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Generative AI in Developing Countries: Adoption Dynamics in Vietnamese Local Government

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Abstract

Generative Artificial Intelligence (GenAI) is rapidly reshaping public-sector operations, yet its adoption in developing countries remains poorly understood. Existing research focuses largely on traditional AI in developed contexts, leaving unanswered questions about how GenAI interacts with institutional, organizational, and governance constraints in resource-limited settings. This study examines the organizational factors shaping GenAI adoption in Vietnamese local government using 25 semi-structured interviews analyzed through the Technology–Organization–Environment (TOE) framework. Findings reveal three central dynamics: (1) the emergence of informal, voluntary, and bottom-up experimentation with GenAI among civil servants; (2) significant institutional capacity constraints—including absent strategies, limited budgets, weak integration, and inadequate training—that prevent formal adoption; and (3) an "AI accountability vacuum" characterized by data security concerns, regulatory ambiguity, and unclear responsibility for AI-generated errors. Together, these factors create a state of governance paralysis in which GenAI is simultaneously encouraged and discouraged. The study contributes to theory by extending the TOE framework with an environment-specific construct—the AI accountability vacuum—and by reframing resistance as a rational response to structural gaps rather than technophobia. Practical implications highlight the need for capacity-building, regulatory guidance, accountable governance structures, and leadership-driven institutional support to enable safe and effective GenAI adoption in developing-country public sectors.

Keywords: digital transformation; Generative AI; local governance; Technology–Organization–Environment; Vietnam

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1. Introduction

Digital technologies have long been recognized as engines of socio-economic development, enabling new forms of productivity, governance, and public service delivery [1]. Among recent technological breakthroughs, Generative Artificial Intelligence (GenAI) represents a particularly disruptive shift. Unlike traditional AI systems that classify, predict, or automate structured processes, GenAI can generate text, images, code, and analytical outputs, thereby supporting a far broader set of cognitive and creative tasks in government settings [2]. Since the public release of ChatGPT in late 2022, GenAI models have rapidly diffused worldwide, transforming communication, knowledge work, and organizational processes across sectors [3]. By 2025, emerging multimodal systems such as

Grok 4.1, Gemini 3, and Claude Opus 4.5 have further expanded GenAI's capabilities, but ChatGPT remains dominant, accounting for nearly 77% of user traffic among 60 major GenAI tools [4]. These adoption patterns indicate that GenAI is increasingly embedded into everyday workflows, not as a specialized expert tool but as a ubiquitous cognitive assistant.

Although global usage has surged—particularly in developing countries such as India, Brazil, Vietnam, and Indonesia—organizational adoption within government remains uneven. Most enterprises and public agencies continue to rely on publicly accessible tools such as ChatGPT and Microsoft Copilot, rather than developing domain-specific GenAI solutions [5]. This gap underscores a broader challenge: the transition from individual experimentation to institutionalized, accountable, and secure GenAI integration.

Across the public sector, GenAI has emerged as a central component of digital transformation strategies [6]. Its capabilities in adaptive problem-solving, complex document drafting, real-time summarization, and automated decision support distinguish it sharply from earlier generations of public-sector technologies [5]. Governments worldwide anticipate that GenAI will reshape policy formulation, service delivery, bureaucratic processes, and internal management routines [7]. Preliminary applications, ranging from automated citizen interaction to enhanced administrative decision support. This signals GenAI's potential as a catalyst of innovation and performance improvement [8].

However, GenAI adoption in government introduces a dual transformation. Externally, GenAI can deepen state–citizen engagement by improving responsiveness, accessibility, and participatory channels [9]. Internally, GenAI promises improved efficiency by automating routine tasks and freeing public employees to focus on higher-value, judgment-based activities [10]. However, these promises coexist with profound challenges. Many public organizations lack the technical infrastructure, human capabilities, and governance systems needed to integrate GenAI effectively and responsibly [11,12]. As a result, despite strong political interest, the actual institutionalization of GenAI remains limited, slow, and fragmented [13].

Vietnam serves as a compelling case of digital transformation in an emerging economy transitioning to middle-income status, with the digital economy contributing approximately 14% of national GDP by 2025 [14,15]. Through the National Digital Transformation Project 2025–2030, the government is actively promoting the development of a digital government, digital economy, and digital society, supported by an internet penetration rate of 84.2% [16,17]. Central to this vision is the National Strategy on Artificial Intelligence, which aims to position Vietnam among the top four ASEAN countries and the top 50 globally in AI research and development by 2030 [18].

To support these ambitions, Vietnam is rapidly upgrading its digital infrastructure. By mid-2025, 5G coverage had reached approximately 26% of the population, with a target of 99% coverage by 2030 [19]. At the same time, the country is expanding domestic data-center capacity to strengthen national computing sovereignty [20]. However, GenAI adoption faces distinct localized hurdles. Strict data-sovereignty regulations, such as Decree No. 13/2023/ND-CP, mandate rigorous compliance requirements for enterprise-level AI deployment [21]. These constraints have, in turn, encouraged the development of "Make in Vietnam" large language models—such as ViGPT and PhoGPT-4B—designed to align with local legal, linguistic, and cultural contexts [22–24].

These tensions are particularly salient in Vietnam, where AI adoption in the public sector, especially at the local government level. This is still in an early developmental phase. While central and provincial authorities have begun experimenting with GenAI tools such as ChatGPT, Gemini, and Copilot, usage is often informal, voluntary, and driven by individual employees rather than by organizational strategies or institutional mandates [25]. Local governments tend to rely on simple or open-source models that can operate on older

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hardware, reflecting financial and technical constraints. More advanced GenAI deployment remains hindered by persistent technological challenges: fragmented databases, lack of interoperability between central and local data systems, and limited procurement flexibility for acquiring AI-related infrastructure [25].

Organizational and human-resource barriers compound these difficulties. Vietnam's public-sector workforce faces shortages of AI-literate personnel, low managerial awareness, and limited institutional capacity for designing, procuring, or governing GenAI systems. Budget structures are not aligned with the costs associated with GenAI development—such as data cleaning, model training, and subscription fees—resulting in minimal or absent financial support for GenAI initiatives. Consequently, civil servants often use free or personal accounts to access GenAI tools, creating inequities and security risks. A further critical challenge is the absence of clear legal and regulatory frameworks governing GenAI use in government. Vietnam currently lacks detailed guidelines on data protection, privacy, model transparency, and accountability for AI-generated outputs [25]. This regulatory uncertainty mirrors a broader pattern observed globally, where technological capabilities outpace legislative development [26,27]. For Vietnamese civil servants, this creates a climate of hesitation, particularly given the bureaucratic emphasis on rule compliance and the potential career risks associated with unauthorized or improperly governed technology use. GenAI's "black box" nature further undermines transparency and complicates the delegation of responsibility for errors or biased outcomes [7].

Despite the growing interest in AI governance, empirical studies on GenAI adoption within public-sector organizations remain scarce. Most existing research addresses traditional AI applications (e.g., predictive analytics, classification algorithms) and is heavily concentrated in developed countries [28,29]. Only a few studies employ structured theoretical frameworks to examine GenAI adoption processes in public administration [30], and even fewer explore the unique constraints of developing countries where political structures, administrative capacity, and digital infrastructure differ substantially from Western contexts. This gap is notable given the rising push for digital transformation across Southeast Asia, including Vietnam, where institutional and organizational dynamics may significantly shape GenAI implementation pathways.

To address this gap, the present study investigates how local governments in a developing context adopt GenAI, focusing specifically on the organizational factors that influence civil servants' intention to use GenAI in daily administrative work. We employ the Technology–Organization–Environment (TOE) framework [31], which provides a structured lens to examine technological characteristics, organizational capabilities, and environmental forces. TOE has been widely applied in research on digital transformation and AI adoption in public agencies [12,32], but its application to GenAI—and to developing countries—remains limited. GenAI introduces distinct challenges related to data governance, accountability, and risk management that may extend or challenge classic TOE assumptions, making it an appropriate framework for analytical exploration. Accordingly, this study is guided by the following research question (RQ):

RQ: *What organizational factors influence the intention to apply GenAI in local government?*

To answer this question, we conducted 25 in-depth semi-structured interviews with civil servants in a provincial government in Vietnam, followed by a reflexive thematic analysis using six-phase approach [33]. The qualitative design enables an exploratory and context-sensitive examination of GenAI adoption at the frontline of public administration, providing insights that quantitative surveys or secondary data alone cannot capture.

This study contributes to the literature by (1) offering one of the first empirical investigations of GenAI adoption in local government in an emerging economy; (2) extending the TOE framework through the identification of a GenAI-specific environmental constraint—an "AI accountability vacuum" characterized by regulatory ambiguity and unclear responsibility; and (3) reframing resistance to GenAI not as technophobia but as a rational response to institutional and organizational capacity gaps. These contributions have implications for both theory and practice, particularly for governments seeking to transition from informal experimentation to safe, accountable, and institutionalized GenAI integration.

2. Literature Review

2.1. Generative AI and Traditional AI: Conceptual Distinctions

GenAI represents a significant departure from earlier forms of artificial intelligence traditionally used in public administration. Classic AI applications—such as predictive analytics, rule-based automation, and classification models—typically rely on structured datasets with clear provenance, limited scope, and deterministic outputs. Their behavior is transparent and easier to evaluate, enabling alignment with existing accountability, audit, and compliance processes in government settings [34]. These systems are often embedded in pre-defined workflows, enabling incremental improvements without requiring major organizational restructuring. By contrast, GenAI introduces an entirely different paradigm. GenAI models are trained on massive, heterogeneous, and often un-curated datasets drawn from the internet, making their data lineage opaque and raising concerns about bias, intellectual property violations, and misinformation. Their outputs are probabilistic rather than rule-based, generating unique responses that vary across prompts and contexts. This creates new challenges for verification, reliability, and public-sector accountability, especially in tasks involving legal interpretation, citizen-facing communication, or policy analysis. As noted, the generative nature of these models complicates governance because it blurs the line between human and machine authorship, making responsibility attribution more difficult [7].

In terms of organizational learning, GenAI offers new opportunities for creativity, analytical augmentation, and rapid content generation. However, effective use requires new competencies—including prompt engineering, critical evaluation of AI-generated outputs, and understanding model limitations—constituting a significant shift from traditional ICT skill requirements [35]. Traditional AI systems typically support structured, incremental improvements, whereas GenAI demands cultural adaptation and deeper integration with knowledge-intensive work. This distinction is crucial in public administration, where bureaucratic processes, risk aversion, and regulatory constraints often limit experimentation with emerging technologies. Thus, GenAI cannot be treated as a simple extension of traditional AI. It introduces new risks, new governance dilemmas, and new capability requirements that must be understood when assessing its adoption in public-sector organizations, particularly in resource-constrained contexts such as Vietnam.

2.2. Empirical Evidence on AI and GenAI Adoption in the Public Sector

2.2.1. Drivers and Enablers of Adoption

A growing body of literature highlights that AI adoption in government is shaped by an interplay of internal (organizational) and external (environmental) drivers. Technological readiness alone is insufficient to explain adoption; factors such as cultural alignment, managerial support, policy mandates, and contextual customization are critical [36]. For GenAI specifically, adoption depends not only on performance expectations but also on linguistic compatibility, data sensitivity constraints, and ethical concerns [7]. Organizational capacity consistently emerges as a major determinant of AI readiness. Studies across European municipalities show that internal resources—such as skilled personnel, financial

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capacity, change management processes, and IT infrastructure—are essential for effective implementation [12]. In the study of Finnish local governments, identify shortages of AI expertise, insufficient budgets, and weak change management structures as the most critical constraints [37]. These studies collectively reinforce that public-sector AI adoption is not merely a technological decision but a comprehensive organizational transformation requiring coordination across structures, processes, and governance frameworks. The sociomateriality perspective strengthens this point, arguing that AI systems reshape and are reshaped by organizational routines, professional norms, and cultural assumptions [38]. Successful adoption therefore requires deep integration—not just access to tools but also the development of new management practices and interdepartmental collaboration to support cross-functional knowledge flows [39].

2.2.2. Barriers: Ethical, Political, and Sociological Considerations

Equally important are the political and ethical tensions that arise when governments incorporate algorithmic systems into public services. Public-sector employees often exhibit uncertainty and caution toward AI technologies, especially those perceived as opaque or risky [40]. Empirical work in the UK shows that civil servants prefer AI in advisory or supportive roles rather than as primary decision-makers, due to concerns about fairness, accountability, and the preservation of human judgment [40]. Studies from Brazil and elsewhere further illustrate the potential for "algorithmic deskilling," where overreliance on automated systems diminishes employees' professional autonomy and judgment [41]. Public acceptance is closely tied to institutional credibility: citizens and employees are more likely to trust algorithmic decisions when institutions demonstrate transparency, explainability, and ethical stewardship [42]. These concerns are amplified in transitioning economies, where regulatory systems are still evolving, and questions of data governance, privacy, and responsibility remain unresolved [43,44].

2.2.3. Developed vs. Developing Countries: Divergent Adoption Patterns

Empirical research consistently highlights stark differences in the adoption of AI between developed and developing countries. In developed countries, particularly those in Europe—digital infrastructures are mature, administrative capacity is robust, and governments generally possess strong technical and regulatory foundations. As a result, the primary challenges are not related to basic technological readiness but to deeper socio-technical integration. These include achieving effective "imbrication," or the seamless embedding of AI into existing organizational routines and professional practices [37], navigating regulatory environments that may be overly cautious or restrictive [12], and managing cultural or professional resistance to algorithmic systems. In these contexts, the barriers are less about infrastructure deficits and more about aligning innovation with established accountability mechanisms, ethical standards, and compliance expectations.

In emerging and transition economies, however, the challenges are more foundational. Governments often confront limited ICT infrastructure, unstable digital ecosystems, fragmented or siloed datasets, and significant security vulnerabilities [45,46]. These structural issues are compounded by cultural norms that reinforce hierarchical leadership and resistance to organizational change, as well as by constrained financial resources that restrict opportunities for AI experimentation and capacity-building [43,44]. Public perceptions of AI also vary widely across contexts. While skepticism tends to dominate in Western settings, some Asian developing countries—such as India—demonstrate comparatively higher levels of confidence in AI capabilities among both citizens and public employees, illustrating how cultural and environmental factors strongly shape attitudes toward algorithmic technologies [47].

Overall, these contrasts indicate that although overarching analytical frameworks such as the Technology–Organization–Environment (TOE) model or sociotechnical systems theory can be applied across different countries, the specific nature, prioritization, and interaction of adoption factors differ substantially. This underscores the importance of conducting country-specific empirical research, particularly in Southeast Asian contexts where AI policy development, administrative capacity, and institutional governance structures are still evolving and have yet to mature.

2.2.4. Gaps in Research on GenAI Adoption in Local Government

Although GenAI has diffused rapidly across sectors worldwide, empirical research on its adoption within local government remains sparse, particularly in emerging and transitioning economies. The majority of existing scholarship continues to concentrate on traditional AI applications—such as predictive analytics, automation, and classification systems—rather than on generative models that introduce fundamentally different technical and governance challenges [28,29]. As a result, critical questions about how GenAI's probabilistic outputs, data risks, and creative capabilities reshape public-sector workflows, accountability structures, and decision-making processes remain largely unexplored. Furthermore, only a limited number of studies employ structured theoretical frameworks, such as the Technology–Organization–Environment (TOE) model, to analyze GenAI adoption in public administration [30]. This gap is significant, as GenAI adoption intersects with distinct considerations—such as explainability, data protection, algorithmic responsibility, and organizational readiness—that extend beyond the scope of traditional AI research. Even fewer studies explicitly investigate how political culture, bureaucratic hierarchy, and resource constraints influence GenAI uptake at the subnational level, where administrative capacity is often most limited and frontline experimentation is most common.

In the case of Vietnam, academic analyses of GenAI integration in government are virtually nonexistent [48]. While national digital strategies emphasize AI development, there is a lack of empirical evidence on how local public organizations navigate GenAI-related opportunities and risks in practice. This absence of context-specific research creates an important gap—both theoretically and practically—given the rapid expansion of GenAI tools and the unique institutional, cultural, and infrastructural conditions shaping their use in Vietnam's local governance system. Accordingly, there is a need for empirical studies that examine GenAI adoption through a framework capable of capturing the interplay of technological, organizational, and environmental factors within emerging economy contexts.

2.3. Technology–Organization–Environment (TOE) Framework

The Technology–Organization–Environment (TOE) framework [31], is one of the most influential models for examining organizational technology adoption across both public and private sectors. The framework conceptualizes adoption as the outcome of three interrelated domains: (1) the technological context, which includes the perceived benefits, complexity, compatibility, and risks associated with the technology, (2) the organizational context, encompassing internal resources, managerial commitment, human capability, cultural readiness, and structural characteristics; and (3) the environmental context, referring to external pressures such as regulatory mandates, market dynamics, institutional norms, and broader technological ecosystems. By integrating these three dimensions, the TOE framework provides a holistic analytical lens for understanding why organizations differ in their willingness and ability to adopt new technologies.

The framework has been widely applied in public-sector research to investigate digital transformation, cloud computing adoption, AI readiness, and other emerging innovations [32,49,50]. Recent studies expand the TOE model by incorporating stakeholder perspectives, acknowledging that technology adoption in government involves complex coordination among administrative agencies, end users, private vendors, and citizens [51]. In the domain of artificial intelligence, TOE has proven especially useful for identifying organizational and policy preconditions necessary for responsible implementation, including data governance capacity, strategic leadership, and institutional support [44,52].

GenAI introduces distinctive challenges and therefore strengthens the relevance of TOE for public administration research. First, GenAI brings new technological risks, such as probabilistic outputs, hallucinations, susceptibility to data leakage, and difficulties with explainability; such issues require careful assessment under the technological dimension. Unlike traditional AI systems, GenAI outputs can be unpredictable and context-dependent, raising concern for accuracy, legality, and ethical compliance in government settings. Second, GenAI amplifies organizational capacity demands. Effective adoption depends on training civil servants in prompt design, critical evaluation of AI-generated content, integration into workflows, and the establishment of ethical review processes. It also requires leadership-driven innovation culture and clear managerial direction; these elements are often underdeveloped in local government settings within developing countries. Third, GenAI adoption is deeply intertwined with the environmental context, particularly in countries where AI regulatory frameworks remain incomplete or ambiguous. Weak data protection laws, unclear accountability for AI-generated decisions, and insufficient national guidelines create uncertainty for public officials. In developing countries, where institutional oversight mechanisms are evolving, such ambiguity directly shapes organizational behavior and risk perception.

For these reasons, the TOE framework provides a robust and comprehensive foundation for analyzing how local governments in Vietnam navigate GenAI adoption. It allows for a structured examination of the interplay between technological characteristics, organizational readiness, and environmental pressures, each of which manifests differently in transition economies. Moreover, applying TOE in this context enables the identification of new, GenAI-specific constructs that extend the framework beyond its traditional domains and reflect the realities of rapidly evolving digital governance environments [53]. Through this lens, the present study contributes to a deeper theoretical understanding of the drivers and barriers shaping GenAI adoption in local government, while offering context-sensitive insights relevant to public-sector innovation in developing countries.

3. Methods

3.1. Research Design

This study adopts a qualitative, exploratory research design to investigate the organizational factors shaping the adoption of GenAI in local government. A qualitative approach is appropriate given that GenAI represents an emerging and fast-evolving technological phenomenon with limited theoretical grounding in public administration research. Prior scholarship emphasizes that qualitative inquiry is indispensable for examining under-conceptualized topics, enabling researchers to capture contextual nuances, emergent practices, and organizational dynamics that quantitative methods may overlook [54,55]. In line with this logic, an exploratory design allows for in-depth probing of civil servants' experiences, perceptions, and behaviors as they navigate GenAI tools within their organizational environment [56].

The TOE framework guided both data collection and analysis. TOE provides a structured lens for identifying how technological characteristics, organizational capacities, and environmental pressures interact to shape technology adoption decisions. This makes it particularly suitable for studying GenAI, which introduces novel risks and capacity demands in the public sector. Because the aim of the study is to understand participants' lived experiences—not to produce statistical generalizations—the sample size was not the primary criterion. Qualitative sample sizes vary widely depending on research purpose, ranging from 4 to 50 participants [57,58]. Instead, adequacy was assessed using the principle of information power, ensuring that the sample was sufficiently specific, information-rich, and theoretically anchored to address the research aim.

3.2. Study Area

The study was conducted in Binh Duong Province, a strategically selected site due to its rapid economic growth, high urbanization rate, and strong governmental commitment to digital innovation. The selection of Binh Duong Province represents an analytically strategic case rather than a statistically representative one. As one of Vietnam's national leaders in digital transformation, foreign direct investment, and smart city innovation, Binh Duong can be understood as an extreme or critical case in which institutional readiness for advanced digital technologies would be expected to be relatively high. From an analytical perspective, this case selection allows the study to examine whether governance, capacity, and accountability barriers to GenAI adoption persist even under comparatively favorable structural conditions. If such constraints are evident in a leading province, they are likely to be equally or more salient in less-resourced local governments. This logic aligns with qualitative case-study approaches that prioritize theoretical insight over representativeness.

As one of Vietnam's leading industrial hubs, Binh Duong province ranked second nationwide in foreign direct investment inflows in 2024, surpassed only by Ho Chi Minh City. It achieved an 87% urbanization rate and an estimated GRDP growth of 8.01%, reflecting its emergence as a premier destination for high-tech and sustainable manufacturing [59]. The province has invested heavily in smart city initiatives, emphasizing data-driven governance, interdepartmental digital integration, and public–private collaborations. Notably, Binh Duong province became the first Vietnamese locality to earn the Intelligent Community of the Year (2023) award from the Intelligent Community Forum, signaling its growing international recognition for innovation [60]. Its consistent placement in the Top 10 National Digital Transformation Index further demonstrates a well-developed digital foundation and strong citizen engagement with e-government services [61]. These structural and institutional characteristics position Binh Duong province as an ideal context for examining GenAI adoption in public administration. The provincial government's support for digital transformation, combined with its openness to public–private partnerships, provides fertile ground for understanding both opportunities and constraints associated with GenAI in a local administrative setting.

It should be noted that shortly after data collection, effective 1 July 2025, an administrative restructuring merged Binh Duong, Ba Ria–Vung Tau, and Ho Chi Minh City into a single administrative entity retaining the name Ho Chi Minh City. This study therefore refers to "Binh Duong province" to reflect the structure at the time of data collection, while the findings represent insights into the northern sector of the expanded metropolitan governance area.

3.3. Data Collection and Participants

Participants were recruited using snowball sampling [62], which is well suited for identifying qualified civil servants who possess relevant knowledge and are accessible within government structures. Eligibility criteria require that participants (1) be government officers working in provincial or departmental offices, and (2) have at least two years of work experience to ensure adequate institutional familiarity. Ethical approval was obtained from the Khon Kaen University Ethics Committee for Human Research (Approval No. HE683189), and informed consent was secured prior to each interview.

A total of 25 semi-structured interviews were conducted in June 2025. Sample adequacy was assessed using Information Power [63], which considers the specificity of the sample, clarity of research aim, application of a theoretical model, quality of dialogue, and analytic strategy. The sample was sufficiently specific focusing on provincial-level government employees with direct experience or awareness of GenAI and strongly anchored in the TOE framework. Diversity across departments and functional roles (e.g., administrative units, planning, public service centers, IT divisions) increased the breadth of insights. While thematic saturation was reached after approximately 20 interviews, an additional five interviews were conducted to ensure stability of themes and representativeness across major administrative sectors. Interviews were conducted either in person, via Google Meet, or by phone, depending on participant availability and preference. Each session lasted 30 to 75 min, was audio-recorded with permission, and subsequently transcribed verbatim.

The semi-structured interview protocol was designed to capture a comprehensive understanding of how provincial-level civil servants perceive, experience, and manage Generative AI within their organizational context. The interview guide covered seven key domains: (1) participants' backgrounds and general perceptions of GenAI; (2) their firsthand experiences with GenAI tools and assessments of technological readiness; (3) perceived benefits, risks, and productivity impacts; (4) organizational strategy, leadership influence, and resource allocation; (5) internal culture, workforce capacity, and change-management challenges; (6) external environmental factors, including regulatory pressures, citizen expectations, and ethical concerns; and (7) open reflections to capture additional insights. This structure ensured that interviews elicited multilayered perspectives on GenAI adoption across the technological, organizational, and environmental dimensions central to the TOE framework. Table 1 provides a summary of participant characteristics.

Table 1. Participant Profile.

ID	Position	Broad Functional Categories	Experience in Public Organization
ID01	Unit Manager	Technology, Data and Information	23 years
ID02	Staff	Technology, Data and Information	2 years
ID03	Staff	Technology, Data and Information	2 years
ID04	Staff	Technology, Data and Information	2 years
ID05	Manager	Infrastructure	20 years
ID06	Staff	Agriculture, Environment & Resource	2 years
ID07	Staff	Administration	3.5 years
ID08	Staff	Agriculture, Environment & Resource	2 years
ID09	Staff	Administration	6 years
ID10	Staff	Legal	11 years
ID11	Unit Manager	Project management	20 years
ID12	Staff	Agriculture, Environment & Resource	25 years
ID13	Staff	Agriculture, Environment & Resource	15 years
ID14	Staff	Agriculture, Environment & Resource	13 years
ID15	Staff	Administration	13 years
ID16	Staff	Technology, Data and Information	17 years
ID17	Staff	Technology, Data and Information	17 years
ID18	Staff	Healthcare	15 years
ID19	Staff	Tax	2 years

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Table 1. *Cont.*

ID	Position	Broad Functional Categories	Experience in Public Organization
ID20	Manager	Administration	17 years
ID21	Staff	Administration	15 years
ID22	Staff	Technology, Data and Information	15 years
ID23	Staff	Administration	17 years
ID24	Manager	Agriculture, Environment & Resource	13 years
ID25	Staff	Culture	8 years

3.4. Data Analysis

Data were analyzed using reflexive thematic analysis, following six-phase framework [33], which supports flexible yet rigorous interpretation of qualitative material and is well suited for theory-informed inquiry. The analysis began with a period of familiarization, during which all interview transcripts were read multiple times to deepen understanding of participants' experiences and contextual meanings. Next, initial coding was conducted manually. Codes were generated inductively from the data but organized with reference to the TOE framework to maintain alignment with the study's theoretical orientation. These codes were subsequently examined during the theme development phase, where conceptually similar codes were grouped into potential themes and subthemes connected to the research question. The emerging themes were then reviewed and refined to ensure conceptual coherence, distinctiveness, and consistency with the coded data. Following this, themes were defined and named, with clear articulation of their boundaries and their relevance to the technological, organizational, and environmental dimensions of the TOE model. Finally, in the reporting phase, the validated themes were synthesized into a coherent analytical narrative that informed the findings and discussion.

To enhance the credibility and trustworthiness of the analysis, the study employed both data triangulation and analyst triangulation [64]. Data triangulation was achieved by recruiting participants from a range of departments and hierarchical levels, ensuring diverse perspectives across the organizational system. Theoretical triangulation was also incorporated by consistently cross-referencing emerging interpretations with TOE constructs throughout the analytic process [65]. For analyst triangulation, one researcher conducted the initial round of coding, and a second researcher independently reviewed the full coding set. Any discrepancies in interpretation were discussed until consensus was reached, thereby strengthening the reliability and stability of theme development [66]. A concise overview of the coding procedure and final thematic structure is presented in Table 2.

Table 2. Coding Structure of GenAI Adoption Factors: Keywords, Codes, Subthemes, and TOE Dimensions.

TOE Dimension	Subtheme	Code	Example Keywords/Interview Excerpts
Technology	Perceived Technological Advantage	Efficiency Gains	"saves about 50% of our time"; "reduce 30–40% working time"
		Perceived Usability	"easier to use"; "does not require high expertise"
		Specialized Tool Value	"Court AI . . . highly accurate"
	Perceived Performance Risk	Mistrust in Output	"accuracy about 85%"; "not absolute"; "unnatural output"

Table 2. *Cont.*

TOE Dimension	Subtheme	Code	Example Keywords/Interview Excerpts
		Tool Performance Issues	"information is not the latest"; "misinformation"
Organization	Soft Support	Leadership Endorsement	"leaders support and encourage use"; "leaders as pioneers"
	Innovative Culture	Open Innovation Culture	"open culture"
	Rational Resistance	User Resistance	"not confident to use"; "not necessary"
		Age-Related Gaps	"officials over 45 rarely use"; "afraid to change"
	Prompt Literacy Gap	Inadequate Training	"only basic training"; "lack of manuals"; "not been trained"
	Double-Check Governance	Mandatory Review Behavior	"need to review results carefully"
	Institutional Capacity Constraint	Strategic Planning Constraints	"no specific plan/orientation for adoption"
		Financial Constraints	"no specific budget"; "pay for premium tools themselves"
		Workflow Integration Barrier	"not integrated into workflows"; "independent application"
		Restrictive Internal Policy	"not allowed to use"
Environment	External Modernization Pressure	External Innovation Pressure	"not to be left behind"; "pressures from digital transformation"
		National Agenda	"national and provincial leaders are involved"
	AI Accountability Vacuum	Pervasive Security Risk	"fear of information leakage"; "national secrets"
		Regulatory Vacuum	"no specific regulations"; "lack of rules and oversight"
		Accountability Ambiguity	"who is responsible if mistakes occur?"
	Workforce Deskilling & Replacement Fear	Job Replacement Fear	"positions may be replaced"
		Deskilling Risk	"dependency reduces critical thinking and creativity"

4. Results

Guided by the TOE framework, our thematic analysis examined how local government employees perceive and engage with GenAI within their daily administrative routines. The findings reveal that GenAI adoption has not progressed into formal institutionalization, nor has it remained in a state of non-use. Instead, it occupies an unofficial, voluntary, and individualized adoption zone. This is not a transitional midpoint but a structurally produced condition, shaped by the tension between powerful drivers pushing civil servants toward GenAI and the organizational and regulatory constraints that prevent formal integration. Three major themes emerged from the analysis: (1) Initiating Drivers that create strong incentives for GenAI uptake; (2) Institutional Capacity Constraints that undermine formalized adoption; and (3) Environmental Barriers and an AI Accountability Vacuum that make employees personally liable for risks arising from GenAI use. The interaction of these themes produces a shadow adoption environment characterized by informal workflows, defensive practices, and ambivalent attitudes.

4.1. The Initiating Drivers

The data illustrates two complementary forces driving GenAI adoption: a strong technological pull, generated by the immediate utility of GenAI tools, and an equally strong institutional and environmental push, rooted in modernization pressures and leadership encouragement. Together, these forces create a compelling momentum for adoption, yet they remain unmatched by organizational readiness.

4.1.1. Technological Pull

Across interviews, employees consistently highlighted the practical benefits of GenAI. The most frequently cited advantage was its ability to accelerate routine administrative tasks, particularly drafting official documents, summarizing information, preparing memos, and generating structured text. Many estimated time reductions of 30–50%, describing GenAI as a meaningful productivity tool: *"Using GenAI makes sentences smoother and easier to understand... it helps us reduce working hours by 30–40%."* (ID01). Automation of low-level tasks allows civil servants to redirect time toward higher-value work, such as reviewing content or contributing more substantively to decision-making processes: *"GenAI shortens the time in drafting and supports our decisions, improving the quality of work."* (ID07). For newer or junior staff with limited experience writing policy documents, GenAI functions as an always-available mentor. They rely on it for structure, explanations, and contextual guidance: *"With abundant sources of information, we can consider GenAI as a colleague who supports and guides us in the work process."* (ID02).

Ease of use further strengthens this technological pull. Participants emphasized that GenAI requires virtually no specialized training or technical literacy. The conversational interface lowers cognitive barriers and contrasts sharply with rigid and complex government software: *"GenAI is easier to use than software because of the way it communicates. Software requires understanding processes and functions."* (ID08). Free or trial versions, along with minimal hardware requirements, also democratize access: *"ChatGPT does not need high hardware, and now it is easy for everyone to reach with free versions."* (ID01). Thus, technologically, GenAI offers immediate, hands-on benefits that appeal directly to the daily needs of public servants.

4.1.2. Institutional Push

Beyond the intrinsic appeal of GenAI, employees described strong external and internal pressures encouraging adoption. At the environmental level, Vietnam's broader digital transformation agenda has created a heightened expectation that civil servants must modernize their work practices. Many respondents expressed a sense of urgency and competition, what several described as a "*fear of being left behind*" (ID03, ID04). National reform is presented by the merging of administrative levels. After merging, the middle administrative level (district) is eliminated so it highlights the role of local government (ward) in administrative tasks, providing public services directly to citizens. Thus, it requires the expansion of one-stop service centers which directly raise the daily workloads of local civil servants to serve more people from lager areas. This means that they are pushed to improve efficiency by adopting technology such as GenAI: "*When the one-stop service becomes a main point after merging, there will be large workloads and employees are overloaded*." (ID07).

Internally, leadership plays a pivotal role in shaping attitudes. Many interviewees emphasized that leaders actively encourage exploration of GenAI and portray it as essential to enhancing efficiency and meeting reform expectations: "*Leadership supports, directs, and creates a culture that encourages employees to be bolder in using AI at work*." (ID01). Leaders' symbolic use of GenAI also signals unofficial approval: "*If leaders are the front-runners, it can be considered an unofficial acceptance of GenAI adoption*." (ID06). This endorsement provides a sense of psychological safety, making employees more willing to experiment even in the absence of formal regulations. Leadership also frames GenAI as an innovation-aligned cultural value: "*There is an innovative culture here... and using GenAI is part of that culture*." (ID15). Together, modernization pressures and leader-driven cultural messaging create a strong institutional push, reinforcing the sense that GenAI adoption is both timely and expected.

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Despite this strong pull-and-push dynamic, employees consistently reported that the organizational systems necessary to support safe, structured adoption are missing. Thus, while enthusiasm is high and leadership rhetoric is strong, these drivers operate without the institutional scaffolding that would enable consistent, secure, and equitable use. This misalignment—between the motivational forces driving adoption and the organizational structures needed to sustain it—sets the stage for the institutional capacity constraints discussed in the next subsection.

4.2. Institutional Capacity Constraints

Despite strong national enthusiasm for GenAI and visible encouragement from provincial leaders, adoption remains unofficial, voluntary, and fragmented. This stalled progress is not due to employee reluctance alone; rather, it reflects a systemic inability to provide the structural conditions necessary for safe, formalized implementation. Four interconnected constraints—lack of planning, inadequate funding, absent system integration, and insufficient training—shift the burden of adoption onto individual employees. In this context, GenAI becomes an individual experiment rather than an organizational transformation.

4.2.1. Absence of Clear Implementation Plans

The most frequently mentioned constraint was the lack of concrete implementation plans. Across departments, employees noted that although provincial leaders promote digital innovation in general terms, no specific strategies, workflows, or usage guidelines have been issued: "*There is no specific plan, only general direction from provincial leaders*." (ID03). Others similarly expressed uncertainty about where GenAI fits into their daily responsibilities: "*We still do not know how GenAI should be applied in our workflow*." (ID14). This absence of planning leaves employees without direction, forcing them to interpret high-level mandates on their own. As a result, GenAI adoption becomes discretionary and inconsistent, varying across departments and individual comfort levels.

4.2.2. Insufficient and Unequal Funding

The second major constraint is limited financial support. Many interviewees reported that no dedicated budget exists for purchasing GenAI subscriptions or developing internal AI tools: "*Financial resources are still limited; there is no funding for this activity*." (ID18). Because departments do not provide paid access, employees frequently resort to personal subscriptions: "*We have to pay for the use ourselves*." (ID02, ID09). This situation creates an unequal innovation environment, where only those who can personally afford subscriptions gain access to more capable or secure tools, while others rely on free versions with limited functionality and weaker data protections. Innovation thus becomes a personal cost rather than an institutional investment, undermining equitable adoption and reinforcing informal use.

4.2.3. Lack of Integration into Government Systems

Even when employees attempt to use GenAI, the tools remain disconnected from official government systems. Participants described GenAI as an "*independent application*" used outside formal workflows (ID04), which prevents its benefits from being scaled or standardized: "*GenAI is not synchronized with our software; information cannot be linked*." (ID03). System integration is further constrained by information-security requirements and multi-level administrative coordination. As one manager explained: "*For specialized GenAI, there must be unity from the highest authority, from ministry to local levels*." (ID05). In the absence of integration and formal approval, GenAI cannot interact with government databases, document management systems, or internal communication platforms. This reinforces its unofficial status: GenAI remains a "side tool," helpful for individuals but invisible to organizational processes.

4.2.4. Basic and Insufficient Training Provision

A fourth constraint concerns the lack of structured and professional GenAI training. While the province has launched introductory programs, such as Bình dân học AI, these sessions were consistently described as rudimentary: "*The training is only at the basic level*." (ID01). Employees emphasized that meaningful GenAI adoption requires deeper competencies, including prompt formulation, data-sensitivity judgement, quality checking, and ethical use: "*To use GenAI effectively, we need more in-depth training classes*." (ID15). Yet such advanced training is absent because the province lacks qualified GenAI trainers: "*There is still no formal or intensive institution for training; the demand is high but service providers are lacking*." (ID07). As a result, most employees rely on self-directed learning: "*We often learn to use GenAI by ourselves*." (ID03). Self-learning reinforces uneven skill levels across departments, contributing to inconsistent usage practices and uncertainty about what constitutes appropriate application.

This combination of encouragement without support creates a contradictory environment: employees are expected to innovate but are not provided with the resources to do so safely. The result is rational resistance, especially among older or more experienced civil servants. The rational resistance is difference from resistance to change; in this study some civil servants do not want to adopt GenAI tools because this technology increases legal liability without significant improvement in outputs. Additionally, the use of GenAI is unnecessary with their task, so keeping working with the current process becomes the safe choice for experienced civil servants. Many participants noted that officials over 45 show greater hesitation: "*Older employees are skeptical about GenAI; they feel their experience is enough*." (ID08). In contrast, younger employees are more adventurous: "*Civil servants below 45 are willing to learn new things, like ChatGPT*." (ID05). This generational divide is not simply attitudinal—it reflects a deeper structural reality. Experienced staff, accustomed to rule-based bureaucratic routines, correctly perceive that using GenAI without regulations, training, or protection exposes them to high personal risk. Their reluctance is thus a logical rejection of a high-risk, low-support model, not resistance to technology.

These four institutional limitations prevent GenAI from moving beyond an unofficial, voluntary tool used mostly at individual discretion. Younger staff may experiment more, but without formal structures, their efforts cannot scale or produce organizational learning. Meanwhile, older staff rationally avoid adoption due to unclear expectations and disproportionate personal liability. Unless these capacity constraints are addressed through concrete planning, institutional budgeting, system integration, and comprehensive training, GenAI adoption will remain trapped in a precarious shadow space. Its transformative potential for public administration will remain unrealized, and the responsibility for innovation will continue to fall unevenly on individual employees rather than the institution as a whole.

4.3. Barriers to Formal Adoption

4.3.1. The AI Accountability Vacuum

One of the most significant barriers preventing formal GenAI adoption in local government is what can be described as an AI accountability vacuum: a structural gap in rules, protections, and institutional responsibility. This vacuum is uniquely acute in the public sector, where employees operate under strict bureaucratic norms and where mistakes carry potentially severe administrative consequences. The data reveals three mutually reinforcing sources of fear: security risks, regulatory void, and accountability ambiguity. Together, they create an environment in which employees perceive official GenAI use as too risky to attempt.

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Security Risks

The strongest and most immediate concern among interviewees was the risk of exposing sensitive administrative information through external GenAI tools. Participants repeatedly highlighted the danger of entering internal data, confidential cases, or citizen information into commercial AI systems: "*Information provided could lead to the leakage of agency information*." (ID21) and "*There are concerns about national secrets being leaked*." (ID03). These concerns extend beyond intentional misuse. Employees worry about accidental leaks, unintended storage, and security vulnerabilities associated with global AI platforms. Given that public sector work often involves personal, legal, or classified information, employees face a high burden of caution. As a result, even those who see the usefulness of GenAI feel trapped between the desire to improve efficiency and the obligation to protect state information.

Regulatory Void

The second dimension of the accountability vacuum concerns the absence of regulatory clarity. Across departments, participants described a complete lack of formal guidelines governing what data can be used, under what conditions, and for which tasks: "*There are no specific regulations on GenAI in the public sector*." (ID03) and "*We have no guidance, so it is difficult to apply GenAI in real work processes*." (ID11). This regulatory vacuum creates what several participants described as a "Wild West" environment: employees face innovation pressures but lack institutional guardrails to protect them. In bureaucratic systems—where rule compliance is expected and deviations may carry penalties—this uncertainty inhibits experimentation. Employees are aware that an inappropriate use of GenAI, even if accidental, may be interpreted as misconduct.

Accountability Ambiguity

A third and particularly paralyzing dimension of the accountability vacuum concerns ambiguity over responsibility when GenAI produces errors or misleading content. Across interviews, participants emphasized that in the absence of formal guidelines or institutional safeguards, accountability effectively defaults on the individual employee. As one respondent explained, "*If mistakes occur, employees will take all responsibility*" (ID19). This places civil servants in a no-win situation: avoiding GenAI risks being perceived as inefficient or resistant to innovation, while using GenAI exposes them to potential blame for inaccuracies, bias, or unintended disclosure. Even those who are enthusiastic about GenAI therefore hesitate to use it in any official capacity, recognizing that the personal risks outweigh the potential benefits. In this sense, the accountability ambiguity—more than technological limitations—emerges as the central barrier preventing the transition from informal, exploratory use to formal, sanctioned adoption within local government.

Together, these three fears effectively paralyze formal adoption. Employees may still experiment privately with public tools, but they avoid using GenAI for official documents, citizen-facing tasks, or legally sensitive work. As one participant summarized: "*Without security, resources, or an approved tool, we can only use GenAI at our own risk*." (ID11). Thus, even when the organizational culture encourages innovation, the institutional environment structurally discourages it.

4.3.2. Shadow Workflows and the Emergence of Hidden Practices

The combined pressure of modernization, individual experimentation, and unresolved institutional risks has pushed employees toward shadow workflows. This shadow presents the unofficial use of GenAI applications with private account instead of using an official portal. In addition, this use is informal because there is lack of official regulation on the uses of GenAI in workplace, has not been integrated into official systems. This shadow space is not an accident; it is a predictable consequence of the institutional capacity constraints and accountability vacuum discussed earlier. Employees feel compelled to innovate yet lack the infrastructure to do so safely and officially. As a result, they engage in GenAI-assisted tasks discreetly, often without informing supervisors or colleagues.

One important mechanism driving shadow workflows is the prompt literacy gap. Because training remains "*at the basic level*" (ID01), employees lack the nuanced skills needed to formulate effective prompts, critique outputs, or determine what kinds of inputs pose security risks. Participants repeatedly emphasized the complexity of learning GenAI effectively: "*To use GenAI effectively, it takes time to learn how to provide requirements and information*." (ID15). This gap feeds into the accountability vacuum: employees do not know how to avoid risky inputs or how to judge hallucinations, creating a cycle of uncertainty. The lack of training ironically makes GenAI both more attractive (because it seems easy to use) and more dangerous (because improper use increases institutional risk). This dynamic pushes GenAI use further into the shadows, where employees experiment individually rather than through shared organizational learning.

4.3.3. The Rise of Double-Check Behavior

A notable behavioral pattern emerging from these shadow workflows is the growing practice of double-checking GenAI outputs. Although employees acknowledge that GenAI offers speed and convenience, they remain uncertain about its accuracy and reliability. As several interviewees noted, "*AI output is not absolute*" (ID08), "*it can be misleading*" (ID14), and "*it is not 100% reliable*" (ID06). Consequently, civil servants routinely cross-verify every AI-generated sentence, table, or recommendation against their own expertise or official documents, with one participant explaining, "*We always have to review the results*" (ID02).

This pattern reveals two important dynamics. First, the expected time savings from GenAI are partially eroded when employees must invest additional effort in verification, reducing the net efficiency gains that initially motivate its use. Second, trust in GenAI varies significantly depending on the system type. Participants reported far greater confidence in specialized, domain-specific systems such as Court AI, which they described as "*highly accurate*" and "*focused on professional issues*" (ID10). This contrast highlights that employees are willing to trust GenAI only when it is formally vetted, professionally tuned, and institutionally endorsed, further demonstrating how the broader accountability vacuum undermines the adoption of general-purpose GenAI tools in local government.

4.3.4. Fears of Deskilling and Replacement

A further consequence of the prompt literacy gap and the widespread practice of double-checking AI outputs is the emergence of deeper anxieties surrounding long-term skills, professional identity, and job relevance. Notably, employees did not fear being replaced by AI itself; instead, they worried about being replaced by peers who were more proficient in using AI tools. As one participant remarked, "*GenAI doesn't make us lose our jobs; only those who don't use AI lose their jobs*" (ID04). This marks a shift from traditional automation anxiety toward competency anxiety, where the perceived threat stems from a lack of AI-related skills rather than technological substitution.

At the same time, several interviewees expressed unease over the possibility that excessive reliance on GenAI could gradually undermine human expertise, highlighting concerns such as reduced critical thinking, declining creativity, and an unhealthy dependence on AI-generated outputs. As participants warned, "*Using GenAI too much may reduce critical thinking and creativity*" (ID01), "*Some colleagues depend on GenAI for every task, even unnecessary ones*" (ID03), and "*Too much dependence can lead to loss of creativity*" (ID07). Together, these perceptions create a paradox: avoiding GenAI risks professional obsolescence, while overusing it raises fears of cognitive deskilling. This unresolved tension magnified by the lack of institutional guidance or training. It contributes to a broader climate of uncertainty that reinforces the cautious, unofficial, and tentative nature of GenAI adoption in local government.

Figure 1 presents the interaction between technological, organizational and environmental factors in the adoption of GenAI of civil servants in Binh Duong province.

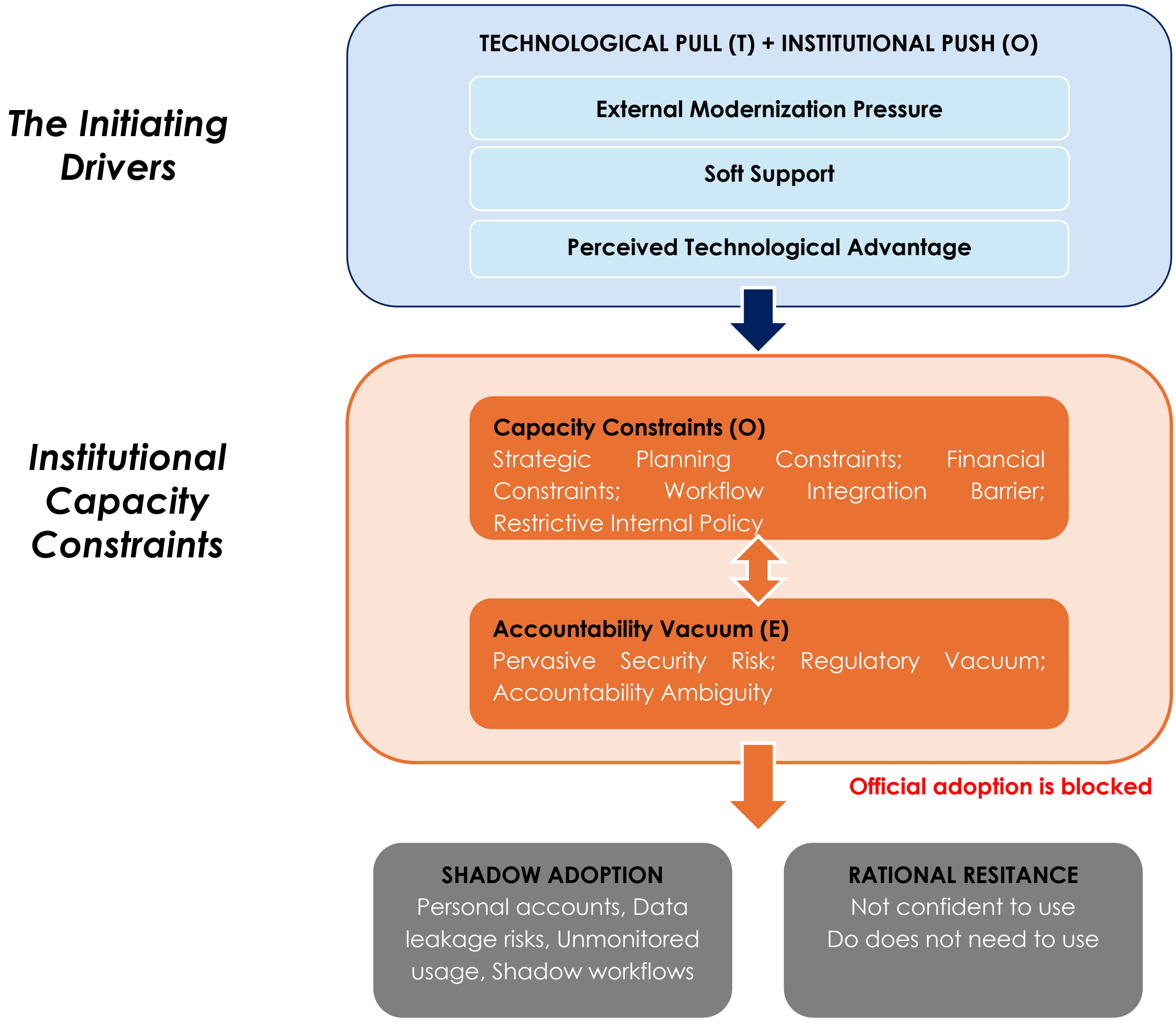

Figure 1. The interaction between the Technological Pull, Institutional Push, Institutional Capacity Constraints, and the AI Accountability Vacuum.

5. Discussion

This study examined the organizational, technological, and environmental factors shaping the adoption of GenAI among provincial government employees in Vietnam. The findings reveal that GenAI adoption has not evolved into formal institutionalization but remains suspended in an unofficial, voluntary, and high-risk zone. This condition is not simply an early stage of adoption but a structurally produced equilibrium, driven by powerful technological and institutional drivers that encourage use, counteracted by organizational constraints and an AI accountability vacuum that renders formal adoption too risky. This section interprets these findings, integrates them into existing theoretical debates, and outlines the conceptual, methodological, and policy implications.

Consistent with prior research, GenAI's strongest facilitator is its perceived technological advantage [67,68]. Civil servants described substantial efficiency gains, particularly in drafting documents, summarizing information, and managing routine tasks. These perceived benefits align with the well-established role of performance expectancy in technology adoption models such as TAM and UTAUT. The conversational interface also reinforces ease of use, reflecting a technologically accessible design that lowers initial resistance. However, this study reveals that the "ease of use" associated with GenAI is deceptively simple. While users can instantly interact with the tool, effective adoption requires a deeper skill set—particularly prompt engineering, domain-sensitive judgment, and the ability to detect hallucinations. This finding echoes [69], who argue that GenAI shifts cognitive labor rather than eliminating it. Our data illustrates a new form of complexity: GenAI appears simple but conceals advanced competencies that users must develop to avoid errors, misinformation, or data leakage. This dynamic extends existing literature by highlighting the difference between approachability (low barrier to initial use) and operational mastery (high barrier to safe, effective use). The findings suggest that GenAI introduces a layered learning curve that traditional AI models did not require. This hidden complexity is particularly problematic in resource-constrained public organizations, where training, governance, and expert support are limited.

A second major insight concerns mistrust and its behavioral consequences. Although concerns about AI accuracy are widely documented [70], this study highlights an important and previously underexplored behavioral adaptation: the institutionalization of "double-check behavior." Rather than rejecting GenAI outright when faced with uncertain accuracy, civil servants increasingly adopt a verification routine in which they cross-check every AI-generated sentence, idea, or table against their own knowledge or official documents. This hybrid workflow has two implications. First, it erodes some of the efficiency gains that initially motivate GenAI use, revealing a hidden labor cost that undermines optimistic narratives about AI-driven productivity. Second, double-checking functions as a grassroots model of algorithmic governance—an informal, human-in-the-loop mechanism created spontaneously by frontline employees to compensate for institutional and regulatory gaps. This demonstrates that civil servants are not passive recipients of AI technologies but active risk managers who develop their own safeguards, even when formal guidelines are absent. In this sense, the emergence of double-check behavior extends existing literature by showing how frontline workers construct informal governance structures when official structures are lacking.

The study's most significant contribution concerns the organizational context and the origin of resistance. Traditional literature often frames resistance to new technologies as attitudinal, driven by fear, age, or technophobia [71]. In contrast, our findings point to what can be described as rational resistance. Employees are not resisting GenAI because they dislike it or fail to understand its potential; rather, they resist because organizational structures expose them to disproportionate risk. Leaders offer rhetorical support for GenAI but do not provide the necessary enabling conditions such as implementation plans, budgets, workflow integration, or advanced training. These would allow employees to use GenAI safely. As a result, civil servants navigate a profound misalignment between symbolic support and practical support. Younger staff, more comfortable experimenting with new tools, tend to adopt GenAI informally, while older and more experienced staff—who understand bureaucratic accountability more deeply—rightly perceive GenAI as a high-risk and low-support activity. Their reluctance is therefore not emotional resistance but a logical response to institutional failures. This finding extends TOE-based studies by emphasizing the need to differentiate between cultural support (leadership encouraging innovation) and structural support (resources, plans, and protections). Our findings suggest that without

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structural support, cultural encouragement may actually intensify risk, pushing employees into unofficial and unsupported experimentation.

The environmental dimension of the TOE framework is typically described as external pressures, regulatory conditions, and institutional norms. It also requires rethinking in light of GenAI. Rather than existing as a stable or well-defined set of rules, the "environment" in this context is characterized by an AI accountability vacuum. This vacuum consists of three interlocking uncertainties: security risks, regulatory void, and accountability ambiguity. The security risks stem from the probabilistic, data-absorbing nature of GenAI tools, which raises concerns about national secrets, sensitive citizen information, and internal administrative data. The regulatory void—where no explicit guidance exists on what can be used, shared, or generated—amplifies this uncertainty. The most paralyzing component, however, is accountability ambiguity. Employees fear that if GenAI produces errors, leaks sensitive content, or generates misleading recommendations, responsibility will fall entirely on them. This fear is reasonable in bureaucratic systems where compliance is strictly monitored, and penalties can be severe. The accountability vacuum therefore creates not only hesitation but also causes institutional paralysis, which is present in the halt of policy implementation and locating budget or investment in research and development due to the ambiguity of existing legal frameworks, overlapping jurisdiction authority of the departments. It comes from the lack of regulations regarding the use or the complexity of the financial proceedings to pay for the account subscription and risk aversion culture regarding unproven technologies. As a result, employees may use GenAI privately but avoid any formal application where risk can be traced. This extends the TOE framework by illustrating that environmental factors are not limited to rules or pressures; they can also manifest as the absence of governance. Such a vacuum is not neutral—it produces unpredictable risks that discourage formal adoption and push innovation into shadow adoption.

The interaction between institutional capacity constraints and the accountability vacuum also reshapes the TOE model's assumptions about linear adoption. In conventional TOE applications, adoption progresses as organizations become more ready and environmental conditions become more supportive. However, our findings indicate that GenAI can instead create a dual-pressure system: modernization demands intensify the push to adopt, while governance gaps intensify the risks of doing so. This interaction produces a stable but undesirable equilibrium where GenAI thrives only as an unofficial tool. Its use is widespread but shallow, encouraged but unsupported, innovative but risky. This equilibrium is likely not unique to Vietnam; many governments globally face similar tensions between rapid technological innovation and slow bureaucratic rulemaking. Therefore, the Vietnamese case provides a window into how GenAI may unfold in developing and developed public sectors alike.

The dynamics observed in this study also highlight broader structural challenges that characterize AI adoption in developing countries. Unlike high-capacity governments that can invest in in-house AI systems, robust data infrastructures, and formal risk-governance frameworks, developing countries often face simultaneous constraints in fiscal resources, digital talent, and institutional agility. As a result, GenAI diffusion tends to occur unevenly accelerated by bottom-up experimentation but stalled by top-down governance gaps. The mismatch between rapid technological change and slower bureaucratic rulemaking is especially pronounced in resource-constrained settings, where public agencies struggle to balance modernization goals with security, legality, and equity concerns.

The Vietnamese case illustrates how developing countries may experience dual pressures: global digital transformation agendas push adoption forward, while limited institutional capacity and ambiguous accountability mechanisms hold it back. This "tension-driven adoption" pattern suggests that GenAI may amplify pre-existing administrative inequalities across regions, agencies, and demographic groups. More broadly, it underscores that the promise of GenAI in developing countries depends not only on technological capability but also on state capacity—the ability of public institutions to build governance architectures, invest in workforce reskilling, and create safe, context-sensitive pathways for innovation. Thus, this study provides insights that resonate across many developing contexts where enthusiasm for GenAI is high but the structural conditions necessary for responsible adoption remain underdeveloped.

6. Conclusions

This study explored the factors shaping the adoption of GenAI in specific provincial government employees in Vietnam. The findings reveal that GenAI has not been formally institutionalized nor rejected outright; instead, it occupies an ambiguous middle ground—an unofficial, voluntary, and high-risk zone of use. This condition is best described as governance paralysis: a structural state in which employees are motivated to use GenAI but constrained by organizational incapacity and environmental uncertainty. Crucially, this paralysis is not driven by technophobia or unwillingness among civil servants. Rather, it emerges from a combination of institutional capacity constraints and a profound AI accountability vacuum.

Although leaders symbolically encourage GenAI and promote a culture of innovation, they do not provide the structural foundations—plans, budgets, secure systems, or professional training—necessary for formal adoption. As a result, employees engage in shadow workflows, relying on personal accounts, self-directed learning, and informal experimentation. These practices expose them to multiple risks, including data-security breaches, misinterpretation of AI-generated content, and personal liability for errors. The double-checking behavior observed in this study underscores that the apparent efficiency benefits of GenAI are often offset by the hidden labor required to verify outputs. At the same time, the prompt literacy gap and absence of standardized training generate skill inequalities and anxiety about long-term professional relevance.

Transitioning from unofficial to official use is further obstructed by the AI accountability vacuum. This vacuum—defined by pervasive security concerns, the absence of regulatory guidance, and ambiguity about responsibility—creates an environment in which employees fear that any misstep will be personally attributed to them. The absence of clear rules or approved tools transforms everyday administrative tasks into high-stakes decisions, making GenAI adoption a risky endeavor for civil servants who operate under strict bureaucratic norms. In this context, continuing with traditional workflows becomes not an expression of resistance, but a rational, risk-minimizing choice.

6.1. Theoretical and Practical Implications

The study offers several theoretical contributions. First, it advances the TOE framework by identifying the AI Accountability Vacuum as a GenAI-specific environmental factor that is not merely a barrier, but a structural void. Unlike traditional environmental constraints such as regulatory hurdles or market conditions. The vacuum described here reflects the absence of rules, protections, and institutional responsibility. This void fundamentally alters the risk calculus of public employees and prevents GenAI from becoming embedded in organizational routines. Consequently, the TOE environment dimension for GenAI in the public sector must be reconceptualized to include conditions of regulatory absence, not only regulatory presence.

Second, the study challenges classic technology-adoption assumptions, particularly the notion that perceived ease of use leads to adoption [72]. While GenAI interfaces are simple, effective use requires new forms of cognitive, evaluative, and ethical skill—what this study conceptualizes as prompt literacy. This complexity disrupts the typical linear relationship between ease of use and adoption intention. In the context of GenAI, ease of access does not equal ease of governance.

Third, the study reframes resistance to change as rational resistance. Rather than viewing older or experienced employees as reluctant or conservative, the findings show that their hesitation reflects strategic risk management under conditions of unclear rules and high personal liability. This interpretation complements and extends scholarship on organizational risk aversion in the public sector, demonstrating that resistance is often a logical response to institutional deficits rather than a psychological barrier to innovation.

Practically, the findings suggest that overcoming governance paralysis in GenAI adoption requires a staged and context-sensitive approach rather than generic calls for "more capacity" or "better regulation." Because GenAI is already being used informally through shadow adoption and shadow workflows, immediate policy interventions should focus not on prohibition but on risk containment and harm reduction. In the short term, public organizations can issue interim usage guidance that explicitly delineates low-risk and high-risk GenAI applications (e.g., drafting internal memos versus handling citizen data), formally legitimizing certain uses while discouraging others. Such provisional guidance can reduce uncertainty and personal liability for civil servants without requiring fully developed AI legislation.

In the medium term, institutionalization efforts should prioritize organizational embedding rather than technological sophistication. This includes allocating modest but dedicated budgets for secure, government-approved GenAI tools; integrating GenAI into existing document management and workflow systems; and establishing internal review protocols that normalize double-check behavior as an organizational safeguard rather than an individual burden. Training programs should move beyond introductory exposure toward role-specific modules that develop prompt literacy, verification skills, and data-sensitivity judgment, particularly for frontline staff and middle managers who mediate between leadership directives and everyday administrative practice.

In the longer term, addressing the AI accountability vacuum requires the consolidation of governance structures at the national and subnational levels. This includes clarifying lines of responsibility for AI-assisted outputs, defining accountability-sharing mechanisms between individuals and institutions, and embedding GenAI oversight within existing audit, compliance, and administrative law frameworks. Importantly, accountability should be designed as a collective organizational function rather than a source of individual blame, thereby reducing rational resistance and enabling safer experimentation.

Taken together, these staged interventions highlight that effective GenAI adoption in developing-country public sectors is not primarily a technical challenge but a governance one. Rather than aiming for rapid, comprehensive deployment, policymakers should focus on gradually aligning institutional capacity, accountability structures, and workforce capabilities with the realities of how GenAI is already being used in practice. This approach is likely to be relevant beyond Vietnam, particularly in contexts where enthusiasm for GenAI outpaces the state's capacity to govern emerging technologies responsibly.

The implications of these findings extend beyond Vietnam. Although some developing countries—most notably India—exhibit comparatively high levels of confidence in AI capabilities among both citizens and public employees [47], such confidence does not necessarily translate into formal and accountable adoption within public-sector organizations. High confidence is often driven by strong cultural narratives of technological progress, dynamic private-sector AI ecosystems, and widespread exposure to digital platforms—factors that at first glance contrast with the more cautious and risk-averse attitudes observed among Vietnamese local civil servants. However, our findings demonstrate that confidence alone is

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insufficient to overcome structural governance barriers. Even in high-confidence contexts, unresolved challenges related to data governance, regulatory clarity, and accountability can similarly channel AI use into informal, experimental, or unsanctioned practices rather than institutionalized integration. From this perspective, the Vietnamese case should not be viewed as an outlier, but as indicative of a broader governance pattern that may emerge across developing countries where enthusiasm for AI advances more rapidly than the institutional capacity to govern it responsibly.

6.2. Limitations and Future Research

This study has limitations that open avenues for further inquiry. Because it focuses on provincial government employees and employs a qualitative design, the findings are not statistically generalized across all administrative levels or regions. Future studies could test the proposed relationships quantitatively, examining how leadership, regulation, and organizational readiness interact to shape GenAI adoption outcomes.

Moreover, the extreme-case nature of Binh Duong imposes important limitations. Because the province benefits from relatively strong leadership commitment, digital infrastructure, and exposure to innovation, the findings should not be interpreted as representative of all Vietnamese local governments. In provinces with lower administrative capacity or weaker digital ecosystems, GenAI adoption may be even more constrained or may not occur at all. Conversely, the presence of adoption barriers in such an advanced context suggests that governance and accountability challenges are structural rather than transitional. Future research should therefore extend this analysis to more typical or resource-constrained local governments, as well as to cross-provincial or comparative designs, to assess how institutional capacity conditions shape different GenAI adoption trajectories.

Additionally, with limited participants, the full diversity of experiences may not have been captured. Longitudinal research over the next 3–5 years would be valuable to observe whether institutions transition out of the unofficial adoption zone or whether this shadow mode becomes a durable—and potentially problematic—form of everyday administrative practice.

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