fuller Eisenberger et al. (1986) measure.

Fourth, the nested structure of 302 employees within eight units was modeled under independence; with non-trivial intraclass correlation, standard errors may be downward-biased, and future analyses should report intraclass correlations, design effects, and cluster-robust estimates, possibly within a three-level structure.

Finally, the sample skews toward staff-level (97.4%) and bachelor’s-degree holders (85.8%), and the scope is confined to informal GenAI support tools, leaving leadership perceptions, other AI technologies, and citizen-facing applications for future research.

## 6. Conclusions

This study integrated PLS-SEM and fsQCA to examine the adoption of generative AI by local government employees in a transitioning Vietnamese province. The integration of these methods reveals a complex phenomenon: GenAI adoption in local government does

not follow traditional top-down institutionalization. Instead, it often takes an informal form, in which motivated employees compensate for weak institutional infrastructure through individual initiative and peer learning. While PLS-SEM assesses the average net effects of independent variables on the intention to adopt GenAI, fsQCA provides a configurational perspective by identifying core and peripheral conditions across multiple equifinal pathways. The comparison highlights both convergent findings (e.g., the critical role of performance expectancy and social influence) and complementary insights, particularly regarding facilitating conditions and organizational support, where fsQCA revealed configurational roles that were not captured by the linear analysis. The most theoretically novel finding is the positive association between perceived risk and adoption intention. However, given the cross-sectional design, this association should not be interpreted as evidence that risk perceptions cause adoption intention. Three explanations remain equally plausible: relevance anxiety, whereby employees may engage with GenAI to maintain professional relevance; reverse causality, whereby employees who are already more inclined to use GenAI become more aware of its risks; and cognitive consistency, whereby employees who support adoption also acknowledge risk as part of a complex but coherent evaluation of the technology. Taken together, these findings advance technology-acceptance theorizing for autonomous GenAI in public bureaucracies and offer concrete implications for digital-government practice in emerging-economy settings.

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## References

- Ababneh, M. A.-K., Al-Jarrah, A. A., & Karagozlu, D. (2020). The role of big data and machine learning in COVID-19. *BRAIN Broad Research in Artificial Intelligence and Neuroscience*, 11(2sup1), 1–20. [CrossRef]
- Ahn, M. J., & Chen, Y. C. (2022). Digital transformation toward AI-augmented public administration: The perception of government employees and the willingness to use AI in government. *Government Information Quarterly*, 39(2), 101664. [CrossRef]
- Alibraheem, M., Abdul-Jabbar, H., & Ibrahim, I. (2019). Electronic tax filing adoption in Jordan: The tax employees' perspectives. *International Journal of Advanced Science and Technology*, 28(17), 681–689.
- Alkaabi, A., Jabeen, F., Dwivedi, A., & Jose, S. (2026). Artificial intelligence adoption in the service industry: Investigating the role of perceived usefulness and ease of use. *International Journal of Productivity and Performance Management*, 75(4), 1049–1071. [CrossRef]
- Al Sayegh, A. J., Ahmad, S. Z., AlFaqeeh, K. M., & Singh, S. K. (2023). Factors affecting e-government adoption in the UAE public sector organisations: The knowledge management perspective. *Journal of Knowledge Management*, 27(3), 717–737. [CrossRef]
- Ashok, M. (2024). *Written evidence submitted to the House of Commons Committee of Public Accounts inquiry on the use of artificial intelligence in government* (AIG0013). UK Parliament. Available online: <https://committees.parliament.uk/writtenevidence/130185/html/> (accessed on 20 July 2026).
- Ashok, M., Al Badi Al Dhaheri, M. S. M., Madan, R., & Dzandu, M. D. (2021). How to counter organisational inertia to enable knowledge management practices adoption in public sector organisations. *Journal of Knowledge Management*, 25(9), 2245–2273. [CrossRef]

- Bentler, P. M., & Bonett, D. G. (1980). Significance tests and goodness of fit in the analysis of covariance structures. *Psychological Bulletin*, 88(3), 588–606. [\[CrossRef\]](#)
- Bentler, P. M., & Chou, C.-P. (1987). Practical issues in structural modeling. *Sociological Methods and Research*, 16(1), 78–117. [\[CrossRef\]](#)
- Bick, A., Blandin, A., & Deming, D. J. (2024). *The rapid adoption of generative AI* (Working Paper 2024-027). Federal Reserve Bank of St. Louis. [\[CrossRef\]](#)
- Blaique, L., Kertechian, K. S., & Farah, A. (2026). Assessing employees' readiness for AI: The case of ChatGPT in the Dubai government. *International Journal of Public Sector Management*, 1–26. [\[CrossRef\]](#)
- Bright, J., Enock, F. E., Esnaashari, S., Francis, J., Hashem, Y., & Morgan, D. (2024). Generative AI is already widespread in the public sector: Evidence from a survey of UK public sector professionals. *Digital Government: Research and Practice*, 6(1), 1–13. [\[CrossRef\]](#)
- Brougham, D., & Haar, J. (2018). Smart technology, artificial intelligence, robotics, and algorithms (STARA): Employees' perceptions of our future workplace. *Journal of Management and Organization*, 24(2), 239–257. [\[CrossRef\]](#)
- Bryman, A., & Bell, E. (2015). *Business research methods* (4th ed.). Oxford University Press.
- Brynjolfsson, E., Li, D., & Raymond, L. R. (2023). *Generative AI at work* (Working Paper 31161). NBER. [\[CrossRef\]](#)
- Budai, B. B., Csuhai, S., & Tózsá, I. (2023). Digital competence development in public administration higher education. *Sustainability*, 15(16), 12462. [\[CrossRef\]](#)
- Calhoun, C. S., Bobko, P., Gallimore, J. J., & Lyons, J. B. (2019). Linking precursors of interpersonal trust to human-automation trust. *Journal of Trust Research*, 9(1), 28–46. [\[CrossRef\]](#)
- Calzada, I., & Eizaguirre, I. (2025). Digital inclusion and urban AI: Strategic roadmapping and policy challenges. *Discover Cities*, 2, 73. [\[CrossRef\]](#)
- Carrasco, M., Habib, C., Felden, F., Sargeant, R., Mills, S., Shenton, S., Ingram, J., & Dando, G. (2023). *Generative AI for the public sector: From opportunities to value* [Report]. Boston Consulting Group.
- Chatterjee, S., Rana, N. P., Khorana, S., Mikalef, P., & Sharma, A. (2023). Assessing organizational users' intentions and behavior to AI-integrated CRM systems: A Meta-UTAUT approach. *Information Systems Frontiers*, 25(4), 1299–1313. [\[CrossRef\]](#)
- Chen, J., & Zhou, W. (2022). Drivers of salespeople's AI acceptance: What do managers think? *Journal of Personal Selling and Sales Management*, 42(2), 107–120. [\[CrossRef\]](#)
- Cho, S., Hur, J. Y., & Kim, D. (2025). Bridging trust in AI and its adoption: The role of organizational support in AI chatbot implementation in Korean government agencies. *Government Information Quarterly*, 42(4), 102081. [\[CrossRef\]](#)
- 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. [\[CrossRef\]](#)
- Chun, S. A., & Noveck, B. S. (2025). Introduction to the special issue on ChatGPT and other generative AI commentaries: AI augmentation in government 4.0: AI augmentation in government 4.0. *Digital Government: Research and Practice*, 6(1), 1–8. [\[CrossRef\]](#) [\[PubMed\]](#)
- Communist Party of Vietnam. (2024). *Resolution No. 57-NQ/TW on breakthroughs in science, technology, innovation, and national digital transformation*. Politburo of the Central Committee of the Communist Party of Vietnam.
- Communist Party of Vietnam. (2025). *Resolution No. 60-NQ/TW on the arrangement and merger of provincial-level and commune-level administrative units and the organisation of the two-tier local government system*. Politburo of the Central Committee of the Communist Party of Vietnam.
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340. [\[CrossRef\]](#) [\[PubMed\]](#)
- Desouza, K. C. (2021). *Artificial intelligence in the public sector: A maturity model* (Report). IBM Center for the Business of Government.
- Distor, C. B., Khaltar, O., & Moon, M. J. (2021). Adoption of artificial intelligence (AI) in local governments: An exploratory study on the attitudes and perceptions of officials in a municipal government in the Philippines. *Journal of Public Affairs and Development*, 8, 33–65.
- Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2019). Re-examining the unified theory of acceptance and use of technology (UTAUT): Towards a revised theoretical model. *Information Systems Frontiers*, 21(3), 719–734. [\[CrossRef\]](#)
- Eisenberger, R., Huntington, R., Hutchison, S., & Sowa, D. (1986). Perceived organizational support. *Journal of Applied Psychology*, 71(3), 500–507. [\[CrossRef\]](#)
- Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: A perceived risk facets perspective. *International Journal of Human-Computer Studies*, 59(4), 451–474. [\[CrossRef\]](#)
- Fiss, P. C. (2011). Building better causal theories: A fuzzy set approach to typologies in organizational research. *Academy of Management Journal*, 54(2), 393–420. [\[CrossRef\]](#)
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39–50. [\[CrossRef\]](#)
- Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, 114, 254–280. [\[CrossRef\]](#)

- Gao, H., Kumar, J., Kumari, J., Huang, J., & Kumar, D. (2026). Investigating behavioral intentions toward DeepSeek adoption using a moderated-mediation analysis with PLS-SEM and fsQCA. *Scientific Reports*, 16(1), 18271. [\[CrossRef\]](#) [\[PubMed\]](#)
- Gerlich, M. (2023). Perceptions and acceptance of artificial intelligence: A multi-dimensional study. *Social Sciences*, 12(9), 502. [\[CrossRef\]](#)
- Gillath, O., Ai, T., Branicky, M., Keshmiri, S., Davison, R., & Spaulding, R. (2021). Attachment and trust in artificial intelligence. *Computers in Human Behavior*, 115, 106607. [\[CrossRef\]](#)
- Government of Vietnam. (2021). *National strategy on artificial intelligence development to 2030*. Government of Vietnam.
- Government of Vietnam. (2025). *Implementation reports on the 2025 administrative reform and the two-tier local government model*. Prime Minister's Office, Ministry of Home Affairs, and Ministry of Information and Communications.
- Greckhamer, T., Furnari, S., Fiss, P. C., & Aguilera, R. V. (2018). Studying configurations with qualitative comparative analysis: Best practices in strategy and organization research. *Strategic Organization*, 16(4), 482–495. [\[CrossRef\]](#)
- Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). Sage Publications.
- Henseler, J., Hubona, G., & Ray, P. A. (2016). Using PLS path modeling in new technology research: Updated guidelines. *Industrial Management and Data Systems*, 116(1), 2–20. [\[CrossRef\]](#)
- Hernández-Tamurejo, Á., Bužinskienė, R., Barbosa, B., Miceikienė, A., & Saura, J. R. (2026). Generative artificial intelligence use in the workplace: Implications for management practice. *Review of Managerial Science*, 20(8), 2693–2725. [\[CrossRef\]](#)
- Herzberg, F., Mausner, B., & Snyderman, B. B. (1959). *The motivation to work*. John Wiley.
- Hmoud, B. I., & Várallyai, L. (2020). Artificial intelligence in human resources information systems: Investigating its trust and adoption determinants. *International Journal of Engineering and Management Sciences*, 5(1), 749–765. [\[CrossRef\]](#)
- Hoyle, R. H., & Gottfredson, N. C. (2015). Sample size considerations in prevention research applications of multilevel modeling and structural equation modeling. *Prevention Science*, 16(7), 987–996. [\[CrossRef\]](#) [\[PubMed\]](#)
- Jain, R., Garg, N., & Khera, S. N. (2022). Adoption of AI-enabled tools in social development organizations in India: An extension of UTAUT model. *Frontiers in Psychology*, 13, 893691. [\[CrossRef\]](#) [\[PubMed\]](#)
- Jeyaraj, A., Dwivedi, Y. K., & Venkatesh, V. (2023). Intention in information systems adoption and use: Current state and research directions. *International Journal of Information Management*, 73, 102680. [\[CrossRef\]](#)
- Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons*, 62(1), 15–25. [\[CrossRef\]](#)
- Khaksar, S. M. S., Khosla, R., Singaraju, S., & Slade, B. (2021). Carer's perception on social assistive technology acceptance and adoption: Moderating effects of perceived risks. *Behaviour and Information Technology*, 40(4), 337–360. [\[CrossRef\]](#)
- Kijisanayotin, B., Pannarunothai, S., & Speedie, S. M. (2009). Factors influencing health information technology adoption in Thailand's community health centers: Applying the UTAUT model. *International Journal of Medical Informatics*, 78(6), 404–416. [\[CrossRef\]](#) [\[PubMed\]](#)
- Kim, H.-W., & Kankanhalli, A. (2009). Investigating user resistance to information systems implementation: A status quo bias perspective. *MIS Quarterly*, 33(3), 567–582. [\[CrossRef\]](#)
- Kline, R. B. (2011). *Principles and practice of structural equation modeling* (3rd ed.). Guilford Press.
- Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration*, 11(4), 1–10. [\[CrossRef\]](#)
- Lankton, N. K., Harrison McKnight, D., & Tripp, J. (2015). Technology, humanness, and trust: Rethinking trust in technology. *Journal of the Association for Information Systems*, 16(10), 880–918. [\[CrossRef\]](#)
- Liu, Y., Mezei, J., Kostakos, V., & Li, H. (2017). Applying configurational analysis to IS behavioural research: A methodological alternative for modelling combinatorial complexities. *Information Systems Journal*, 27(1), 59–89. [\[CrossRef\]](#)
- Madan, R., & Ashok, M. (2023). AI adoption and diffusion in public administration: A systematic literature review and future research agenda. *Government Information Quarterly*, 40(1), 101774. [\[CrossRef\]](#)
- Madan, R., & Ashok, M. (2025). Making sense of AI benefits: A mixed-method study in Canadian public administration. *Information Systems Frontiers*, 27(3), 889–923. [\[CrossRef\]](#)
- Mahusin, N., Sallehudin, H., & Satar, N. S. M. (2024). Malaysia public sector challenges of implementation of Artificial Intelligence (AI). *IEEE Access*, 12, 121035–121051. [\[CrossRef\]](#)
- Majrashi, K. (2024). Determinants of public sector managers' intentions to adopt AI in the workplace. *International Journal of Public Administration in the Digital Age*, 11(1), 1–26. [\[CrossRef\]](#)
- Maragno, G., Tangi, L., Gastaldi, L., & Benedetti, M. (2023). Exploring the factors, affordances and constraints outlining the implementation of artificial intelligence in public sector organizations. *International Journal of Information Management*, 73, 102686. [\[CrossRef\]](#)
- Marimon, F., Mas-Machuca, M., & Akhmedova, A. (2025). Trusting in generative AI: Catalyst for employee performance and engagement in the workplace. *International Journal of Human-Computer Interaction*, 41(11), 7076–7091. [\[CrossRef\]](#)

- Masa'deh, R., Almajali, D. A., Alsokkar, A. A. M., Alshinwan, M., & Shehadeh, M. (2023). Antecedents of intention to use e-auction: An empirical study. *Sustainability*, 15(6), 4871. [\[CrossRef\]](#)
- Mercuri, F., Quaglieri, L., Ramírez-Hurtado, J. M., & Quattrociochi, B. (2026). Technological, organizational and environmental determinants influencing the intention to adopt GEN-AI of public sector organizations: A cross-country comparative analysis. *European Journal of Innovation Management*, 29, 2175–2200. [\[CrossRef\]](#)
- Mergel, I., Dickinson, H., Stenvall, J., & Gasco, M. (2023). Implementing AI in the public sector. *Public Management Review*, 1–14. [\[CrossRef\]](#)
- National Assembly of Vietnam. (2025). *Resolution No. 202/2025/QH15 on the reorganisation of provincial-level administrative units*. National Assembly of the Socialist Republic of Vietnam.
- Neumann, O., Guirguis, K., & Steiner, R. (2024). Exploring artificial intelligence adoption in public organizations: A comparative case study. *Public Management Review*, 26(1), 114–141. [\[CrossRef\]](#)
- Nguyen, M., Rundle-Thiele, S., Malik, A., & Budhwar, P. (2023). Impact of technology-based knowledge sharing on employee outcomes: Moderation effects of training, support and leadership. *Journal of Knowledge Management*, 27(8), 2283–2301. [\[CrossRef\]](#)
- Nguyen, T. T., Phan, D. M., Le, A. H., & Nguyen, L. T. N. (2020). The determinants of citizens' satisfaction of e-government: An empirical study in Vietnam. *Journal of Asian Finance, Economics and Business*, 7(8), 519–531. [\[CrossRef\]](#)
- Nguyen Duy, P., Ruangthamsing, C., Kamnuansilpa, P., Lowatcharin, G., & Setthasuravich, P. (2026). Generative AI in developing countries: Adoption dynamics in Vietnamese local government. *Informatics*, 13(2), 22. [\[CrossRef\]](#)
- Omonov, M. S., & Ahn, Y. (2025). Towards smart public administration: A TOE-based empirical study of AI chatbot adoption in a transitioning government context. *Administrative Sciences*, 15(8), 324. [\[CrossRef\]](#)
- Pappas, I. O., & Woodside, A. G. (2021). Fuzzy-set qualitative comparative analysis (fsQCA): Guidelines for research practice in information systems and marketing. *International Journal of Information Management*, 58, 102310. [\[CrossRef\]](#)
- Parasuraman, A., & Colby, C. L. (2015). An updated and streamlined technology readiness index: TRI 2.0. *Journal of Service Research*, 18(1), 59–74. [\[CrossRef\]](#)
- Patton, M. Q. (2015). *Qualitative research and evaluation methods: Integrating theory and practice* (4th ed.). Sage Publishing.
- Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879–903. [\[CrossRef\]](#) [\[PubMed\]](#)
- Prachumrasee, K., Kamnuansilpa, P., & Setthasuravich, P. (2025). Digital public service ecosystems in local governance: Insights from Northeastern Thailand's local administrative organizations. *FWU Journal of Social Sciences*, 19(2), 111–135. [\[CrossRef\]](#) [\[PubMed\]](#)
- Prime Minister of Vietnam. (2020). *Decision No. 749/QĐ-TTg on the approval of the National Digital Transformation Programme to 2025, with a vision to 2030*. Government of Vietnam.
- Prime Minister of Vietnam. (2025). *Decision No. 759/QĐ-TTg on the plan to rearrange and merge provincial-level and commune-level administrative units*. Government of Vietnam.
- Ragin, C. C. (2008). *Redesigning social inquiry: Fuzzy sets and beyond*. University of Chicago Press. [\[CrossRef\]](#)
- Rana, M. M., Siddiquee, 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), e37569. [\[CrossRef\]](#) [\[PubMed\]](#)
- Rasoolimanesh, S. M., Ringle, C. M., Sarstedt, M., & Olya, H. (2021). The combined use of symmetric and asymmetric approaches: Partial least squares-structural equation modeling and fuzzy-set qualitative comparative analysis. *International Journal of Contemporary Hospitality Management*, 33(5), 1571–1592. [\[CrossRef\]](#)
- Rodriguez Müller, A. P., Tangi, L., & Lerusse, A. (2025). Understanding the adoption of artificial intelligence in local government decision-making: The influence of institutional pressures and managerial perceptions. *Public Administration*, 1–17. [\[CrossRef\]](#)
- Salah, M., Alnoor, A., Abdelfattah, F., Ahmad, A. B., Al Halbusi, H., & Al Arai, A. (2026). The role of generative artificial intelligence use in street-level bureaucrats' discretion and enforcement styles: A multigroup analysis. *International Journal of Public Administration*, 1–23. [\[CrossRef\]](#)
- Salam, N. R. A., & Ali, S. (2020). Determining factors of cloud computing adoption: A study of Indonesian local government employees. *Journal of Accounting and Investment*, 21(2), 312–333. [\[CrossRef\]](#)
- Schneider, C. Q., & Wagemann, C. (2012). *Set-theoretic methods for the social sciences: A guide to qualitative comparative analysis*. Cambridge University Press. [\[CrossRef\]](#)
- Setthasuravich, P., Sirikhan, K., & Kato, H. (2024). Spatial econometric analysis of the digital divide in Thailand at the sub-district level: Patterns and determinants. *Telecommunications Policy*, 48(8), 102818. [\[CrossRef\]](#)
- Shahzad, M. F., Xu, S., & Baheer, R. (2024). Assessing the factors influencing the intention to use information and communication technology implementation and acceptance in China's education sector. *Humanities and Social Sciences Communications*, 11(1), 283. [\[CrossRef\]](#)
- Smutny, Z., & Sudzina, F. (2026). What affects work performance when using AI chatbots? Investigating mediations and factors affecting performance expectancy and intentions to use ChatGPT. *International Journal of Human-Computer Interaction*, 42(12), 8826–8850. [\[CrossRef\]](#)

- Sobrinho-García, I. (2021). Artificial intelligence risks and challenges in the Spanish public administration: An exploratory analysis through expert judgements. *Administrative Sciences*, 11(3), 102. [CrossRef]
- Sun, T. Q., & Medaglia, R. (2019). Mapping the challenges of artificial intelligence in the public sector: Evidence from public healthcare. *Government Information Quarterly*, 36(2), 368–383. [CrossRef]
- Tangi, L., Rodriguez Müller, A. P., & Combetto, M. (2025). A silent partner: The shadow presence of generative artificial intelligence in public administrations. In *Lecture notes in computer science*. Springer. [CrossRef]
- United Nations Development Programme (UNDP). (2025). *A quick review of artificial intelligence applications in government agencies in Vietnam: Policy recommendations*. Available online: [https://ips.org.vn/en/library/\[executive-summary\]-a-quick-review-of-artificial-intelligence-applications-in-government-agencies-in-vietnam-policy-recommendations-ct302.html](https://ips.org.vn/en/library/[executive-summary]-a-quick-review-of-artificial-intelligence-applications-in-government-agencies-in-vietnam-policy-recommendations-ct302.html) (accessed on 20 July 2026).
- van Noordt, C., & Misuraca, G. (2022). Artificial intelligence for the public sector: Results of landscaping the use of AI in government across the European Union. *Government Information Quarterly*, 39(3), 101714. [CrossRef]
- van Noordt, C., & Tangi, L. (2023). The dynamics of AI capability and its influence on public value creation of AI within public administration. *Government Information Quarterly*, 40(4), 101860. [CrossRef]
- Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, 46(2), 186–204. [CrossRef]
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478. [CrossRef]
- Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 36(1), 157–178. [CrossRef]
- Vrontis, D., Christofi, M., Pereira, V., Tarba, S., Makrides, A., & Trichina, E. (2022). Artificial intelligence, robotics, advanced technologies and human resource management: A systematic review. *International Journal of Human Resource Management*, 33(6), 1237–1266. [CrossRef]
- Wang, G., Obrenovic, B., Gu, X., & Godinic, D. (2025). Fear of the new technology: Investigating the factors that influence individual attitudes toward generative artificial intelligence (AI). *Current Psychology*, 44(9), 8050–8067. [CrossRef]
- Wu, C.-H., Twu, R.-D., & Huang, K.-C. (2025). The impact of performance expectations and perceived behavioral control on employees' AI adoption. *HighTech and Innovation Journal*, 6(4), 1315–1332. [CrossRef]
- Yamane, T. (1967). *Statistics: An introductory analysis* (2nd ed.). Harper and Row.
- Yigitcanlar, T., Degirmenci, K., & Inkinen, T. (2024). Drivers behind the public perception of artificial intelligence: Insights from major Australian cities. *AI and Society*, 39(3), 833–853. [CrossRef] [PubMed]

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