Understanding the Agitation Adopting Artificial Intelligence in Frontline Public Service Delivery: A Context-Value-Behavior Framework

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Abstract

While Artificial Intelligence (AI) is frequently championed as a transformative tool for public services, its frontline implementation is often characterized by "agitation" rather than seamless integration. Moving beyond the cognitive appraisal of Technology Acceptance Model, this study investigates the sustained state of uncertainty and negotiation among frontline public service deliverers. Drawing on 19 in-depth interviews with frontline public service deliverers in China, this study develops a Context-Value-Behavior framework to deconstruct this complexity. Our findings reveal a fundamental tension: the algorithmic logic of AI, which prioritizes standardized efficiency, directly clashes with the professional logic of frontline public service deliverers, which is rooted in contextual intelligence and human-centric directions. They employ a range of behavioral strategies—from deep integration to deliberate disengagement—while constantly wrestling with the trade-offs between systemic efficiency and core professional values under constrained resources. The primary contribution of this study is to extend the Technology Acceptance Model by situating it within the messy realities of frontline service delivery, demonstrating that technology adoption is an ongoing, agentic process of co-evolution. We conclude that for AI to be truly enabling, policy must recognize, actively engage with, and adapt to the lived experience of frontline agitation.

Keywords: Frontline public service deliverers, Artificial Intelligence, Agitation, Context-Value-Behavior Framework, Technology Acceptance Model

Comprender la agitación que genera la adopción de la inteligencia artificial en la prestación de servicios públicos de primera línea: un marco de contexto, valor y comportamiento

Resumen

Si bien la Inteligencia Artificial (IA) se suele presentar como una herramienta transformadora para los servicios públicos, su implementación en primera línea a menudo se caracteriza por la incertidumbre en lugar de una integración fluida. Más allá de la evaluación cognitiva del Modelo de Aceptación de la Tecnología, este estudio investiga el estado persistente de incertidumbre y negociación entre los profesionales que prestan servicios públicos en primera línea. A partir de 19 entrevistas en profundidad con profesionales de estos servicios en China, este estudio desarrolla un marco de Contexto-Valor-Comportamiento para desglosar esta complejidad. Nuestros hallazgos revelan una tensión fundamental: la lógica algorítmica de la IA, que prioriza la eficiencia estandarizada, choca directamente con la lógica profesional de los profesionales que prestan servicios públicos en primera línea, la cual se basa en la inteligencia contextual y en un enfoque centrado en el ser humano. Estos profesionales emplean diversas estrategias de comportamiento —desde la integración profunda hasta el distanciamiento deliberado— mientras lidian constantemente con las compensaciones entre la eficiencia sistémica y los valores profesionales fundamentales en un contexto de recursos limitados. La principal contribución de este estudio radica en ampliar el Modelo de Aceptación Tecnológica, situándolo en la compleja realidad de la prestación de servicios en primera línea. Esto demuestra que la adopción de tecnología es un proceso continuo y participativo de coevolución. Concluimos que, para que la IA sea realmente transformadora, las políticas deben reconocer, abordar activamente y adaptarse a la experiencia vivida de la agitación en primera línea.

Palabras clave: Prestadores de servicios públicos de primera línea, Inteligencia artificial, Agitación, Marco de contexto-valor-comportamiento, Modelo de aceptación de la tecnología

理解一线公共服务中采用人工智能的躁动：一个情境-价值-行为框架

摘要

尽管人工智能常被誉为公共服务的变革性工具，但在实际的一线应用中，其特征往往是“躁动”，而非无缝衔接。本研究超越了传统技术接受模型的认知评估视角，深入探讨了一线公共服务人员在人工智能应用中持续存在的这种躁动状态。通过对中国19位一线公共服务递送者的深度访谈，本研究构建了一个“情境-价值-行为”框架来解构这一复杂性。研究发现，AI的应用引发了一种根本性的张力：优先考虑标准化效率的“算法逻辑”，与扎根于情境智慧和以人为本的“专业逻辑”之间存在直接冲突。 一线公共服务递送者并非消极地接受技术，而是在一个动态过程中进行博弈：他们采用了一系列行为策略——从深度整合到刻意脱离——同时在资源有限的情况下，不断地在系统效率和核心专业价值之间进行权衡。本研究的主要贡献在于通过将技术接受模型置于一线服务的复杂现实场域中，对其进行了扩展，证明了技术采纳是一个持续的、具有主体性的共演过程。我们得出结论：若要使人工智能真正发挥赋能作用，政策必须承认、积极应对一线公共服务递送者在实践中所经历的这种“躁动”。

关键词：一线公共服务递送者；人工智能；躁动；“情境-价值-行为”框架；技术接受模型

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1. Introduction

Artificial Intelligence (AI) is profoundly reshaping frontline public service delivery, particularly for street-level bureaucrats such as police officers, social workers and non-profit organization employees, improving their decision-making process and enhancing the quality of service provided (An et al. 2025; Selten et al. 2023; Schiff et al. 2025; Young et al. 2019; Zhang et al. 2025). However, a more complex and unsettled reality is emerging. Beyond the grand narrative of technological empowerment, empirical observations reveal a landscape marked by palpable “agitation”—a widespread sense of uncertainty and underlying tensions among frontline public service deliverers (FPSDs), which seems completely different from previous adoption of new technologies such as computers or mobile communications (Golgeci et al. 2025; Raisch and Krakowski 2021). This agitation stems from a core dilemma that distinguishes AI from previous technologies—it directly augments, and at times supplants, the core discretionary and judgmental processes that define professional expertise (Jones 2024; Spring et al. 2022). Unlike resistance, which implies outright opposition to technology (Kruger 2025), or ambivalence, which captures the coexistence of positive and negative attitudes toward an innovation (Dagtekin and Kabakus 2025), and distinct from motivated skepticism, understood as a form of defensive bias to protect existing beliefs (Bhattacherjee and Premkumar, 2004), "agitation" refers to a sustained, unsolved oscillatory state characterized by alternating attraction and hesitation. Analytically, it comprises two constitutive dimensions—a behavioral dimension of vacillation between adoption and disengagement, and a value dimension of irresolvable tension among competing professional commitments. These two dimensions are mutually reinforcing—value tensions manifest as behavioral vacillation, while behavioral oscillation, in turn, deepens the underlying value conflicts. Accordingly, these responses are fragmented and often contradictory, manifesting as a spectrum from eager adoption to strategic avoidance, reflecting a state of unresolved tension rather than a clear path forward (Meijer et al. 2021; Selten et al. 2023). This phenomenon of agitation is continuing and expanding, which is quite different from the impact of the emergence of other new technologies such as the Internet or mobile Internet on public service delivery. Therefore, it is necessary to expand the focus of research from the acceptance of new technologies to more complex directions.

Existing research on AI in frontline public service delivery has predominantly emphasized its impact on the user end, particularly concerning user experience and service outcomes (Chen et al. 2021; Gesk and Leyer 2022; Willems et al. 2023). As a result, there remains a notable scarcity of practical insight into how AI impacts FPSDs (Selten et al. 2023). Technology Acceptance Model (TAM) and its variants provide a starting point but falls short of explaining the complex agitation. The TAM, which posits that adoption is primarily driven by perceived usefulness and perceived ease of use (Venkatesh and Davis 2000), offers a valuable yet simplistic and decontextualized lens, failing to capture the fundamental tensions with professional logics and public value trade-offs that define public service settings (Cordella and Tempini 2015; Sun and Medaglia 2019). Specifically, a disjuncture becomes critical when an algorithmic logic of standardization and efficiency confronts the deep-rooted professional logic of street-level bureaucrats, which is grounded in professional discretion, contextual ethics, and empathy (Møller et al. 2022; Selten et al. 2023). Therefore, TAM might predict whether a tool is seen as useful or easy to use in a vacuum, but it cannot adequately explain why a FPSD who finds AI useful might resist it to protect their professional discretion, or why another might be forced to use an AI they perceive as ethically risky. In short, TAM illuminates the initial pull of technology but is silent on the push-and-pull of daily practice that generates sustained agitation.

To address this gap, our study moves from predicting acceptance to understanding agitation. We pose the following research question: What constitutes the FPSDs' agitation surrounding AI adoption, and how is this state produced by the complex interplay of contextual constraints, value-based reasoning, and behavioral adaptations? To investigate this issue, we conducted in-depth interviews with 19 FPSDs from China's social service sectors, where the tension between algorithmic recommendations and professional discretion is particularly salient due to the requirement for high-stakes, contextualized professional judgment. Notably, we focus specifically on social workers, non-profit organizations' employees and other service deliverers in China for three interrelated reasons. First, China offers a uniquely revealing context for studying frontline agitation. FPSDs in China operate at the nexus of stringent top-down policy directives and substantial on-the-ground discretion (Lu et al. 2025). This convergence of rapid technological advancement and the inherent adaptability of frontline practice make them especially sensitive to the tensions between efficiency mandates and the relational, trust-based nature of their work, offering an ideal setting to observe how agitation unfolds and evolves. Second, the essence of social work lies in high-stakes, contextualized professional judgment, making it an ideal context to observe the core tension between algorithmic recommendations and professional logics. Third, within China's public service ecosystem, numerous services are delivered through government procurement from qualified social service sectors, a mechanism that tightly couples policy initiatives with localized implementation, further sharpening the contradictions that give rise to agitation.

The primary theoretical contribution of this study is to leverage and extend the TAM perspective by proposing a Context-Value-Behavior (CVB) framework that dissects the inner workings of the agitation. Rather than replacing TAM, our framework explains its limitations in the adoption of AI. We argue that the core TAM constructs are profoundly mediated and reshaped by the situated context, intense value trade-offs involving professional values and public ethics, and the resulting behavioral strategies that characterize frontline public service delivery. It is the dynamic and often conflicting interplay of these three dimensions that co-produces the observed state of agitation. By doing so, this research opens a new agenda for studying AI in public services, one that takes the unsettled reality of frontline practice as its central focus and offers a more nuanced understanding of the journey from technological potential to grounded use.

2. Literature Review

2.1 The Paradox of AI Empowerment and Frontline Agitation

AI is widely championed for its potential to revolutionize public service delivery by enhancing efficiency, accuracy, and consistency, thereby ultimately promising improved outcomes for citizens (Bullock 2019; Wirtz et al. 2019). For FPSDs, it is envisioned as a powerful tool to alleviate administrative burdens, augment decision-making, and manage complex caseloads (Grimmelikhuijsen 2022). However, this optimistic narrative appears to diverge from the empirical facts observed at the frontline. Rather than seamless adoption, a growing body of studies reveal a landscape characterized by a state of palpable "agitation"—a heterogeneous and often contradictory mix of behavioral responses ranging from active integration to strategic avoidance and outright resistance (Meijer et al. 2021; Selten et al. 2023). This disparity poses a critical puzzle: if AI is so objectively empowering, why does its introduction provoke such widespread and unresolved agitation among the FPSDs?

The research gap becomes increasingly apparent when the focus shifts from merely documenting the diverse patterns of AI usage to explaining the underlying drivers of these behaviors. The persistence of skepticism among FPSDs, who often place greater trust in their professional discretion and practical experience than in AI-generated recommendations, underscores the limitations of purely optimistic, top-down narratives of AI (Kunda 1990; Meijer et al. 2021; Snow 2021; Selten et al. 2023; Taber and Lodge 2006). To unravel this paradox, it is necessary to examine the theoretical lenses offered to explain technology adoption. The TAM, as a dominant framework, provides a foundational starting point by linking adoption to perceived usefulness and ease of use (Davis 1989; Taherdoost 2018). Yet its individualistic and decontextualized nature renders it insufficient for fully capturing the complex realities of frontline public service delivery. The following analysis will critically assess TAM's utility and, crucially, its limitations in explaining the agitation observed in the AI adoption of FPSDs.

2.2 Technology Acceptance Model: A Foundational Yet Incomplete Lens

The TAM stands as a pivotal theoretical framework for explaining and predicting individual acceptance of information technologies. Grounded in an individual-level cognitive perspective, TAM posits that users' behavioral intentions are primarily determined by two core beliefs: perceived usefulness, defined as the degree to which a person believes that using a system would enhance their job performance, and perceived ease of use, referring to the degree of effort associated with the system's use (Davis 1989; Venkatesh et al. 2016). This parsimonious model has demonstrated remarkable predictive power across a wide range of commercial and organizational contexts, where efficiency and usability are often the paramount concerns. Its predictive utility is contingent upon the relative simplicity of the adoption environment, where individual cost-benefit calculations are the primary drivers of behavior.

The robustness of TAM framework is well-established in commercial and organizational contexts that align with its underlying assumptions of individual rational choice and efficiency maximization (Venkatesh et al. 2003). For instance, studies on the adoption of enterprise resource planning systems or office productivity software within business organizations largely confirm model's core tenets (Venkatesh and Davis 2000). Similarly, e-commerce research typically conceptualizes perceived usefulness in terms of consumer convenience and cost-reduction—a context where the individual user is the primary decision-maker operating with relative discretion (Gefen et al. 2003). In these settings, the dominant logic is efficiency enhancement, process streamlining, and cost-effectiveness, which align seamlessly with TAM's core construct.

However, the translation of TAM to the frontline public service delivery context reveals a fundamental disjuncture. Here, FPSDs are not sovereign consumers or purely efficiency-driven employees. They are street-level bureaucrats whose work is guided by a professional logic that encompasses experiential judgment, ethical reasoning, and empathetic engagement (Møller et al. 2022; Selten et al. 2023). Prior research that has attempted to directly apply TAM to public sector e-government systems often encounters this complexity. For example, studies might find that while perceived usefulness is a significant factor, it is not sufficient to explain adoption, with variables like "trust in government" or "perceived risk" needing to be added as external extensions to the core model (e.g., Bélanger and Carter 2008; Guo et al. 2024). This comparison indicates systematic differences between the two contexts, underscoring that technology adoption in the latter is shaped not only by perceived usefulness but also by a constellation of interrelated normative values. This insight suggests that any framework aiming to explain AI adoption in FPSDs must move beyond TAM's cognition-centered view and treat "Value" as a core analytical dimension.

This observation not only underscores the necessity of integrating a value-oriented dimension but also highlights a fundamental limitation of TAM: its inherently decontextualized and individualistic orientation (Cordella and Tempini 2015; Malatji et al. 2020). Although subsequent extensions of TAM have incorporated facilitating conditions—such as managerial, organizational, and peer support—these factors are conceptualized as perceptions of external control (Venkatesh and Bala 2008), functioning solely as antecedents to perceived ease of use rather than as independent analytical constructs. This limitation renders TAM unable to explain why FPSDs exhibit substantial variation in AI acceptance even under identical facilitating conditions, or why this variation persists over time as sustained "agitation" rather than resolving into acceptance or rejection.

In summary, the explanatory boundaries of the TAM in frontline public service contexts manifest as three persistent theoretical challenges. First, TAM cannot be fully accounted for cases in which FPSDs consciously recognize an AI's system's perceived usefulness and ease of use, yet refrain from adopting it due to normative or ethical concerns, a phenomenon which reflect a systematic decoupling between cognitive evaluations and behavioral intention. Second, existing extensions of TAM conceptualize contextual factors as exogenous antecedents rather than endogenous components integral to the decision-making process. Consequently, these extensions do not adequately account for how contextual factors dynamically reshape individual's value priorities and recalibrate their behavioral strategies. Third, the explanatory logic of TAM is grounded in an assumption that adoption culminates in a relatively stable endpoint of acceptance or rejection, which offers limited theoretical leverage for capturing the emergence and persistence of "agitation." Collectively, these limitations expose a foundational theoretical gap: current model and frameworks cannot explain how structural conditions, normative commitments, and contextually situated behavioral strategies dynamically interact to generate and sustain "agitation." This gap is fundamentally a question of dynamic interplay rather than static factors. The CVB framework is developed to address this gap, with its three dimensions corresponding respectively to these neglected analytical domains.

2.3 Toward an Integrated Framework: Context, Value, and Behavior

Building on the gaps identified above, the CVB framework is developed around three core dimensions: Context, Value, and Behavior. First, "Context (C)" refers to the external structural conditions that shaped FPSDs access to and engagement with AI. The term of "structural" refers to systematically patterned conditions embedded in organizational hierarchies and policy framework, including resource availability, organizational directives and regulatory ambiguity. It might address TAM's treatment of facilitating conditions solely as antecedents to cognitive beliefs. Beyond enabling or constraining adoption, the contextual conditions play a generative role: they activate and intensify specific value trade-offs that would otherwise remain latent for FPSDs. Second, "Value (V)" reflects the competing professional and ethical considerations that FPSDs navigate, including the tensions among algorithmic efficiency, professional directions, and public service values. These value claims often override purely cognitive assessments of usefulness. Critically, these heightened value conflicts do not merely coexist, they directly guide the selection of behavioral strategies, as FPSDs attempt to provisionally resolve professional dilemmas. Finally, "Behavior (B)" indicates the observable strategies and adaptive practices through which FPSDs negotiate their relationship with AI, ranging from deep integration to strategic resistance. These behaviors are not static outcomes but evolve over time and feed back into "Context" and "Value." It is this self-reinforcing feedback loop that systematically reproduces frontline agitation as a sustained, unresolved state rather than a transient reaction to technological change. This tripartite conceptual framework aligns with core analytical distinctions in organizational research—namely, structural conditions, interpretive frameworks, and enacted practices—while maintaining deliberate theoretical parsimony (Bolman and Deal, 2013).

Collectively, the analytical novelty of the CVB framework resides in the dynamic, reciprocal interplay among these three dimensions. Specifically, contextual conditions activates and intensifies latent value tensions (C→V). These heightened tensions, in turn, shape FPSDs' strategic behavioral response, ranging from selective compliance to active resistance (V→B). Subsequently, such recurring behavioral patterns institutionalize over time, feeding back into the structural environment by reshaping organizational norms, routines, and implementation practices (B→C). Within this loop, agitation is not a separate outcome to be explained; it is the very state that the CVB system exhibits when value conflicts remain unresolved and behavioral vacillation persists—a state sustained by the recursive failure of Context, Value, and Behavior to settle into a stable configuration. This self-reinforcing feedback loop explains how agitation is systematically produced and sustained as a chronic state rather than a transient reaction to technological change, an insight that fundamentally distinguishes the CVB framework from the endpoint-oriented logic of TAM.

3. Methods

This study employs a qualitative, multiple-case study design to investigate the complex and contextualized phenomenon of AI adoption among FPSDs. Given that the AI adoption is deeply embedded in and inseparable from the context of frontline public service delivery, we turned to qualitative methodology, which Yin (2018) defines as an empirical inquiry that investigates a contemporary phenomenon in depth within its real-life context. This approach is therefore particularly appropriate for addressing "how" and "why" questions surrounding the heterogeneous patterns of AI use. Moreover, qualitative methodology, especially case study research, is particularly valuable when a research domain is still in a nascent stage (Benbasat et al. 1987), as is the case with AI implementation in frontline public service. This methodology enables the construction of a richly descriptive analysis grounded in diverse and in-depth sources of information, which is a necessity for capturing the multi-faceted complexity of the phenomenon (Hancock et al. 2021; Merriam and Tisdell 2015). Importantly, this method is deemed optimal for practice-based problems where the experiences of the actors are important, and the context of action is critical (Benbasat et al. 1987).

Our research is guided by an integrated CVB framework, which moves beyond siloed theoretical explanations to capture the dynamic interplay between external constraints, internal reasoning, and situated practices. The research design is uniquely suited to this framework, as it enables an in-depth exploration of how contextual conditions, value trade-offs, and behavioral strategies collectively shape the differential patterns of AI adoption, thereby directly aligning with and addressing our core research questions (R. Subudhi et al. 2019).

3.1 Participant Recruitment

Table 1. Basic Information Table of Interviewees

No.	The Interviewee's Workplace	Age	Length of Service	Service Field	Educational Background
LMH	SWO	25	1.5	Migrant workers	Law
CXK	SWO	26	2	Migrant workers	International Business
LC	F	37	13	Teenagers	Social work
ZYS	CSW	34	4	Community residents	Chinese language
WCL	CSW	31	3	Community residents	Law
HF	SSWS	32	6	Street residents	Social work
XHL	SWO	27	2.5	Women	Social work
WQM	CSW	32	5	Community residents	Psychology
LRN	SSWS	31	4.5	Street residents	Social work
HSQ	SWO	38	15	Children, Family	Social work
MJH	F	42	9	The elderly	Journalism
ZL	CSW	27	7	Community residents	Marketing
WLY	SSWS	29	4	Street residents	Sociology
CTH	SWO	28	3	Migrant women	Human Resources
LZH	F	35	3.5	Teenagers	Social work
LMJ	SWO	43	8	The elderly	Social work
CXY	SWO	27	3.5	Migrant children	Accounting
WCF	SSWS	30	4	Street residents	Sociology
LZX	SWO	27	3	People with disabilities	Social work

**Note: The abbreviation for the interviewee's workplace is defined as follows: SWO stands for Social Work Organization, F stands for Foundation, CSW stands for Community Social Workers, SSWS stands for Street-level Social Work Station. Age and length of service are expressed in whole years.*

Eligibility criteria required participants must be frontline professionals with a minimum of one year of direct service experience and consistent, routine exposure to AI-based tools in their day-to-day professional practice. Meanwhile, guided by the principle of maximum variation (Patton 2015), we purposively sampled participants diverse in geographic coverage, organizational affiliations, service population, and individual demographics. This intentional heterogeneity captures the diverse realities encountered on the front lines. Importantly, participant recruitment was conducted using a dual-strategy sampling approach that integrated purposive and snowball sampling methods. Initial participants were identified through organizational gatekeepers, and subsequent participants were recruited through a snowball sampling strategy, leveraging referrals from previously enrolled participants.

Based on these criteria and strategies, this study selected 19 FPSDs from five types of practitioners within China's public service ecosystem: community social workers, street-level social work stations' workers, social work organizations' workers and foundations employees (As shown in Table 1). Respondents were recruited from five Chinese cities—Beijing, Guangzhou, Xiamen, Zhuhai, and Karamay—spanning eastern, southern, southeastern, and northwestern regions. This selection encompasses both economically advanced coastal metropolises and strategically important inland urban centers, thereby reflecting diverse levels of socioeconomic development, regional policy contexts, and institutional frameworks. The primary beneficiaries of the participants' services include migrant workers, youth, older adults, women, children, persons with disabilities, and general community residents—reflecting a deliberate commitment to serving both historically marginalized groups and populations affected by emerging societal challenges. The participants also vary significantly in key demographic attributes: length of service ranges from 1.5 years to 15 years, forming a clear career development ladder; educational backgrounds range from associate degree to postgraduate level, encompassing a diverse array of academic disciplines; gender composition reflects the gender distribution of the social work profession in China; ages range from 25 to 43, capturing both younger and mid-career perspectives. This combination of breadth and depth satisfies both the "maximum variation" and "typical case" criteria in social science research.

3.2 Data Collection

We collected primary data through in-depth, semi-structured interviews with the 19 selected participants. Semi-structured interviews were conducted both in person and remotely, with duration ranging from 45 to 90 minutes (mean = 65 minutes). The interview protocol was designed around the core dimensions of TAM while remaining attentive to the specificities of frontline public service practice. This allowed participants to provide detailed narratives of their experiences with AI. The interviews followed a semi-structured format with open-ended questions, which provided a flexible yet guided conversational path (Karatsareas 2022). We first asked participants to describe their professional roles, daily responsibilities, and the broader organizational and policy context of their work. We then guided the conversation toward their specific interactions with AI systems, inquiring about typical use scenarios, perceived benefits, and encountered challenges. Finally, we posed probing questions designed to elicit the underlying reasoning and tensions in their practice, such as how they navigated situations where AI recommendations conflicted with their professional judgment. Throughout the process, we encouraged participants to elaborate on their responses and provide concrete examples, ensuring the collection of rich, contextualized data.

3.3 Data Analysis

For data analysis, we employed a mixed deductive-inductive thematic analysis approach, facilitated by Nvivo 15 software (Several of the encoding results are presented in Table 2). First, after speech-to-text conversion and error correction, we imported the transcribed records into Nvivo 15. Drawing on our CVB framework, we conducted first-level deductive coding by initial identifying three broad categories, Context, Value, and Behavior. Next, through second-level deductive coding, we performed line-by-line analysis to extract central statements according to constraint contextual conditions, value tension, and strategy-adaptation. Subsequently, we carried out third-level inductive coding: through iterative analysis we generated 56 first-order analytic units. At this stage, no predetermined theoretical structure was imposed. Through sustained comparison among these emergent units and dialogue with the literature, we recognized that certain recurring code—such as concerns over data security and fears of de-professionalization—could not be adequately accommodated within existing TAM logic. This recognition compelled us to construct an independent Value dimension and to reconfigure the relationships among Context, Value, and Behavior. The three-dimensional CVB structure thus crystallized through this iterative movement between data, emergent codes, and theoretical reflection. For example, initial practitioner concerns, such as "concerns about the erosion of professional competence" and "AI's inability to account for clients' unique contextual circumstances," were systematically aggregated and refined into the higher-order thematic category "threats to professional discretion," which subsequently informed the Value dimension of the CVB framework. Building on this, by engaging with the literature and theoretical dialogue we constructed an analytical framework encompassing technical suspension, regulation and training, reducing the burden of paperwork, value-based exclusion, and instrumental dependence. To enhance coding reliability, a representative subset of transcripts was independently coded by two trained members of the research team. Discrepancies between coders were systematically addressed through consensus meetings, during which code definitions were clarified, boundary case reviewed, and coding guideline refined. The final coding framework from iterative discussion and collective agreement among all team members. Finally, we conducted a saturation check: after coding the 15th transcript, the analytic units stabilized, and by the 19th transcript no new core concepts emerged, indicating that theoretical saturation had been reached.

3.4 Ethical Considerations

This study adhered to the rigorous ethical standards throughout the research process. Firstly, prior to each interview, we obtained informed consent from all participants. We clearly explained the research purpose, procedures, and potential risks and benefits, emphasizing the voluntary nature of their participation and their right to withdraw at any time without penalty. Secondly, to protect the privacy and confidentiality of all individuals and organizations involved, we anonymized all data during transcription, using pseudonyms for participants and avoiding any identifiable information in subsequent reporting. Third, recognizing that researcher subjectivity is an inherent part of qualitative inquiry, we engaged in critical reflexivity to ensure the trustworthiness of our findings (Guillemin and Gillam 2004). This continuous reflexive practice helped us to challenge our assumptions, consider alternative explanations, and ensure that our emergent themes and conclusions were firmly grounded in the participants' narratives rather than our own biases.

Table 2. Several of the Encoding Results

Core Dimension	Theoretical category	Empirical representation (Three-level coding)	Representative original interview texts (Excerpts)
Contextual Logic	Resource Endowment	Technical Suspension	"The working hours of the workers we serve have been so long that they simply don't have the energy to participate in the activities... This is not a problem we can solve." (Social Work Organization -CXK)
	External Environment	Regulation and Training	"Our organization clearly stipulates that it is not allowed to include service recipients... Upload the document table to the platform, voice-to-text... It must be manually reviewed." (Social Work Organization -LMJ)
Value Logic	Efficiency Gain	Reduce the Burden of Paperwork	"That kind of administrative work is a bit too routine and burdensome... With AI, a lot of pressure from paperwork will be reduced." (Street Social Work Station -WCF)
	Professional Discretion	Value-based Exclusion	"They randomly generate a supervision record... It's just a bit perfunctory... In fact, it is often the case that records provide guidance for a social worker's work." (Social Work Organization -HSQ)
Behavior Logic	Deep Integration Strategy	Instrumental Dependence	"Almost every day, I use AI to check problems for me or polish the text... It saves me the time of looking for it myself." (Social Work Organization -XHL)

4. Findings

Our research has yielded a distinct formation logic, namely the explanatory framework of CVB, which facilitates a comprehensive understanding and allows us to systematically analyze how external structures, internal reasoning, and situated practices interact to co-produce the diverse AI adoption patterns observed at the frontline, thereby directly addressing our core puzzle: Why are they differences?

4.1 Contextual Logic: The Combined Effect of Resources and Environment

4.1.1 The Differentiation of Resource Endowments

During the research process, we observed that most FPSDs do not inherently resist the adoption of AI. Rather, limited access to this technology is primarily attributable to disparities in resource availability and allocation.

> *Our organization aims to establish a more equal and friendly environment ... But now their working hours have become so long that they simply don't have the energy to participate. It's extremely tricky. We are very distressed. This is not a problem we can solve.* (Social Work Organization -CXK)

This suggests that resource constraints and task complexity in frontline settings inherently restrict FPSDs' access to emerging technologies. Their cautious approach to AI adoption is typically not rooted in resistance to technological change, but rather in a pragmatic awareness that resource-scarce environment cannot support its meaningful integration. Moreover, they often lack the sufficient resources and time to develop a comprehensive understanding of AI. This phenomenon can be aptly described as technological suspension—the underutilization of new technologies arising not from intrinsic reluctance, but from structural inequities in resource distribution that produce unequal access to technological advancements.

> *We are a grassroots frontline organization, so we actually don't have too many requirements for data organization or image generation ... Then there would be no need to deliberately organize the data. For instance, image generation is rarely used, so there would be no need to use it very often.* (Social Work Organization -LMH)

> *We are affiliated with a grassroots organization rather than a social work station ... This distinction may stem from the relatively limited resources available to grassroots entities. In contrast, social work stations typically operate with an official institutional background, which enables them to receive formal support and allocated resources. In this case, if the business work itself is not complicated or not much, ai is actually not needed at all.* (Social Work Organization - CXK)

The phenomenon of technological suspension becomes increasingly pronounced when differences in resource endowments are examined through horizontal comparison, as evidenced by the original transcripts of the two interviews. It vividly illustrates the severe resource constraints confronting frontline service settings, leading to the depletion of FPSDs' time and energy, limited complexity in service tasks, and an uneven allocation of service resources. Within this survival mode, the integration of AI technology becomes unfeasible. This pattern reflects a distinctive institutional feature of China's public service ecosystem: the hierarchical resource allocation system, wherein grassroots organizations without official institutional backing face disproportionate resource scarcity compared to government-affiliated entities such as social work stations (Hou 2025). Social work stations, as organizations directly anchored within the official administrative structure, receive systematic policy support and allocated resources, including regular AI training and technology access initiatives. By contrast, grassroots social work organizations operating outside the formal institutional framework confront a markedly different reality, lacking both the organizational mandate and the resource channels to prioritize technological integration.

4.1.2 The Pressure of the Environment: Wavering between Calls and Concerns

Although within well-established organizations that possess relatively abundant resources, disparities in AI adoption persist. This observation underscores the need to temporarily set aside disparities in resource endowment to further explore underlying factors—specifically, the intricate psychological dynamics of FPSDs facing external environmental pressures.

> *As for AI, our organization is still actively using it now. We have found that many local governments are proactively integrating ai systems to achieve public service delivery, and we are also making attempts in this regard.* (Foundation - LC)

Therefore, due to sustained government support and policy-driven initiatives, FPSDs are expected to continue actively engaging with and adopting AI technologies. Nevertheless, certain barriers may impede widespread adoption, despite the proactive efforts of some organizations and individuals within this group.

> *The government has not yet regulated this artificial intelligence platform, but people are quite proactive in accepting it ... At least no one has told us what you should pay attention to when using AI.* (Community Social Worker - ZYS)

> *I wanna AI to assist in my community governance, but during the analysis, it may steal my information. So, if I have relevant regulations in the future, what should I do when I trace it back?* (Community Social Worker - WCL)

FPSDs perceive a clear disconnect—while the government actively promotes AI adoption, they find the practical guidelines for its safe use critically lacking. This misalignment between top-down enthusiasm and on-the-ground support has placed them in a dilemma, which has left them feeling anxious and uncertain. While eager to comply with the organizational directive, FPSDs may remain hesitant to adopt the AI due to serious concerns regarding data security and potential future accountability. More importantly, this concern is explicitly reflected in the organization's internal policies and leadership communications, thereby reinforcing a cautious approach toward AI adoption.

> *Our organization has now clearly stipulated that documents and forms containing service recipients or communities cannot be uploaded to the platform. Light use of voice-to-text conversion must be manually reviewed.* (Social Work Organization - LMJ)

> *Our leader believes that AI can be used, but we should not rely on it completely. If you rely entirely on this AI, you will eventually be replaced by it. Therefore, you need to be flexible in using this thing.* (Social Work Organization - XHL)

These directives and restrictions imposed by upper management have intensified the psychological conflict experienced by FPSDs, who are caught between external pressures to adopt emerging AI and internal organizational caution, resulting in heightened vigilance in their actions and increased psychological unease.

Therefore, from the phenomenon of technological suspension, government promotion, perceived risks and internal organizational regulation and training, it is evident that the internal and external organizational environment play a critical role in shaping the differentiated adoption of AI among FPSDs. First, disparities in resource allocation exacerbate the technological suspension phenomenon, leaving FPSDs or their units at the survival stage unable to access or prioritize technological integration, thereby producing initial differentiation. More significantly, even when organizations progress to a growth or developmental phase, FPSDs continue to confront challenges related to regulatory risk perception and organizational compliance demands, which further contribute to the emergence of new forms of differentiation. These layered constraints collectively form the contextual logic that not only shapes FPSDs' access to AI but also conditions the value trade-off they subsequently confront, thereby setting the stage for the entire CVB cycle.

4.2 Value Logic: The Wavering between Efficiency, Professional Discretion, and Public Values

4.2.1 The Primary Trade-off: Efficiency Gain and the Loss of Localization

In the actual working process, the integration of AI can assist FPSDs in reducing administrative burdens. This reduction in documentation requirements highlights that AI adoption is primarily driven by the pursuit of operational efficiency.

> *That kind of administrative work is a bit too routine and burdensome ... With AI, a lot of pressure from paperwork will be reduced.* (Street-level Social Work Station - WCF)

> *The materials that social workers are required to produce often entail significant documentation demands. By providing clear instructions, AI can assist in structuring these documents and generating appropriate content accordingly.* (Community Social Worker - WCL)

However, FPSDs have observed that the content generated by AI often lacks contextual relevance and a human-centered perspective. Therefore, the perceived effectiveness of such algorithmic processes is frequently called into question when applied to the complexities of real-world implementation.

> *Some of the event plans he generates will definitely be revised by himself later. You need to localize them, that is, use some of the language or style of that community.* (Social Work Organization - LMH)

It is evident that they are continuously navigating the tension between efficiency improvement and content distortion, cultivating an ambivalent mindset of both reliance and distrust towards AI.

> *In fact, it needs to guide you to answer questions. According to the project, some frameworks may have some questions that need to be answered, but if you put them in for questioning, they actually don't … Because they don't understand the community's information.* (Social Work Organization - CXK)

This reveals a fundamental tension, constituting the primary trade-off in the value assessment of FPSDs: the generalized efficiency offered by AI stands in direct opposition to the localized, intelligence essential to professional social work. FPSDs quickly discover that while AI accelerates tasks, its outputs often lack the specificity and local contextual features. Thus, the promise of algorithmic efficiency is inherently limited by its inability to adapt to context-specific realities, revealing a fundamental and irreconcilable tension between efficiency and local relevance.

4.2.2 The Second Trade-off: The Defense and Adjustment of Professional Discretion

This study observed that the confrontation between algorithmic output and professional discretion often manifests as FPSD's deliberate assertion of their own judgment to safeguard their role in the decision-making process. Despite the improvement in efficiency, they continue to exhibit varied patterns of AI adoption, reflecting their distinct trade-offs and considerations regarding efficiency, which in turn influence their service behaviors.

> *The current supervision records are not well written, and then AI generates a supervision record ... I think they are a bit perfunctory.* (Social Work Organization - HSQ)

> *I'm rather reluctant to use this thing ... Because we are serving the living, it is a warm substance. ... AI might also have some influence. However, the decisive factor still lies in the professional ability of the social worker themselves. They must do a good job in communication between people, which is something that AI can never replace.* (Community Social Worker - WQM)

Addressing the potential de-professionalization associated with the advancement of AI, FPSDs may exhibit resistance toward AI integration. This resistance stems from their emphasis on the irreplaceable value of human expertise in areas such as empathetic care and interpersonal communication. In response to perceived threats to their professional discretion, some FPSDs actively uphold their professional identity and assert their unique contributions, leading to a phenomenon referred to as value-based resistance to AI. During this process, certain FPSDs, influenced by regulations, continue to engage in various trade-offs, ultimately exhibiting a pattern of conditional compliance.

> *Because our institution has been using artificial intelligence for a long time... But we have realized that we should have a boundary for usage.* (Social Work Organization - LMJ)

The defense of professional discretion introduces a second and more profound dimension of trade-off. The core consideration thereby deepens beyond the balance between task efficiency and output relevance, to safeguarding the very dignity of profession, resisting the replacement of human-centered service by algorithmic governance.

4.2.3 The Third Trade-off: Questioning Public Value

Following an examination of efficiency-driven practices and the professional discretion defense orientation, this study has further identified that FPSDs harbor significant concerns regarding the implications of AI-driven efficiency, including issues related to data security, algorithmic fairness, and the risk of occupational displacement.

> *Because in your field of social work, there must be some confidentiality ... How can I guarantee that I won't become part of its dataset?* (Foundation - MJH)

> *At present, it's not yet the case that we can make decisions with AI. But when I use it, I will find that sometimes things about disadvantaged groups or remote areas cannot be found online ... It may exacerbate some inequalities.* (Social Work Organization - LMH)

> *I think AI technology should be used with caution and should not be forced upon the lower-class*

working people. (Social Work Organization - CXK)

Therefore, the adoption of AI forces a third and most fundamental ethical trade-off. At this level, considerations transcend operational efficiency and professional discretion, requiring FPSDs to carefully evaluate AI's benefits against its potential erosion of core public values, such as equity, accountability, transparency and social justice. This highest-order trade-off challenges not merely the methods or identity of public service, but its ultimate purpose and for whom it exists.

Building upon the previous discussion, it is evident that at the level of value dimension, this differentiation originated from proactive government promotion. FPSDs have gradually adopted and experimented with AI tools, recognizing their potential to enhance operational efficiency. However, they are not passive recipients of technology, but active agents engaged in navigating this tripartite value conflict.

The intensity of this value struggle is compounded by institutional features of the Chinese context. First, the semi-institutionalized status of the social work profession heightens the second trade-off: unlike fields such as medicine or law, where professional boundaries are legally codified, social work in China remains in an ongoing process of professionalization, with qualification standards, ethical codes, and jurisdictional claims over core domains not yet firmly established (Ke et al. 2025). In this context, AI's encroachment into core professional tasks is experienced as an existential threat, making the defense of professional discretion a matter of professional survival rather than mere preference. Second, the policy-driven push for AI adoption, coupled with a persistent regulatory lag in data governance, intensifies the third trade-off—FPSDs experience simultaneously the pressure to embrace AI and the anxiety of operating without adequate legal safeguards, sharpening the tension between efficiency pursuit and public ethics concerns. It is within this protracted conflict that the central psychological agitation arises, a tension which, as demonstrated below, manifests externally in specific behavioral responses and helps explain why a technically beneficial tool may still encounter skepticism, resistance, or only conditional acceptance.

4.3 Behavior Logic: Strategic Shift from Deep Integration to Deliberate Disengagement

Finally, we adopted an analysis at the behavioral dimension, as the content of prior contextual and value-related elements is more explicitly and profoundly manifested at this element. Based on our direct engagement in frontline public service delivery, we identified that this differentiated phenomenon can be broadly categorized into three distinct types amidst psychological unease and value instability: deep integration, instrumental limitation, and strategic alienation. These strategies—and the underlying phenomena they represent—are not static, rather, they evolve dynamically, typically manifesting as a process of adaptive practice.

4.3.1 The Strategy of Deep Integration

FPSDs generally perceive AI as a process-oriented and institutionalized tool for alleviating administrative burdens. Its most frequent applications are concentrated in standardized tasks. Interview data indicate that over half of FPSDs use AI to assist in generating application forms and related documents more than three times daily, with cumulative usage exceeding one hour per day, establishing a form of instrumental dependence.

> *AI has really greatly improved my efficiency. Almost every day, I use AI to check problems for me or polish the text ... Sometimes I ask him to generate some application forms for me, which saves me the time of looking for them by myself.* (Social Work Organization - XHL)

> *The development and writing of work plans, as well as the sorting out of some ideas for articles, sometimes we really need ai to generate certain content.* (Community Social Worker - ZYS)

This pattern of deep integration illustrates a specific CVB configuration. The Context, characterized by high administrative workload, standardized task architectures, and institutional imperatives for documentation efficiency, activates the Value of algorithmic efficiency while temporarily attenuating countervailing concerns regarding professional discretion. Such value prioritization shapes Behavior toward instrumental dependence: FPSDs systematically delegate routine, repetitive tasks to AI systems and reallocate cognitive and temporal resources toward higher-order, judgment-intensive interactions. As this delegation becomes institutionalized through repeated practice, it recursively reinforces the Context itself—normalizing AI as an embedded, infrastructural element of everyday work and thereby perpetuating the conditions that enable sustained deep integration. This self-reinforcing dynamic extends Acemoglu and Restrepo's (2020) foundational insight: the CVB framework not only identifies which tasks are displaced by automation but also explicates how displacement is institutionally sustained through recursive interplay among task design, value activation, and behavioral routinization.

4.3.2 The Strategy of Instrumental Limitation

A significant number of FPSDs adopt a posture of instrumental limitation, strategically confining their use of AI to specific, low-risk tasks. This is not outright rejection, but a conscious conditional use that establishes clear boundaries between human and algorithmic domains.

> *For us community workers, our work is more about communicating with residents ... for instance, if a sewer is blocked, we have to figure out how to handle it and coordinate with different parties. These are matters that current AI tools simply cannot replace.* (Community Worker - ZL)

Within the bounded areas where AI is applied, its use is frequently characterized by a process of instructional trial-and-error. FPSDs find they must invest considerable effort in refining their prompts to achieve usable results. This often involves detailed, iterative input, which can itself become a deterrent. During the usage process, they frequently encounter the frustration of debugging instructions.

> *I need to input very detailed and specific descriptions for it to give me specific results ... Sometimes I'd rather just write it myself because the process of adjusting the instructions is too troublesome.* (Social Work Organization - XHL)

This strategy reflects a calculated trade-off, where the potential utility of AI is carefully weighed against the costs to workflow fluidity and the imperative to protect core professional domains from algorithmic encroachment.

4.3.3 The Strategy of Distancing

In response to perceived threats to professional discretion or the integrity of their core values, some FPSDs enact a strategy of strategic alienation. This involves a conscious and deliberate effort to minimize interaction with AI systems. A key behavior here is cautiously controlling contact, driven by the desire to preserve independent critical thinking and professional judgment. This strategic distancing is a form of active resistance, safeguarding the human-centric core of their profession against potential technological determinism.

> *About eighty to ninety percent of my work is written by myself ... I'm afraid that the more I use it, the more my thinking might become rigid. So, I try my best to control my reliance on it and give myself more time to write things in my own way.* (Social Work Organization - XHL).

4.3.4 Adaptive Practices: The Dynamic Response in Agitation

The acceptance of AI by FPSDs extends beyond mere technological adoption; it constitutes a dynamic process of continuous adaptation within structural constraints and psychological tensions. Amid ambivalent attitudes characterized by wanting to use but hesitating to adopt, using without full confidence, and avoiding use while fearing obsolescence, they have developed three distinct coping strategies, engaging in ongoing micro-adjustments such as capability enhancement, procedural reconfiguration, and risk boundary setting in their daily operations.

Several FPSDs are actively engaging in skills development initiatives to enhance their utilization of AI. Rather than passively awaiting training, they actively seek out techniques to strengthen their competence. This self-driven skill acquisition allows them not only to complete tasks more efficiently but also to increase their confidence in using AI tools.

> *I discovered that after using AI, my output was better than that of my older colleagues. I believe it can enhance my work efficiency*

and capability, so I took the initiative to learn some prompt techniques to improve my ability to use AI. (Foundation - MJH).

A colleague used AI to do it. Just today when I asked, he finished it. It can be said that it has already been applied in practice. (Community Social Worker - ZL)

As AI becomes embedded in daily practice, it also triggers subtle yet pervasive shifts in work habits. Many FPSDs unconsciously adjust their routines—turning to AI almost instinctively to brainstorm, outline, or refine content. This reflects not just tool adoption, but a deeper cognitive and procedural shift.

Since many of my colleagues are using it to varying degrees, I've adapted my work habits. For example, when writing articles, I now instinctively turn to AI to broaden my mind or adjust my logic (Social Work Organization - LMJ)

Perhaps the most critical adaptation lies in how FPSDs individually navigate AI-related risks. In the absence of clear regulations, they develop their own informal safeguard—limiting data sharing, avoiding sensitive documents, and controlling how deeply they engage with the AI.

I sometimes worry about data leaks ... Once I found it had collected my name and address, so now I reduce direct document uploads and switch to simple dialogues ... I strictly limit my usage and would never upload files containing community information. (Social Work Organization - XHL)

Importantly, these behavioral strategies do not entail rigid typologies of practitioners; rather, they represent contextually contingent patterns of engagement that frequently co-occur within a single FPSD. For example, the aforementioned social worker (XHL) alternated between deep instrumental reliance on AI and intentional disengagement from it, depending on task characteristics. In routine administrative tasks—characterized by high procedural volume and well-defined regulatory requirements—she leveraged AI primarily as an efficiency-enhancing tool, thereby prioritizing procedural expediency. By contrast, in cases demanding core professional judgment—marked by substantial outcome uncertainty and ethical complexity—she actively withheld endorsement of AI-generated recommendations, foregrounding the primacy of professional discretion. This situational variability demonstrates how contextual features systematically shape value priorities, which in turn inform corresponding behavioral adaptations—even within the practice of a single FPSD. Such intra-individual flexibility reflects the dynamic, reciprocal adaptation between FPSDs and AI systems: the three identified adaptive responses—capability enhancement, procedural reconfiguration, and risk boundary setting—are not static dispositions but responsive, calibratable strategies deployed iteratively as FPSDs continuously negotiate their evolving relationship with AI. In summary, these adaptive behaviors reciprocally reinforce the structural environment, thereby sustaining the recursive CVB loop that perpetuates sustained agitation—a dynamic elaborated in greater detail in the following section.

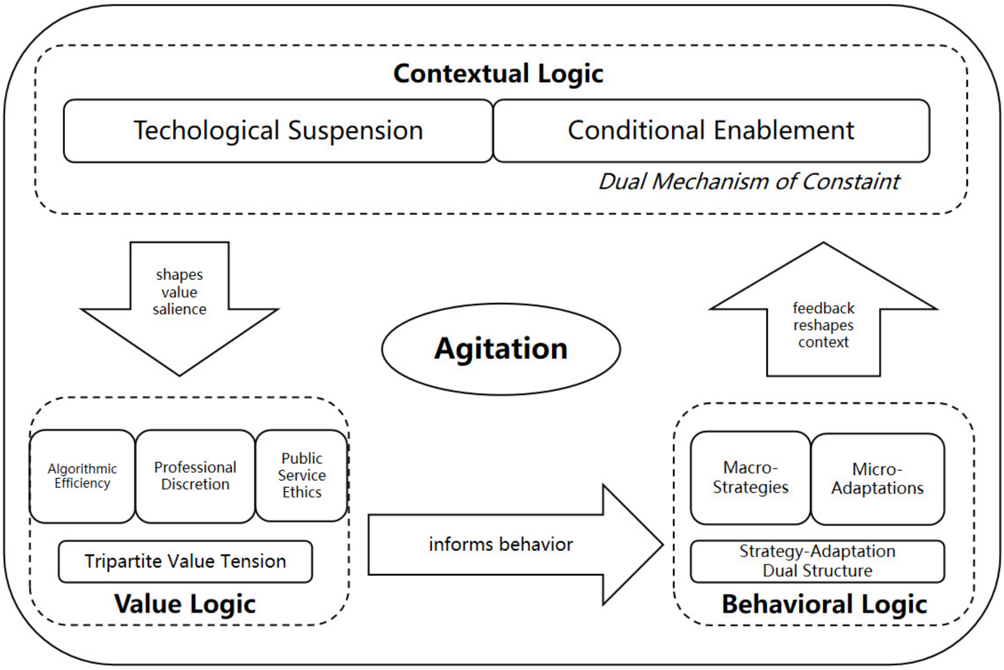

Figure 1. Context-Value-Behavior Operating Mechanism

4.4 The CVB Operating Mechanism: A Recursive System

In summary, the frontline agitation surrounding AI is not a simple reaction, but the product of a dynamic mechanism. As our findings demonstrate, agitation varies both intra-individually and inter-individually. On the one hand, the same FPSD oscillates between behavioral strategies, as illustrated by XHL, who moved between deep instrumental reliance and deliberate distancing depending on the task at hand. On the other hand, agitation takes divergent forms across organizational contexts—FPSDs such as ZYS and WCF gravitated toward instrumental dependence, whereas WQM and CXK leaned toward deliberate distancing. Taken together, this dual-axis variation manifests as sustained behavioral vacillation, rooted in unresolved value tensions—the two constitutive dimensions of agitation. Our findings integrate into the CVB operating mechanism illustrated in Figure 1, which explains how this state is both produced and sustained.

The process originates within the contextual logic. Disparities in resource endowments create a fundamental divide. For organizations in a survival stage, severe resource constraints lead to technological suspension, where AI is inaccessible. For those in a developmental stage, access to AI has become increasingly possible, yet they operate within a complex and often contradictory environment, characterized by proactive governmental promotion on one hand and significant regulatory uncertainty on the other. This context acts not merely as a passive backdrop, but as an active force that enables, constrains, and triggers the subsequent cognitive and behavioral processes. These external pressures catalyze the core value logic. FPSDs are caught in a persistent trade-off among algorithmic efficiency, professional discretion and public values. Crucially, this value negotiation mediates and often overrides initial perceptions of AI's usefulness, reframing adoption as an ethical and professional dilemma rather than a mere efficiency calculation. Consequently, this internal conflict is provisionally resolved through behavioral logic, manifesting as a spectrum from deep integration to strategic alienation.

A central insight is the dynamic, recursive feedback loop among context, values, and behavior—FPSDs' behavioral adaptations generate new experiences that, in turn, influence their value judgments and collectively reshape the organizational and policy environment over time. Crucially, these three dimensions do not operate in a unidirectional or linear causal sequence. Rather, they constitute an interdependent, self-reinforcing system. Specifically, contextual conditions determine which values become salient; value orientations guide the selection and enactment of behavioral strategies; and behavioral outcomes generate consequential feedback that modifies contextual conditions and recalibrates value priorities across time. Consequently, agitation represents a sustained state of co-evolution, dynamically reproduced through the iterative, reciprocal interactions among context, values, and behavior. To validate the comprehensiveness of the proposed three-dimensional framework, we conducted a rigorous inductive assessment of alternative candidate dimensions, including emotional responses or social influence, to determine whether they constituted empirically distinct analytical categories. Drawing on iterative coding and comparative analysis, we observed that neither dimension attained empirical saturation as an autonomous explanatory construct. Instead, both are consistently embedded within value conflicts or contingent upon contextual conditions and observable behavioral patterns. This confirms that the three identified dimensions collectively represent the core generative mechanism, achieving theoretical coherence and empirical saturation.

5. Discussion

While scholars have recently begun to explore how AI influences street bureaucrats (Duan et al. 2019; Janssen et al. 2020; Selten et al. 2023), the underlying drivers of the pervasive "agitation" in FPSD's adoption behaviors remain poorly understood. This study moves beyond documenting varied usage to explain the systemic production of this unsettled state. We argue that FPSDs are not merely assessing AI's usefulness, but rather actively navigating a complex interplay of contextual constraints such as resource disparities and regulatory directives, and profound value trade-off between algorithmic efficiency, professional discretion, and public service ethics. This navigation gives rise to a repertoire of behavioral strategies—from deep integration to strategic resistance—that are contextual, strategic, and dynamic, reflecting an ongoing process of agitation rather than a static decision to accept or reject.

The primary theoretical contribution of this study lies in constructing an integrated CVB analytical framework, which extends the TAM model to better account for the realities of frontline public service. While TAM effectively captures the initial cognitive assessment especially the potential of a technology (Davis 1989; Venkatesh et al. 2016), our CVB framework elucidates how this assessment is subsequently mediated, refracted, and often overridden by the structural and normative complexities of the work environment. Specifically, we find that perceptions of AI's usefulness and ease of use are filtered by the contextual reality of technological suspension and subsequently shaped by a profound tripartite value struggle at the frontline—namely, the tension among efficiency, discretion, and public ethics (Mahroof et al. 2025). This ongoing struggle generates the core psychological agitation, which explains why a technically useful tool may still be met with skepticism or adopted only under conditional terms. By synthesizing the micro-level logic of TAM with the meso-level context of street-level discretion and macro-level environmental pressures, the CVB framework provides a more holistic and systematic explanation for why a technology that is perceived as useful may still be used reluctantly, selectively, or not at all. This study extends the TAM by integrating its core constructs into the dynamic CVB cycle, demonstrating cognitive assessment is not an endpoint but a starting point that is profoundly shaped by situational constraints and value conflicts (Rodriguez et al. 2025). Moreover, this study also extends street-level bureaucracy theory (Lipsky 1980; 2010) in the digital age, emphasizing that FPSDs are not passive recipients but active agents who exercise agency in response to the challenges AI poses to their professional discretion within an evolving context of algorithmic management (Busch and Henriksen 2018; Busch et al. 2018). This aligns with discussions by scholars like Grimmelikhuijsen (2022) on algorithmic trust and the evolution of discretion, clarifying that technology adoption is co-shaped by the external environment and individual agency.

Our findings sound a warning: a top-down, one-size-fits-all approach to AI promotion risks transforming purported empowerment into a tangible burden, potentially exacerbating inequalities and eroding the human-centric core of public service (Binns 2020; Zuiderwijk et al. 2021). This disconnect suggests that any pre-mature, rigid institutional arrangement is likely to be ineffective or even counterproductive. The central policy implication, therefore, is not to design meticulous, universal plans, but to acknowledge, engage with, and respond to this pervasive state of uncertainty. Policymakers and administrators must shift their mindset from implementing predetermined technological solutions toward fostering a context-sensitive and adaptive evolution (Peeters and Widlak 2018). Specifically, the CVB framework outlines a concrete path for this transformation—one informed by a central insight: for AI to become a sustainable and legitimate component of frontline operations, it is essential to actively facilitate the co-evolution of algorithmic systems and professional practices. This means designing for adaptability rather than standardization (Northcott 2025)—providing differentiated implementation guidelines and targeted capacity-building initiatives tailored to the Chinese context that can be locally configured, rather than imposing monolithic systems, especially given the reality of "technological suspension" and the divergent needs of organizations at different stages. It also necessitates building responsive feedback channels to truly understand the frontline dilemmas and channel collective agitation into constructive, situated exploration (Carreno 2024). Moreover, ensuring inclusive co-evolution requires targeted support to bridge the resource and capability gaps that lead to technological suspension, through targeted measures such as facilitated technology access, skill-building programs, and peer support networks, so that the benefits and burdens of AI transformation are equitably shared across the entire public service ecosystem (Liu et al. 2025). Ultimately, the goal is to move with, rather than against, the currents of frontline practice.

As an exploratory study, this research opens more questions than it resolves, thereby outlining a rich agenda for future inquiry centered on the phenomenon of frontline agitation. Several limitations and corresponding directions emerge. First, while in-depth interviews effectively uncover complex reasoning and situated practices, the proposed Context-Value-Behavior framework requires further empirical substantiation. Future studies could employ large-scale surveys or Q-methodology to prioritize the refinement and validation of the CVB framework and test the causal pathways between these dimensions and their relative explanatory power regarding usage behavior (Venkatesh et al. 2016). Second, the present study offers a cross-sectional snapshot. A critical next step is longitudinal research to trace how agitation evolves as technologies mature and early implementation experiences accumulate. Tracking whether this state resolves, intensifies, or transforms over time is essential for understanding the long-term dynamics of human–AI co-evolution in public service settings (Acemoglu and Restrepo 2020). Finally, although focused on the social service sector in China, the CVB framework invites comparative extension. Future research could examine its applicability across sectors—such as healthcare, education, or administrative agencies—to discern how differing professional logics and regulatory environments shape AI adoption. Cross-cultural comparisons could further clarify the framework's boundary conditions and refine our understanding of how institutional and cultural contexts moderate the experience of frontline agitation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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