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Original Article

Research on the Intention of Grassroots Civil Servants for Human-AI Collaboration Based on the Integrative Framework for Collaborative Governance

Xinqi Wen[1]*, Junxiang Xiao[1], Heling Wang[1]

[1]School of Government Management, Shenzhen University, China, Shenzhen

***Corresponding Author: Xinqi Wen**

Abstract:
With the deep integration of artificial intelligence (AI) in grassroots governance, the collaboration between grassroots civil servants and intelligent systems has become a key issue in the construction of a digital government. Based on the Integrative Framework for Collaborative Governance, this paper constructs a comprehensive model that includes two types of drivers (interdependence, consequential incentives), three types of mediating variables (principled engagement, shared motivation, capacity for joint action), and collaboration intention, starting from the logic of "institutional environment—collaboration dynamics—collaboration intention." Empirical data from grassroots civil servants are used to test the model. The research results indicate: (1) Both interdependence and consequential incentives have a significant positive impact on the grassroots civil servants' intention to collaborate with AI; (2) Principled engagement, shared motivation, and capacity for joint action all play partial mediating roles between the two types of drivers and the collaboration intention. The study reveals the mechanisms behind the formation of grassroots civil servants' collaboration intention with AI. In the future, this collaboration can be promoted through institutionalized participation mechanisms and capacity co-construction.
Keywords: Human-AI collaboration; Integrative framework for collaborative governance; Grassroots civil servants; Algorithmic bureaucrats

Introduction

With the deep penetration of technologies such as artificial intelligence and big data in the public sector, traditional experience-driven decision-making is transitioning to a human-AI collaborative intelligent decision-making model. Algorithmic systems have shown great potential in improving government service efficiency and the quality of public decision-making. The core lies in breaking through the efficiency bottlenecks of traditional administrative models through human-AI collaboration. The "2024 E-Government Survey" report by the United Nations Department of Economic and Social Affairs (UN DESA) shows that the integration of intelligent technology with public governance has become a key strategic direction for building digital governments in various countries. Many local government systems have begun to integrate large language models, significantly enhancing the efficiency and quality of government services through functions such as intelligent Q&A and policy interpretation. However, in the practice of grassroots government governance, the introduction of AI technology has changed traditional work patterns, with its applications presenting a dual reality of both empowerment and new obstacles. On the one hand, intelligent systems release governance efficiency through functions such as process automation and data aggregation analysis; on the other hand, the implementation of technology encounters deep-seated resistance: civil servants may develop algorithm aversion when errors occur in the algorithm (Dietvorst et al., 2015), or they may lack trust in AI or perceive AI as a threat to their professional identity, leading to resistance and hindering the implementation and continuous optimization of technology (Mirbabaie et al., 2022). As the "last mile" implementers of policy execution, grassroots civil servants play a crucial role in whether the technological dividends can be effectively transformed into governance efficiency. Enhancing the grassroots civil servants' intention to collaborate with AI is the key. Therefore, overcoming the obstacles to human-AI collaboration and improving the acceptance of algorithms by grassroots civil servants have become important issues in the current transformation of digital government.

Currently, academia often uses frameworks such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) to study the mechanisms of intention formation, focusing on individual variables like perceived usefulness and ease of use. However, in the practice of grassroots government governance, AI systems are not neutral tools but are deeply embedded in administrative processes, performance evaluations, accountability structures, and organizational norms. Their usage behavior is simultaneously influenced by institutional constraints, organizational power relations, accountability mechanisms, and public responsibility ethics. Therefore, in contrast, the integrative framework for collaborative governance emphasizes the formation of cooperative relationships and action intentions among different entities through interactive processes under the influence of political, socio-economic, and other factors. Its analytical focus not only includes individual motivations but also encompasses multi-layered factors such as institutional design, organizational environment, and interaction mechanisms. This framework can better depict the relationship between grassroots civil servants, AI systems, and organizational institutions, helping to explain the acceptance level and collaboration effectiveness of grassroots civil servants after the introduction of AI. Therefore, this study constructs an analytical model of "drivers—collaboration dynamics—collaboration intention" based on the integrative framework for collaborative governance. The AI systems that have transitioned from the role of "tool" to "collaborator" (Ren M et al., 2023) are regarded as "quasi-subjects" and incorporated into the analytical framework of collaborative governance, systematically exploring the formation logic of grassroots civil servants' intention to collaborate with AI. It not only addresses the limitations of existing theoretical explanations but also provides a new perspective for understanding the the mechanisms of resistance to technology adoption in the public sector. Through institutional design and organizational support, enhancing the intention of grassroots civil servants to use AI is both a prerequisite for achieving the goal of intelligent governance and a necessary path to ensure the creation of public value. The research not only provides practical guidelines for organizational changes in the construction of a digital government but also offers empirical evidence for optimizing the design logic of AI government systems.

1. Literature Review and Research Hypotheses

1.1. Literature Review

"Human-AI Collaboration Intention" refers to the degree of acceptance and enthusiasm individuals have toward working collaboratively with AI systems during decision-making or execution processes. This concept differs from mere "technology acceptance" by emphasizing the bidirectional process of interaction and jointly completing tasks (Schmidtler et al., 2015;Chen, 2025). "Collaboration" refers to the partnership established by different agents to achieve a common goal (Terveen, 1995). Existing research has revealed multiple factors influencing the intention for human-AI collaboration, which can be summarized into a three-dimensional structure of "technological characteristics—organizational environment—individual cognition."

A large number of studies have started from the individual level, focusing on how users' subjective perceptions of AI and individual characteristics influence their collaboration intention. Early research primarily used the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Theory of Planned Behavior (TPB) as analytical frameworks to explore the impact of perceived usefulness, perceived ease of use, subjective norms, and perceived behavioral control on technology adoption (Davis, 1989; Venkatesh et al., 2003). TAM emphasizes the direct impact of perceived usefulness and perceived ease of use on collaborative intention (Davis, 1989); UTAUT further points out the significant role of social influence and facilitating conditions on technology adoption (Venkatesh et al., 2003). In recent years, many studies have found that factors such as users' expectations, cognitive load, and role identity also influence individuals' intention to collaborate with AI (Lee et al., 2021; Zhou et al., 2020; Jung & Camarena, 2024). Whether users' needs and expectations for AI match the system design directly affects the sustainability of collaboration: if the system's functions misalign with user expectations, even if the initial collaboration intention is high, it may weaken due to the gap in experience (Lee et al., 2021). In a low cognitive load state, users can more fully analyze system logic, which results in higher trust and collaboration intention (Zhou et al., 2020). The "black box" and "decentralization" of platform-based AI systems can exacerbate individuals' anxiety about role boundaries, triggering fears of their roles being replaced or weakened, thereby reducing their collaboration intention (Jung & Camarena, 2024).

The collaboration intention is not solely determined by the individual characteristics of the users but is also significantly constrained by the characteristics of the AI system itself. Related research focuses on factors such as explainability, transparency, reliability, safety, and human-AI compatibility, with their mechanisms of action either mediated by trust or directly influencing the collaboration intention (Bach et al., 2024; Aoki et al., 2024; Afroog et al., 2024; Hafenbrädl et al., 2016). Algorithmic explainability and transparency are key to building trust (Lee & See, 2004). Clearly explaining to users how the algorithm works, the basis for its decisions, its performance limitations, and risk factors can significantly enhance users' understanding and trust in the system (Glikson & Woolley, 2020; Barda et al., 2020). In high-risk decision-making scenarios, users have a lower trust threshold for AI, and safety issues can lead to a rapid collapse of trust. Therefore, improving the reliability and transparency of technology is an important way to enhance the intention to collaborate with AI (Chen, 2024). Human-AI compatibility is key to achieving effective collaboration. If the decision-making logic of AI differs too much from human thinking patterns, it can also weaken users' intention to adopt AI recommendations. Human-AI compatibility involves external compatibility and internal compatibility, with cognitive compatibility within internal compatibility being particularly important in the field of decision support, as it significantly affects the quality of human-AI collaborative decision-making. In order to enhance the intention for human-AI collaboration, the design of artificial intelligence needs to take human thinking patterns into greater consideration. In addition to increasing the transparency of decision-making algorithms, it is also important to moderately adopt heuristic decision-making principles (Hafenbrädl et al., 2016).

Apart from individual and technical factors, an increasing number of studies are focusing on the role of organizational, environmental, and institutional factors in shaping human-AI collaboration intention. The ambiguity in the division of responsibility for AI applications is a significant barrier to trust and collaboration—when harm occurs, unclear attribution of responsibility can reduce users' trust expectations in the system, leading them to avoid collaboration (O'Sullivan et al., 2019). Therefore, creating a safe and fair collaborative environment will continuously provide a guarantee for building trust and sustaining collaboration. In the context of the public sector, the superior department's policy requirements for AI applications, performance evaluation mechanisms, organizational training arrangements, and the level of leadership support will all affect whether civil servants view AI as a reliable collaborator. Different types of organizational support (emotional support, informational support, instrumental support) all positively promote employees' intention to adopt AI, especially when management actively invests in training and resource support, significantly increasing the intention to adopt AI. Organizational support systems are an important condition for promoting the technology adoption of grassroots civil servants (Chang et al., 2024).

Current research has the following limitations: First, the depth of research on grassroots civil servants is insufficient. Most findings do not integrate the characteristics of public sector responsibilities and value constraints, as well as the specific situations and needs faced by grassroots civil servants, to explore their collaboration intention with AI. Second, the theoretical perspectives are fragmented, and an integrated theoretical framework has not yet been established. Many studies focus on a single perspective of technology acceptance or the technical characteristics of algorithms embedded in the public sector (Aoki et al., 2024), without conducting research across organizational boundaries from the perspective of institutional arrangements that promote collaboration. Finally, the research has certain delays, which starkly contrasts with the urgent demand for digital government construction—AI is transitioning from a mere tool to a collaborator for civil servants (Ren M et al., 2023). This shift urgently requires academia to deeply explore how to stimulate civil servants' intention to collaborate, thereby optimizing the public governance efficiency of human-AI collaboration.

To this end, this paper, based on the public responsibility characteristics of grassroots civil servants and the special context of grassroots governance, introduces an integrative framework for collaborative governance. It examines the intention of grassroots civil servants to collaborate with AI within the macro context of digital government transformation and public governance reconstruction. By integrating individual perceptions and institutional environmental variables, it breaks through the research limitations of focusing solely on technical characteristics (such as algorithm interpretability) or single acceptance variables. It establishes a linked analysis framework of "macro institutional environment—meso organizational support—micro individual cognition": the macro level focuses on the policy orientation of digital government, such as organizational training and resource allocation. Recognizing AI's evolving role from a "tool" to a "collaborator" (Ren et al., 2023), this paper innovatively incorporates AI as a "quasi-subject" (Zhang, 2025) into the collaborative governance analysis, systematically exploring the inter-subjective collaborative mechanisms between AI and grassroots civil servants. On this basis, the innovative significance of this study lies in: addressing the shortcomings of previous research that overlooked the context of public administration, filling the research gap in human-AI collaboration among grassroots civil servants in the field of public services, and enriching the understanding of the concept of "subject" in collaborative governance theory, thereby responding to the practical needs of digital government transformation. Previous research on collaborative governance mainly focused on the cooperation between human organizations (between departments, between organizations). At its core, it is the boundary-spanning interactions among multiple human agents or human-constituted organizations.. Incorporating AI systems into the analysis of collaborative governance makes it more adaptable to the new characteristics of governance practices in the digital age. At the same time, the research findings can directly provide practical guidance for grassroots governance: they can offer empirical evidence for designing technical training and incentive mechanisms at the organizational level, as well as provide direction for optimizing AI government systems. This will promote the transformation of human-AI collaboration from "technical application" to "governance efficiency enhancement," bridging the gap between theoretical research and the practice of building a digital government.

1.2. Theoretical Framework and Research Hypotheses

The Integrative Framework for Collaborative Governance (IFCG) is a three-tiered nested systemic theoretical framework that elucidates the dynamic mechanisms and operational logic of cross-boundary collaboration. System Context, as the outermost dimension, encompasses various influencing factors such as political, legal, socio-economic, and environmental aspects. These factors not only provide opportunities and constraints for the formation of collaborative governance regimes but are also influenced by the actions of these mechanisms. From the system context, key drivers for initiating collaborative governance regimes emerge, including Leadership, Consequential Incentives, Interdependence, and Uncertainty. Among them, leadership can drive the initiation of collaboration and integrate resources, consequential incentives can be internal or external crises, opportunities, or resource needs, interdependence means that participants cannot achieve their goals alone and must collaborate, and uncertainty arises from the complexity of issues or lack of information, making joint responses necessary. Drivers (leadership, consequential incentives, interdependence, uncertainty) initiate the collaborative governance regime, providing the impetus and direction for its launch. Through collaborative dynamics, collaborative actions are generated, which in turn bring about impacts and drive adaptive changes. The Collaborative Governance Regime (CGR) is situated in the middle layer, encompassing both collaboration dynamics and collaborative actions. It serves as the core operational system for cross-boundary collaboration. Its concept draws on Krasner's (1982) definition of "institutions," including the implicit and explicit principles, rules, norms, and decision-making procedures that form around collaboration. It is a collective of participants' behavioral expectations, generating specific collaborative actions through internal collaboration dynamics. These actions, in turn, influence the system's context and self-adjust according to environmental changes. Collaboration Dynamics is the innermost dimension and the core operational mechanism of the Collaborative Governance Regime (CGR). It consists of three interacting components: Principled Engagement, Shared Motivation, and Capacity for Joint Action, which form a cyclical iterative relationship. Principled engagement is the process through which cross-boundary stakeholders address issues and resolve conflicts by discovering, defining, deliberating, and deciding through four dynamic iterative elements, aiming to establish shared goals and action theories. Shared motivation is a self-reinforcing cycle formed through interpersonal interactions that include mutual trust, mutual understanding, internal legitimacy, and commitment, providing the emotional and relational foundation for sustained collaboration, and forming a "virtuous cycle" with principled engagement. Capacity for joint action is the resource and mechanism guarantee for achieving collaborative goals, including procedural and institutional arrangements, leadership, knowledge, and resources, which are the key support for the transition from process to outcome in collaboration. These three components interact like gears, collectively giving rise to "Actions"—specific behaviors such as policy formulation and resource allocation generated by the collaborative governance regime (CGR) through the aforementioned dynamic processes. These actions are direct means to achieve shared goals and cannot be accomplished independently by a single entity. Moreover, the framework also involves the aspects of influence and adaptation. Influence refers to the actual changes that collaborative actions bring to the system context, including both intentional and unintentional outcomes. Adaptation, on the other hand, is the adjustments made by the system context or the collaborative governance regime itself based on these influences. This is the key to the sustainability of the collaborative governance regime (Emerson et al., 2012).

In the system context, political policies, laws and regulations, and organizational culture collectively shape the initiation conditions for human-AI collaboration among grassroots civil servants. The digital government construction strategy, artificial intelligence ethical norms, and the demand for digital transformation in grassroots governance constitute the macro environment for collaboration. In this context, key drivers for initiating the collaborative governance regime emerged, driving the launch of the Collaborative Governance Regime (CGR) and continuously promoting collaboration. Among them, interdependence and consequential incentives are important drivers. Interdependence is reflected in the "goal achievement constraint" of grassroots civil servants in administrative practice. When a single actor cannot independently accomplish public task goals, collaboration becomes a rational choice (Logsdon, 1991; Emerson et al., 2012). For example, when faced with tasks such as verifying vast amounts of social security data, relying solely on human effort cannot efficiently achieve the goals; it is necessary to depend on AI's data analysis capabilities. In the case of low-income subsidy eligibility verification, while AI can capture abnormal income data, it requires civil servants to supplement with unstructured information from home visits, making both indispensable. For the complex requirements of tasks, the collaboration between humans and AI can achieve higher performance than working unilaterally. AI excels at quickly processing large amounts of structured data, while humans still possess irreplaceable advantages in interpreting complex situations and applying experiential knowledge. This asymmetry in the structure of capabilities makes the handling of public affairs exhibit the technical constraint characteristic of "one party cannot complete the task independently," thereby reinforcing civil servants' need for and psychological acceptance of human-AI collaboration. When AI and humans each leverage their strengths, their abilities complement each other. This complementarity helps enhance collaborative efficiency and increases individuals' need for collaboration (Hemmer et al., 2025). Consequential incentives include internal and external motivating factors that promote cooperative actions (Emerson et al., 2012). External incentives include the public's continuous expectations for improved efficiency in government services, while internal incentives include the pressure of digital transformation of organizational performance goals, such as the normalization of the assessment of 'One-stop online government services'. The behavior choices of civil servants are influenced not only by intrinsic public service motivation and internal performance evaluation and accountability systems, but also significantly shaped by external incentives such as public evaluation (Heinrich & Marschke, 2010). Incentives can be both positive and negative (Hossu et al., 2018). When AI systems can significantly enhance administrative efficiency, reduce error rates, and improve public satisfaction, they not only create incentives for individuals but are often incorporated into the performance evaluation systems of organizations. This leads to the formation of institutionalized incentives within the organization, encouraging civil servants to actively use and deepen their collaboration with AI systems. Conversely, external public opinion pressure and internal transformation pressure will also force the development of collaboration, forming a "problem-driven—promoting collaboration" cycle. Based on this, this paper proposes the following hypothesis.

H1: Drivers have a positive impact on the intention of grassroots civil servants to collaborate with AI.

H1a: Among the drivers, interdependence has a positive impact on the intention of grassroots civil servants to collaborate with AI.

H1b: Among the drivers, consequential incentives have a positive impact on the intention of grassroots civil servants to collaborate with AI.

Drivers do not only directly translate into collaboration intention but also play a role through key interactive mechanisms during the collaborative process. When the key mechanism, the Collaborative Governance Regime (CGR), is initiated, the interactive cycle of principled engagement, shared motivation, and capacity for joint action promotes collaboration. Among them, principled engagement emphasizes the interaction between humans and AI through the four stages of discovery, definition, deliberation, and determination to construct fair and inclusive collaboration rules (Emerson et al., 2012). As AI is integrated into grassroots governance practices, two types of drivers—interdependence and consequential incentives—further shape the intention of grassroots civil servants to engage in human-AI collaboration by influencing their participation in the collaborative process. In the discovery phase, grassroots civil servants and AI systems reveal common governance pain points through data interaction. For example, in the review of subsistence allowance eligibility, the AI system captures abnormal income data, while civil servants supplement unstructured information based on their field investigation experience, jointly uncovering issues of fraud in the subsistence allowance system. This process helps civil servants recognize the tool value and limitations of AI, and initially establish a cognitive framework of "human-AI complementarity." The definition phase focuses on calibrating the division of labor between humans and AI: through the streamlining of administrative processes, clarifying that AI is responsible for standardized tasks such as policy text matching and initial material screening, while civil servants handle non-standardized tasks such as complex demand communication and discretionary decisions in special situations. The deliberation phase is characterized by continuous two-way feedback: civil servants help optimize the algorithm by annotating erroneous cases, while AI assists civil servants in understanding reasoning logic by generating "decision basis explanations." This "human-technology" dialog mechanism enhances civil servants' sense of control over the collaboration process. In the determination phase, a standardized collaboration process is established, such as "AI initial judgment—manual review—result feedback," allowing civil servants to perceive the normativity and predictability of the collaboration, thereby enhancing their collaboration intention (Emerson et al., 2018).

On the one hand, when grassroots civil servants realize that their abilities are complementary to those of AI in complex administrative scenarios and that they need to be interdependent in their work, this interdependence encourages them to more actively incorporate AI into the problem definition and solution generation processes. They become more involved in the decision-making, discussion, and feedback stages of human-AI collaboration, coordinating human-AI division of labor, correcting algorithmic suggestions through communication and negotiation, and jointly advancing the achievement of goals, thereby strengthening principled engagement (Spitzmueller et al., 2020; Belrhiti et al., 2024). On the other hand, in the context of digital government construction and performance management, consequential incentives make grassroots civil servants perceive that collaborating with AI can lead to efficiency improvements, performance enhancements, or organizational recognition. This institutionalized incentive and pressure further enhance their motivation to participate in human-AI collaboration, prompting them to more systematically engage in the discussion, interpretation, and correction of AI suggestions during decision-making, thereby strengthening the degree of principled engagement (Silumbwe et al., 2023). The collaborative interactions enhanced by principled engagement help to increase the trust and recognition of the collaborative mechanism among the participants, further enhancing their intention to continue collaborating. It can be seen that interdependence and consequential incentives not only directly affect the intention of grassroots civil servants to collaborate with AI but can also exert an indirect influence by enhancing their principled engagement. Based on this, this paper proposes the following hypothesis.

H2: Principled engagement mediates the relationship between drivers and the intention of grassroots civil servants to collaborate with AI.

H2a: Principled engagement mediates the relationship between the interdependence of drivers and the intention of grassroots civil servants to collaborate with AI. That is, interdependence indirectly enhances the intention of grassroots civil servants to collaborate with AI by increasing the degree of principled engagement.

H2b: Principled engagement mediates the relationship between the consequential incentives of drivers and the intention of grassroots civil servants to collaborate with AI. That is, consequential incentives indirectly enhance the intention of grassroots civil servants to collaborate with AI by increasing the degree of principled engagement.

In the context of human-AI collaborative governance, shared motivation is an important psychological foundation that drives grassroots civil servants to actively participate in human-AI collaboration. drivers do not directly translate into collaborative behavior; their impact needs to be conveyed through the Collaborative Governance Regime (CGR) (Emerson et al., 2012). In this process, Shared Motivation is an important component of CGR. It provides psychological support for collaboration intention through a self-reinforcing cycle of mutual trust, understanding, internal legitimacy, and commitment (Emerson et al., 2012; Emerson et al., 2018). In the context of human-AI collaborative governance, an individual's intention to actively participate and deepen collaboration with AI systems largely depends on shared motivation. Commitment is reflected in the intention to continue participating: when civil servants experience improved work efficiency or feel an expansion of their professional capabilities through collaboration, they will actively explore more collaborative scenarios, forming a cycle of "positive experience—stronger commitment."

The generation of shared motivation is first reflected in the establishment of trust relationships, as trust is the foundation and key factor of collaboration (Emerson et al., 2018; Rapp & Claire, 2020). Due to the internal operating mechanisms of AI systems often being difficult to directly perceive, grassroots civil servants' trust in them usually stems from consistent and reliable performance (Kaplan, 2023). When AI systems maintain a high level of judgment accuracy in government work over the long term, or effectively avoid the errors that often occur in manual decision-making during data verification and process management, civil servants will gradually form a stable expectation of the technology's reliability, thereby viewing AI systems as dependable collaborators. At the same time, the motivation to share also depends on the gradual deepening of mutual understanding. This understanding does not require a complete grasp of each other's internal mechanisms but rather manifests as a clear recognition and acceptance of each other's differences (Emerson et al., 2012). This state of "knowing oneself and knowing others" helps to reduce uncertainty in collaboration and enhances the stable expectations of the collaborative relationship. On this basis, shared motivation is further consolidated through internal legitimacy and commitment mechanisms. Internal legitimacy mainly stems from the institutionalized recognition of human-AI collaboration at the organizational level. When human-AI collaboration is given clear value through typical case promotion, experience summaries, and other means, grassroots civil servants are more likely to see it as an organizationally recognized legitimate work method, rather than an additional burden or short-term task requirement. This organizational-level legitimization process helps transform external institutional pressures into internal normative recognition, thereby strengthening the stability of shared motivation (Mosley & Wong, 2021). Furthermore, the shared commitment to collaboration will also be strengthened, forming more stable cooperation (Sukma & Yamnill, 2025). The core role of shared motivation lies in gradually establishing the psychological support for collaboration during this process, transforming the collaboration intention from a passive response to organizational demands into a self-driven initiative based on trust and recognition.

Interdependence and consequential incentives indirectly influence both grassroots civil servants' collaboration intention with AI by affecting the formation and reinforcement pathways of the aforementioned shared motivation. On the one hand, the interdependence between civil servants and AI promotes the generation of shared motivation by enhancing trust, understanding, and a sense of common goals. On the other hand, consequential incentives provide institutional conditions for the internalization of shared motivation by shaping the benefits and expectations of collaborative behavior. When incentives such as efficiency dividends, performance recognition, and shared responsibilities are continuously perceived and transformed into positive collaborative experiences, the motivation to share is consolidated and further enhances the collaboration intention. Based on this, the following hypothesis is proposed.

H3: Shared motivation mediates the relationship between drivers and the intention of grassroots civil servants to collaborate with AI. H3a: Shared motivation mediates the relationship between the interdependence of drivers and the intention of grassroots civil servants to collaborate with AI.

H3b: Shared motivation mediates the relationship between the consequential incentives of drivers and the intention of grassroots civil servants to collaborate with AI. That is, consequential incentives indirectly enhance the intention of grassroots civil servants to collaborate by increasing shared motivation.

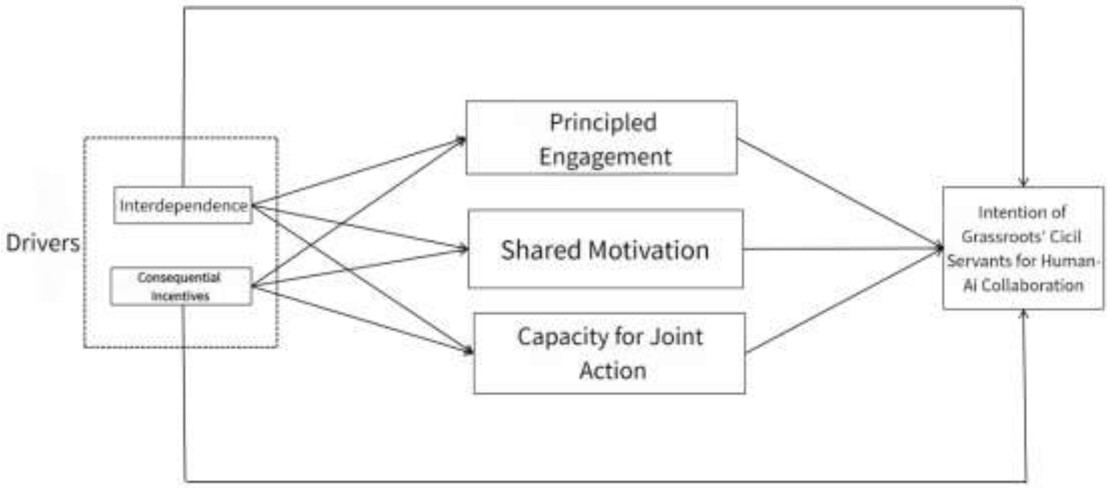
In the context of public administration, human-AI collaboration not only depends on individual attitudes and motivations but also on whether civil servants and AI possess the capability structure for effective collaborative task execution. Capacity for joint action, through procedural and institutional arrangements, leadership, and the coordinated supply of knowledge and resources, provides sustainable support for collaboration intention (Emerson et al., 2012; Emerson et al., 2018). That is, structural guaranties at the organizational level and procedural support at the process level can provide crucial support for the initiation and advancement of collaboration, by reducing collaboration costs, enhancing collaboration value, and thereby strengthening the collaboration intention (Sicilia et al., 2019). Procedures and institutional arrangements build the foundational rules for collaboration. By clarifying collaboration rules and establishing coordination mechanisms, they provide structural guaranties for collaboration that are "rule-based" (Sicilia et al., 2019). Their core functions include clarifying role boundaries and responsibilities (Radnor et al., 2014). Clear procedures and systems can help grassroots civil servants perceive the normativity and controllability of collaboration, thereby strengthening their collaboration intention. The role of leadership is reflected in resource integration and directional guidance, by empowering professionals, coordinating collaborative relationships, and clearing collaboration obstacles (Sicilia et al., 2019; Bianchi et al., 2021). Sustained leadership is the core of capacity for joint action. In human-AI collaboration, the leadership of grassroots department leaders can be reflected in: resource integration, coordinating technical departments to develop adaptive tools, reducing the technical threshold for collaboration; skill empowerment, organizing training to promote the sharing of professional and technical knowledge, helping grassroots civil servants enhance the skills needed for collaboration; risk coordination, proactively taking on a coordinating role during algorithm disputes or collaboration dilemmas, applying for error tolerance space from superiors, alleviating the collaborative pressure on grassroots civil servants. Continuous leadership support can effectively stimulate collaboration enthusiasm, which means that by enhancing capacity for joint action, thereby indirectly improving the intention of grassroots civil servants to collaborate with AI. Knowledge is the key to capacity for joint action. The need for knowledge arises from the requirement for all parties in collaboration to have shared knowledge (Sicilia et al., 2019; Emerson et al., 2012).

In the context of human-AI collaboration, the bidirectional flow of knowledge between civil servants and AI not only enhances the quality of collaboration but also strengthens grassroots civil servants' perception of the value of collaboration—when they realize that human-AI collaboration can compensate for their own capability shortcomings and improve work efficiency, their collaboration intention significantly increases. Resources are the guarantee of capacity for joint action and are considered the fundamental conditions for collaboration, including key resources such as funding, time, and technology (Emerson et al., 2012; Emerson & Gerlak, 2014). Effective resource provision can significantly reduce the participation costs of collaboration. In human-AI collaboration, sufficient resource support can help grassroots civil servants perceive the feasibility and benefits of collaboration, thereby maintaining their long-term intention to collaborate. When the four elements of collaborative action capacity work together—clear responsibilities in the system, leadership support, knowledge value addition, and resource supply—civil servants will perceive that "collaboration is feasible and beneficial," thereby maintaining their long-term collaboration intention. Based on this, this paper proposes the following hypothesis.

H4: Capacity for joint action mediates the relationship between drivers and the intention of grassroots civil servants to collaborate with AI.

H4a: Capacity for joint action mediates the relationship between the interdependence of drivers and the intention of grassroots civil servants to collaborate with AI. That is, interdependence indirectly enhances the intention of grassroots civil servants to collaborate with AI by improving capacity for joint action. H4b: Capacity for joint action mediates the relationship between the consequential incentives of drivers and the intention of grassroots civil servants to collaborate with AI. That is, consequential incentives indirectly strengthen the intention of grassroots civil servants to collaborate with AI by enhancing capacity for joint action.

Based on the above analysis, the framework diagram of the variable relationships is as follows.



Source: Author's own creation

Figure 1 Theoretical Framework

2. Research Design

2.1. Data Sources and Questionnaire Design

This study conducted a survey through the Wenjuanxing platform, using Likert Scale Templates for data collection. The primary focus was on Shenzhen, a city with significant AI usage. A total of 387 questionnaires were distributed, and after excluding some that were incomplete or improperly filled out, 309 valid questionnaires were collected, resulting in a valid response rate of 79.84%. Due to objective constraints, the survey did not obtain sample data covering the entire country, but factors such as gender, years of work experience, job level, and frequency of using AI systems for official duties were considered when distributing the questionnaire (see the table below). Overall, the sample is reasonably representative of cities in eastern China.

Table 1 Descriptive Statistics

Categorical Variable	Measurement	Frequency	Proportion (%)
Gender	Male	173	56
	Female	136	44
Age Group	25 years old and below	20	6.5
	26—35 years old	140	45.3
	36—45 years old	90	29.1
	46—55 years old	31	10.0
	56 years old and above	28	9.1
Highest Degree	High school/technical secondary school and below	3	1.0
	Associate degree	26	8.4
	Bachelor's degree	185	59.9
	Master's degree and above	95	30.7
Job Level	Level 2 officer/administrative law enforcement officer	96	31.1
	Level 1 officer/professional technician/level 1 administrative law enforcement officer	157	50.8
	Level 3 to 4 chief officer/supervisor/primary officer	35	11.3
	Level 1 to 2 chief officer/supervisor/primary officer	14	4.5
	Other	7	2.3
Years of Work Experience	Less than 1 year	7	2.3
	1—5 years	77	24.9
	6—10 years	80	25.9
	11—20 years	47	15.2
	Over 20 years	98	31.7
Continuous Variable	Value Range	Sample Size	Mean (standard deviation)
Frequency of using AI systems to handle official duties	1—5	309	4.17 (0.685)
Interdependence	1—5	309	3.61(1.040)
Consequential incentives	1—5	309	3.67 (0.943)
Principled engagement	1—5	309	3.65 (0.916)
Shared motivation	1—5	309	3.65 (0.976)
Capacity for joint action	1—5	309	3.68 (0.940)

Intention of grassroots civil servants to collaborate with AI	1—5	309	3.53（0.919）

Source: Author's own creation

2.2. Variable Operationalization

Based on the Integrative Framework for Collaborative Governance (IFCG) and existing empirical research in the field of human-AI collaboration in the public sector, combined with the work scenarios of grassroots civil servants (such as social security, administrative approval, petition handling, etc.), the dependent variables, independent variables, mediating variables, and control variables are operationally defined, ensuring that all scales use a five-point Likert scale (1=strongly disagree, 5=strongly agree, with some categorical variables being exceptions).

The dependent variable is the intention of grassroots civil servants to collaborate with AI, referring to the degree of acceptance, inclination to actively participate, and intention to expand scenarios in the process of decision-making or executing administrative tasks (such as low-income qualification review and social security data verification) when working with AI systems. This differs from mere "technology acceptance" by emphasizing the collaborative nature of human-AI interaction and the joint achievement of administrative goals (Schmidtler et al., 2015). Based on the multidimensional scales of You S & Robert L.P. (2018) and Chiocchio et al. (2012), and adapted to the context of grassroots government practice, the items cover dimensions such as "active participation," "scenario expansion," and "continuous optimization." The "active participation" dimension focuses on human-AI information and resource sharing, such as "I am willing to share government information (such as records of services for special groups, local policy details) with AI to complete tasks together." The "Scenario Expansion" dimension focuses on the extension of collaboration scope, such as "I support promoting human-AI collaboration models in more government scenarios like cross-departmental data verification and policy implementation effect analysis." The "Continuous Optimization" dimension reflects the proactivity in skill enhancement, such as "I will proactively learn AI functionality operations, human-AI collaboration strategies, and other related skills to improve the quality of collaborative work." The higher the total score on the scale, the stronger the intention of grassroots civil servants to collaborate with AI.

The independent variable as a driving factor, based on the IFCG framework, refers to the core motivation that initiates and drives human-AI collaboration among grassroots civil servants, encompassing two dimensions: interdependence and consequential incentives. Among them, interdependence refers to the collaborative needs of grassroots civil servants in administrative practice due to the inability to achieve goals independently. This reflects the goal complementarity and capability dependence between humans and AI. Based on the specific task scenarios of grassroots civil servants and the Pearce & Gregersen (1991) scale, items are designed from the dimensions of task dependence and capability dependence: the task dependence dimension addresses massive or complex tasks; the capability dependence dimension focuses on the complementary boundaries of human and AI capabilities, such as "AI excels at standardized tasks like initial material screening but cannot handle non-standardized tasks like communicating with special interest groups, requiring collaboration between me and AI to complete the entire work." Consequential incentives refer to the positive benefits or negative consequences related to human-AI collaboration perceived by grassroots civil servants, based on Majrashi's (2024) research, focusing on core dimensions such as "efficiency dividends" and "responsibility pressure": the efficiency dividends dimension reflects the improvement in collaboration efficiency, such as "After using AI to assist in administrative work, my work efficiency has significantly improved." Responsibility pressure encompasses external public expectations and internal organizational digital transformation pressure, such as "the pressure of having digital transformation goals within the organization (e.g., the assessment of 'One Network for All Services')" and "the strong public expectation for the digitalization of government services (e.g., using AI to initially classify types of requests in 'One Network for All Services' to achieve quick distribution and response to requests)."

The mediating variables include principled engagement, shared motivation, and capacity for joint action, all designed based on the IFCG framework, serving as mediators between drivers and the intention for human-AI collaboration. Principled engagement refers to the dynamic process through which grassroots civil servants and AI collaboratively establish cooperation rules through the four stages of "discovery—definition—review—determination." The core of this process is human-AI collaboration to address governance pain points and standardize procedures. Based on the scales by Kiesewetter & Fischer (2015) and the research by Biddle et al., (2017), and in conjunction with practical governance scenarios, specific items were designed: For the "discovery" stage, items such as "I will work with the AI system to identify governance pain points and work priorities (e.g., through AI data analysis + human experience supplementation, jointly identifying gaps in public needs)" were included; for the "definition" stage, items such as "In human-AI collaborative work, the division of labor between me and the AI is clear and defined: AI is responsible for the initial screening of materials and other standardized tasks, and outputs preliminary results. I am responsible for discretionary decisions in special cases, communication of complex requests, and other non-standardized tasks, and I will review AI's preliminary results to determine the final outcome. Shared motivation refers to the self-reinforcing psychological cycle formed by grassroots civil servants and AI during collaboration, which includes mutual trust, mutual understanding, internal legitimacy, and shared commitment, providing emotional support for collaboration. Based on the research of Jian et al. (2000) and Biddle et al.et al.(2017), specific items were designed, such as "I trust AI's performance in government affairs" and "I understand the capability boundaries of AI systems and the needs for their optimization." Capacity for joint action refers to the resources and mechanisms that support the implementation of human-AI collaboration, including procedural and institutional arrangements, leadership, knowledge, and resources. Based on the research by Biddle et al. (2017) and Emerson & Gerlak (2014), specific items are designed, such as "I can input implicit knowledge of grassroots governance into AI and also understand the analysis results output by AI."

Control variables are used to account for the potential influence of individual characteristics on research results. Based on empirical research in the field of technology acceptance in the public sector, variables such as gender, age, education level, years of service, job rank, and AI usage frequency are selected: gender is represented as a binary categorical variable (male/female); age is recorded as a categorical variable, capturing the age range of grassroots civil servants; education level is categorized into four levels: high school/vocational school and below; Years of service is a categorical variable, measuring the number of years grassroots civil servants have been engaged in government work; AI usage frequency is also a categorical variable, categorized based on the frequency of daily AI system usage into "multiple times a day/daily once/2-3 times a week/once a week/a few times a month or less." All control variables were directly collected through a questionnaire survey to ensure the accuracy and reliability of the research results.

2.3. Model Setup

Based on the characteristics of the research variables, this study employs multiple econometric strategies.
1. Benchmark Model: Multiple Linear Regression Model (OLS)

The dependent variable in this study—the intention of grassroots civil servants to collaborate with AI—is a continuous variable, making it suitable for baseline estimation using a multiple linear regression model (Ordinary Least Squares, OLS) to examine the direction and significance of the impact of core independent variables on the collaboration intention with AI.

2. Mediation effect test: Stepwise regression + Bootstrap

To examine the pathways of "interdependence—collaboration dynamics—cooperative intention" and "consequential incentives—collaboration dynamics—cooperative intention," this study employs the stepwise regression method proposed by Baron & Kenny (1986). This method is intuitive and easy to interpret, but it relies on the assumption of normal distribution under large samples and uses the Sobel test to determine the significance of the indirect effect ab. This may lead to insufficient statistical power in small samples or non-normally distributed data. However, Preacher and Hayes (2007) pointed out that when the data exhibit skewed distribution, traditional methods based on the normality assumption may produce biased estimates. Compared to the traditional Sobel test, the Bootstrap method does not require the normality assumption for the coefficient distribution, making it more effective in handling the skewed distribution characteristics of psychological and cognitive variables (Preacher & Hayes, 2008). Therefore, this study will combine the Bootstrap confidence interval method recommended by Hayes and Scharkow (2013) to test the mediation effect. The mediating variables include: principled engagement, shared motivation, and capacity for joint action. This study uses 5,000 bootstrap samples to obtain the 95% confidence interval of the indirect effect; if the interval does not include 0, it is considered a significant mediating effect. Through the Bootstrap estimation of the indirect effect (ab), we can test whether the mediating effect of the collaborative dynamics variable between core drivers and collaborative intention holds.

3. Research Results

3.1. Main Effect Test: Hypothesis Testing of Drivers on Grassroots Civil Servants' Intention for Human-AI Collaboration

To examine the direct impact of drivers on the intention of grassroots civil servants to collaborate with AI, a multiple linear regression analysis was conducted, using "interdependence" and "consequential incentives" as independent variables and "the intention of grassroots civil servants to collaborate with AI" as the dependent variable. Table 2 presents the results of three baseline regression models for the intention of grassroots civil servants to collaborate with AI. From the overall fit perspective, Model 1, which only includes control variables, has an insignificant F-value ($F=0.607$, $p=0.724$). This indicates that solely relying on demographic characteristics, job attributes, and usage experience cannot effectively explain the differences in human-AI collaboration intention, and the model as a whole lacks explanatory power. After adding consequential incentives to Model (2), the overall model significantly improved ($F=50.747$, $p<0.001$), with R^2 increasing to 0.154. This indicates that consequential incentives significantly enhanced the model's explanatory power, underscoring its role as a key driver of collaboration intention. Further adding interdependence to Model (3), the model remains significant ($F=20.738$, $p<0.001$), with R^2 increasing to 0.209, indicating that interdependence also contributes incrementally to explaining the intention to collaborate with AI.

Regarding the core independent variables, both "consequential incentives" and "interdependence" show a significant positive impact. Model (2) indicates that the regression coefficient for consequential incentives is 0.372 ($p<0.01$), and in Model (3), consequential incentives are significant ($\beta=0.302$, $p<0.01$), indicating that the incentive mechanism can significantly enhance the intention of grassroots civil servants to collaborate with AI. Model (3) shows that the coefficient of interdependence is 0.218 ($p<0.01$), indicating that the stronger the interdependence in the task structure, the more likely grassroots civil servants are to collaborate with intelligent systems. This result suggests that in grassroots governance practices, "task necessity" (interdependence) and "incentive orientation" (consequential incentives) together constitute an important mechanism for promoting human-AI collaboration among civil servants. Thus, it is assumed that both H1a and H1b receive empirical support.

In terms of control variables, gender, age, job level, years of service, and AI usage frequency did not reach significant levels in any of the models, indicating that demographic characteristics and usage experience are not the main influencing factors for human-AI collaboration intention. Education level showed a weakly significant positive impact in model (2) ($p<0.1$), but it was no longer significant in model (3), further reinforcing that collaboration intention is mainly influenced by interdependence and consequential incentives.

Overall, the benchmark model validates the logical pathway of "drivers—collaboration intention" in the Integrative Framework for Collaborative Governance (IFCG): interdependence provides the structural constraint of "having to collaborate," while consequential incentives offer the psychological and institutional motivations for "willing to collaborate." Together, these factors drive the generation and enhancement of human-AI collaboration intention. "Interdependence" reflects the role of structural constraints in collaborative governance tasks. When grassroots civil servants realize that it is difficult to achieve governance goals solely through individual efforts or manual processes in complex matters, their reliance on AI increases, prompting them to form a proactive collaboration intention in practice (Emerson et al., 2012). This "functional complementarity" is precisely the core driver in the initiation phase of collaborative governance. "Interdependence" also reveals the interactive logic of task structures in organizational design. The interdependence of tasks, goals, and knowledge is the micro-foundation of organizational collaboration. It shapes the interactions between individuals and between humans and AI, requiring members to share resources, coordinate decisions, and jointly bear performance outcomes when completing tasks. When task interdependence increases, collaboration becomes a necessary choice (Raveendran et al., 2020). In grassroots administrative scenarios, this "task dependency" is not only reflected in the division of labor among civil servants but also in the coupling between civil servants and AI systems. After AI is deeply embedded in administrative scenarios, the division of labor between civil servants and intelligent systems becomes clearer—AI excels at structured data analysis and high-frequency task processing, while civil servants are adept at situational recognition and interpersonal communication. When the capability boundaries of the two complement each other, the positive attitude of grassroots civil servants toward human-AI collaboration significantly improves (Goodhue & Thompson, 1995; Hemmer et al., 2025). The practical experience of grassroots governance in reality fully confirms this point: in the qualification review for subsidy distribution, AI can quickly capture structured data to identify eligible recipients, but it must further rely on civil servants to supplement with unstructured information such as special policies to form a complete review conclusion. This reflects the specific manifestation of interdependence in terms of workload and task complexity. "Consequential incentives" reflect the guiding role of the incentive mechanism. Financial or non-financial incentives (such as performance rewards, honor systems, and resource support) can strengthen civil servants' positive attitudes toward new collaboration methods (including collaboration with artificial intelligence). There is a significant relationship between the incentives received by public sector employees and their investment (Van Triest S, 2024). In the context of this study, when organizations provide clear incentives (such as performance evaluations, resource allocation, and promotions) to civil servants collaborating with AI systems, civil servants are more likely to view "human-AI collaboration" as a worthwhile endeavor, thereby significantly enhancing their collaboration intention. Moreover, in the context of digital transformation, performance evaluation goals (such as "One-stop online government services" and "response rate to requests") are closely linked to the use of AI, making AI collaboration an inevitable path to achieving organizational performance. Consequently, external performance pressure and internal institutional incentives together form a motivation for collaboration. This result reveals that the human-AI collaboration of grassroots civil servants is not solely determined by technical factors or individual preferences, but is deeply embedded within the structure of governance tasks, organizational incentive systems, and the digital governance environment.

Table 2 Results of the Multiple Linear Regression Benchmark Model

Variables	(1) collaboration intention	(2) collaboration intention	(3) collaboration intention
Gender	0.029(0.106)	-0.004(0.099)	-0.007(0.096)
Age	0.057(0.051)	0.044(0.048)	0.036(0.046)
Highest Education Level	0.086(0.086)	0.144(0.080)*	0.116(0.078)
Current Job Level	0.026(0.059)	0.029(0.055)	0.056(0.053)
Years of Work	-0.010(0.043)	-0.017(0.040)	-0.018(0.038)
AI Usage Frequency	-0.085(0.077)	-0.042(0.072)	-0.034(0.070)
Consequential Incentives	—	0.372(0.052)***	0.302(0.053)***
Interdependence	—	—	0.218(0.048)***
Constant Term	3.402(0.517)***	1.771(0.531)***	1.272(0.526)*
N	309	309	309
R^2	0.012	0.154***	0.209***
Adjusted R^2	-0.008	0.135***	0.188***

Note: The values in parentheses are standard errors; *p<0.1, **p<0.05, ***p<0.01.

3.2. Mediation Effect Analysis: The Mediating Role of Principled Engagement, Shared Motivation, and Capacity for Joint Action

This section tests hypotheses H2a–H4b, aiming to explore how different drivers (interdependence and consequential incentives) influence the intention of grassroots civil servants to collaborate with AI through principled engagement, shared motivation, and capacity for joint action. A Bootstrap test was conducted with 5000 samples, and the confidence interval was set at 95%. The results are shown in Table 3.

Table 3 Test Results of the Mediating Effect of Drivers on Human-AI Collaboration Intention

Path	Coefficient c′ (direct effect)	Coefficient a	Coefficient b	Coefficient c (total effect)	a×b (indirect effect)	a×b (indirect effect) Boot 95% CI	Type of Effect
interdependence - principled engagement - collaboration intention	0.175**	0.225***	0.264***	0.296***	0.060	[0.023,0.107]	Partial Mediation
interdependence - shared motivation - collaboration intention	0.175**	0.232***	0.126*	0.296***	0.029	[0.005,0.064]	Partial Mediation
interdependence - capacity for joint action - collaboration intention	0.175**	0.214***	0.152**	0.296***	0.033	[0.007,0.068]	Partial Mediation
consequential incentives - principled engagement - collaboration intention	0.156**	0.417***	0.252***	0.366***	0.105	[0.049,0.175]	Partial Mediation
consequential incentives - shared motivation - collaboration intention	0.156**	0.411***	0.118*	0.366***	0.049	[0.005,0.101]	Partial Mediation
consequential incentives - capacity for joint action - collaboration intention	0.156**	0.394***	0.144**	0.366***	0.057	[0.011,0.113]	Partial Mediation

Note: *** $p<0.001$, ** $p<0.01$, * $p<0.05$.

Source: Author's own creation

First, the "interdependence—principled engagement, shared motivation, and capacity for joint action—collaboration intention" model was tested. The results confirmed that all three mediation paths were significant, indicating that interdependence significantly enhances the intention of grassroots civil servants to collaborate with AI through the mechanisms of principled engagement, shared motivation, and capacity for joint action. The indirect effect of the "interdependence - principled engagement - collaboration intention" pathway is significant (a×b=0.060, 95% CI=[0.023,0.107], does not include 0), indicating that higher task dependence can promote fair and inclusive procedural interactions between civil servants and AI systems in decision-making processes, thereby enhancing the intention for human-AI cooperation. This confirms H2a: principled engagement plays a significant mediating role between interdependence and collaboration intention. At the same time, the path effects of "interdependence - shared motivation - collaboration intention" (a×b=0.029, 95% CI=[0.005,0.064], does not include 0) and "interdependence - capacity for joint action - collaboration intention" (a×b=0.033, 95% CI=[0.007,0.068], does not include 0) are also significant. This suggests that workplace interdependence also enhances emotional and motivational mechanisms such as mutual trust, mutual understanding, and action coordination, further promoting civil servants' collaboration intention, thereby supporting H3a and H4a.

Secondly, the "consequential incentives—principled engagement, shared motivation, capacity for joint action—collaboration intention" model was tested. The results indicate that consequential incentives have a significant positive impact on principled engagement, shared motivation, and capacity for joint action, and indirectly influence collaboration intention through them. The mediating effect of "principled engagement" is significant (a×b=0.105, 95% CI=[0.049,0.175], does not include 0), indicating that results-oriented incentives can significantly enhance civil servants' adherence to and awareness of normative participation in human-AI collaboration processes, thereby increasing their proactive engagement in collaboration, which verifies H2b. The paths of "shared motivation" (a×b=0.049, 95% CI=[0.005,0.101], does not include 0) and "capacity for joint action" (a×b=0.057, 95% CI=[0.011,0.113], does not include 0) are also significant, supporting H3b and H4b. This indicates that internal and external incentives not only directly drive the intention to collaborate but also indirectly promote it by stimulating civil servants' sense of sharing and coordination abilities. Thus, it is evident that H2b~H4b have been fully validated, as consequential incentives significantly enhance the collaboration intention between humans and AI by strengthening the institutional participation, shared motivation, and action coordination abilities of the collaborative entities.

The mediation effect models of the two independent variables both exhibit the same operational logic. Whether it is the driving factor of "interdependence" or the driving factor of "consequential incentives," interdependence reflects the constraints of task structure, and consequential incentives reflect performance-oriented motivation. Both significantly enhance the psychological intention of grassroots civil servants to collaborate with AI systems through three mediation paths: principled engagement, shared motivation, and capacity for joint action. First, principled engagement reflects the process of constructing procedural justice and institutional trust within public organizations. When grassroots civil servants form interdependent relationships with AI systems during task execution, the degree of proceduralization, transparency, and standardization in the decision-making process significantly increases, thereby enhancing their collaboration intention (Emerson et al., 2012). After the introduction of artificial intelligence in the public sector, procedural participation helps reduce the resistance caused by technological uncertainty, thereby enhancing civil servants' institutional trust and collaborative attitudes (Aoki et al., 2024). Secondly, shared motivation, as the emotional bond of collaborative governance, emphasizes trust, mutual understanding, and joint commitment among the participants. Consequential incentives, by establishing a fair and reasonable performance system and outcome-oriented mechanism, enable civil servants to psychologically form a positive identification of "working with AI," thereby transforming external drives into internal motivation. This is consistent with research on the relationship between human-AI trust and organizational motivation, which indicates that incentive systems can significantly enhance collaborative trust and increase the intention for human-AI joint decision-making (Romeo & Conti, 2026; Tangi, 2025). Again, the capacity for joint action includes elements such as organizational support, resource coordination, leadership, and knowledge sharing. Empirical results indicate that consequential incentives can not only stimulate civil servants' enthusiasm for collaboration but also enhance their ability to effectively coordinate and communicate with AI systems through institutional design and training investments. Enhancing the organizational level of action coordination is the key pathway to ensuring the long-term and normalized human-AI collaboration. Real-world grassroots administrative practices fully corroborate this point. In departments such as the public service section of government service centers, where grassroots civil servants frequently collaborate with AI, the high dependency on AI due to the nature of the work tasks often leads units and leaders to provide targeted support, such as technical adaptation and optimization, as well as guidance on collaborative processes. This also reflects the path logic of "interdependence → capacity for joint action → collaboration intention."

Overall, this study verifies the transmission mechanism of "drivers—collaboration dynamics—collaboration intention," demonstrating that structural dependence and institutional incentives jointly promote the generation and sustainability of grassroots civil servants' intention for human-AI collaboration by stimulating principled engagement, cultivating shared motivation, and enhancing action capabilities. This finding not only expands the application boundaries of the collaborative governance framework but also reveals the interactive logic between organizational behavior and technology adoption: technological collaboration does not solely stem from the performance of AI systems themselves but also depends on whether institutional design can stimulate human participation, trust, and capability.

4. Conclusion

Drawing on collaborative governance theory, this study focuses on the intention mechanisms of grassroots civil servants to collaborate with artificial intelligence. It aims to reveal how drivers (interdependence and consequential incentives) influence the intention of grassroots civil servants to collaborate with AI through three dynamic elements of collaboration (principled engagement, shared motivation, and capacity for joint action). Using questionnaire surveys and statistical analyses (including reliability and validity tests, correlation analysis, main effect regression analysis, and mediation effect tests), this study systematically tested the proposed model and hypotheses, leading to the following conclusions.

First, drivers have a significant positive impact on collaboration intention, supporting H1a and H1b. The results indicate that interdependence (total effect $c=0.296$, $p<0.001$) and consequential incentives (total effect c=0.366, p<0.001) both significantly predict the collaboration intention of grassroots civil servants. It indicates that in the context of grassroots governance, there are both "forced/structural collaboration demands" arising from task interdependence and performance/result-oriented incentive mechanisms, which together promote the transition of civil servants toward collaboration with intelligent systems. Among these, the coefficient (or influence) of consequential incentives is slightly larger than that of interdependence, indicating that internal and external incentives are key prerequisites for encouraging civil servants to actively participate in human-AI collaboration.

Second, principled engagement, shared motivation, and capacity for joint action play a mediating role between drivers and collaboration intention, with H2–H4 all receiving support. Mediation analysis using PROCESS Model 4 revealed that principled engagement and shared motivation both play significant mediating roles in the influence paths of interdependence and consequential incentives on collaboration intention. This indicates that when civil servants participate in human-AI decision-making collaboration through a regulated process and form trust, commitment, and recognition during interactions, their collaboration intention significantly increases. The mediation effects observed were partial, rather than full, mediation. The two types of drivers still maintain significant direct effects on collaboration intention after controlling for mediating variables (interdependence c′=0.1751, p=0.0002; consequential incentives c′=0.1561, p=0.0066), indicating that the drivers can both indirectly influence intention through the three dynamic elements of collaboration and directly affect collaboration intention. Among them, principled engagement shows significant and strong mediating effects in the paths of both types of drivers → collaboration intention (indirect effect of the interdependence path a×b=0.0595, 95% CI[0.0232,0.1065]; indirect effect of the consequential incentive path a×b=0.1051, 95% CI[0.0475,0.1723]). This indicates that when collaboration is institutionalized as a participatory and deliberative process, civil servants' institutional identification and sense of control are enhanced, making them more likely to accept the human-AI collaboration model (Lee & See, 2004; Aoki et al., 2024). Shared motivation and capacity for joint action both exhibit significant mediating effects (with indirect effects ranging from approximately 0.029 to 0.057, and 95% CI not including 0), indicating that emotional/relational capital (trust, commitment, organizational legitimacy) and institutional-resource capability support help transform external drives into stable collaborative intentions (Alon-Barkat & Busuioc, 2023; Selten et al., 2023).

This study provides important practical insights for improving the human-AI collaboration governance mechanism in the context of digital government. Firstly, at the institutional level, the rules of human-AI collaboration should be solidified through institutionalized participation procedures. Clear collaboration rules and responsibility boundaries help alleviate the uncertainty of responsibility brought by algorithmic decisions, enhancing civil servants' sense of control and institutional recognition in the collaboration process. In high-frequency grassroots administrative scenarios, it is necessary to define the boundaries of human-AI division of labor in a hierarchical and categorized manner. Through the process design of "algorithm assistance—human discretion—manual review," the paths for human correction and the rules for responsibility allocation should be clarified, thereby reducing grassroots civil servants' perception of the risks associated with algorithm collaboration. At the same time, a dynamic review mechanism involving multiple parties should be established to incorporate the practical experience and knowledge of civil servants into the continuous iteration process of algorithm governance, promoting the formation of a co-construction model for human-AI collaboration. Secondly, at the incentive level, a parallel institutional design of "incentives—tolerance" should be implemented to activate the intrinsic motivation for human-AI collaboration among grassroots civil servants. If the application of algorithms is only seen as a performance evaluation tool without corresponding incentives and exemption arrangements, it can easily lead to negative responses and even covert resistance at the grassroots level toward algorithmic decisions. Therefore, it is necessary to incorporate the effectiveness of human-AI collaboration into the performance evaluation system and simultaneously establish a fault-tolerance mechanism for non-subjective algorithmic errors to institutionalize the mitigation of psychological pressure of "algorithm errors—personal accountability." On a technical level, the adaptability of government AI systems to grassroots governance scenarios should be strengthened by enhancing system interpretability and user-friendliness to lower collaboration thresholds. "Black box" algorithms lacking interpretability can undermine user trust and reduce their collaboration intention, while contextualized and traceable algorithm explanations can help improve the stability of human-AI collaboration. Finally, at the capability level, a bidirectional empowerment system for human-AI collaboration should be established. This can be achieved through training and knowledge-sharing mechanisms to complement the professional judgment of civil servants with algorithmic tools. On the one hand, it enhances civil servants' ability to understand and use algorithmic systems; on the other hand, it transforms grassroots governance experience into important inputs for algorithmic rules and model optimization, thereby laying a foundational capability for the sustainable operation of human-AI collaboration.

Although this study reveals to some extent the mechanisms behind the formation of grassroots civil servants' collaboration intention with AI, there are still several limitations that need to be further explored. Firstly, in terms of research methods, this study primarily relies on questionnaire survey data, making it difficult to completely avoid the influence of self-report bias. In the context of organizational digital transformation, respondents may overestimate their acceptance and trust in algorithmic systems due to organizational norms or policy directions, thereby amplifying the correlation between variables. At the same time, this study did not incorporate objective usage data at the organizational level and feedback from service recipients for cross-validation, leaving the match between subjective perception and actual collaborative practice unverified. Secondly, regarding the sample structure and generalizability, although the research sample covers different demographic characteristics, there are still limitations in terms of regional distribution, job types, and administrative levels. The differences in task risk, discretionary space, and degree of technological dependence across different business areas and administrative levels may significantly affect civil servants' risk perception and behavioral orientation toward algorithmic collaboration. However, this study did not systematically compare these heterogeneities, which limits the contextual applicability of the conclusions. In the theoretical model setting, this study primarily relies on a static regression framework to examine the transmission paths between variables, failing to fully reveal the dynamic evolution process of human-AI collaboration intention within organizational contexts. Individual collaboration attitudes and behaviors can, in turn, shape organizational institutional arrangements and technological design directions, but this feedback mechanism has not been tested in this paper. Moreover, the model does not systematically incorporate key moderating factors such as technological complexity, algorithmic interpretability, organizational digital culture, and individual technological literacy. It also does not test the cross-level interaction between the macro institutional environment and micro cognition through multi-level models or structural equation models, thereby somewhat weakening its explanatory power regarding the differences in complex contexts. Future research should address these limitations by conducting comparative studies across regions, positions, and administrative levels using multi-source and longitudinal data, and further deepen the understanding of the causal mechanisms behind human-AI collaboration intention and its behavioral outcomes by incorporating experimental methods.

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Conflict of interest

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

Author contributions

Xinqi Wen: Conceptualization, Methodology, Data Curation, Formal Analysis, Writing - Original Draft and Supervision. **Junxiang Xiao:**Data Curation,Methodology and Writing - Review & Editing. **Heling Wang:**Investigation and Formal Analysis.

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