Exploring generative AI effects on Korean civil servants' performance: Power and motivation

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Abstract. This study explores the factors influencing civil servants' perceptions of generative AI-assisted work performance, focusing on extrinsic and intrinsic motivations and the moderating role of organizational power, as measured by government level and organizational rank. Artificial Intelligence (AI) has emerged as one of the most influential technologies, driving transformation in both government and society. Generative AI, as a subfield of AI, has gained recognition for its capabilities to automate routine tasks, enhance decision-making, and improve work productivity. However, little is known about who perceives the positive effects of these tools on performance and why. Drawing on the notion that motivations affect work performance and the reinforcement politics model, this study analyzes survey data from 1,608 Korean civil servants collected by the Korean Institute of Public Administration (KIPA) in April 2023, when generative AI was still in its early stages of development. The survey targeted civil servants from central, provincial, and local governments to gauge their perspectives on generative AI-assisted work performance. This study employed partial least squares structural equation modeling (PLS-SEM), an appropriate method for predictive modeling and identifying key driving factors in complex relationships to investigate the connection between two types of motivation and perceived work performance. The findings reveal that extrinsic and intrinsic motivations positively influence perceived work performance, with intrinsic motivation having a more substantial effect. Also, extrinsic motivation significantly enhances intrinsic motivation, highlighting the dynamic interaction between the two constructs. However, the moderating effects of government level and organizational rank on the relationship between motivations and perceived work performance were not statistically significant. These results underscore the critical role of individual motivation in shaping perceptions of generative AI tools while suggesting that organizational power may play a less significant role in this context than previously anticipated. Theoretically, this study provides empirical evidence supporting the idea that motivations affect work performance by demonstrating the effectiveness of generative AI tools in public administration while challenging the reinforcement politics model. It challenges the foundational assumption of the model that organizational power makes a significant impact on the adoption and effectiveness of generative AI tools.

Keywords. Generative Artificial Intelligence, ChatGPT, Reinforcement Theory, Extrinsic Motivation, Intrinsic Motivation, Civil Servant
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1. Introduction

Artificial Intelligence (AI) refers to "a cluster of technologies that enables machines to learn and autonomously solve cognitive problems without human intervention" (Madan & Ashok, 2022). AI has emerged as one of the most significant technologies, facilitating digital transformation in government and society. We expect it to significantly transform the work environment, driving efficiency and innovation across various sectors (Boyd & Wilson, 2017). Generative AI, a subfield of AI, is "a computational technique capable of producing new and meaningful content, such as text, images, audio, video, and even computer code, from training data" (Feuerriegel et al., 2023). This technology serves as a transformative force that can potentially drive significant change. It replicates complex data distributions to generate outputs that closely resemble or surpass the quality of real-world data (Banh & Strobel, 2023; Lehmann & Buschek, 2020; Tomczak, 2024). Generative AI tools have been widely and rapidly diffused. Since its release in November 2022, ChatGPT has reached over 200 million weekly active users by August 2024, doubling its user base from the previous year. Its subscription-based service, ChatGPT Plus, serves approximately 10 million users (Backlinko, 2024).

Advocates claim that generative AI tools facilitate task performance by efficiently handling routine or resource-intensive activities (e.g., drafting and reviewing documents, analyzing data to identify patterns, and automating repetitive tasks like filing, scheduling, or data entry) (Brynjolfsson et al., 2023). These advantages allow individuals to focus on more highly valued activities—a benefit particularly significant for civil servants, who spend up to 30% of their time on paperwork and administrative duties (Gmyrek et al., 2023; Viechnicki & Eggers, 2017). Conversely, critics raise concerns about ethical and legal challenges, including the risk of producing inaccurate, biased, or irrelevant outputs, which could hinder their reliability and task performance (Bloch-Wehba, 2021; Bender et al., 2021). Despite these controversies and its early stages of development, some public administration scholars and government professionals have paid significant attention to its impact on the government (Wirtz et al., 2018; Salah et al., 2023). However, little is known about who perceives the positive effects of these tools on work performance and why, particularly in the context of the public sector.

Empirical studies on generative AI tools in public administration have been limited in recent years. Most research (Noonpakdee, 2024) primarily focuses on adoption as the technology remains in its early stages of development (Al Naqbi et al., 2024; Bright et al., 2024). These studies provide valuable insights into the government's adoption of technology. However, there is a limited understanding of how individuals, particularly government employees, perceive the benefits of their work performance and the factors that influence these perceptions. To address this gap, this study examines how civil servants' organizational power and extrinsic and intrinsic motivations influence their perceptions of generative AI-assisted work performance. It is important to note that adopting generative AI tools—without exploring their effectiveness—may not ensure meaningful implementation in the public sector. We draw on extrinsic and intrinsic motivations and the reinforcement politics model, as these frameworks provide complementary perspectives on how individual and organizational factors shape perceptions of work performance. By employing the partial least squares structural equation modeling (PLS-SEM), we analyze survey data from civil servants collected by the Korea Institute of Public Administration (KIPA) in April 2023, when generative AI tools were still in their early development stages. This survey targeted civil servants from the central, provincial, and local governments to evaluate their perspectives on generative AI-assisted work performance. By analyzing these relationships, this study provides theoretical insights into the adoption of generative AI and its impact on public administration and practical implications for effective implementation. These findings will assist policymakers and government officials in understanding the conditions under which generative AI tools enhance work performance.

The paper is organized as follows: Section 2 presents a literature review that examines generative AI tools and their impact on public administration. Section 3 outlines the theoretical framework, drawing on the two types of motivations and the reinforcement politics model to establish the foundation for the study's conceptual model and hypotheses. Section 4 represents the theoretical model and nine hypotheses. Section 5 describes the data collected by KIPA and details the dependent, independent, moderator, and control variables. Section 6 draws the results of the PLS-SEM, underscoring the significant effects of two types of motivations on perceived work performance and the non-significant moderating role of organizational power. Section 7 interprets the findings based on the results and discusses their theoretical and practical implications. Section 8 summarizes the core findings and recommends effectively implementing generative AI tools into public administration.

2. LITERATURE REVIEW

2.1 Generative AI Tools

AI encompasses a range of technologies that enable machines to learn and autonomously solve cognitive problems without human intervention (Madan & Ashok, 2022). It drives innovation across various sectors by using machine and deep learning to analyze data, identify patterns, and enhance decision-making independently (Brynjolfsson & Mitchell, 2017; Brynjolfsson et al., 2023). The McKinsey Global Institute predicts that AI will significantly improve productivity, leading to transformative shifts in workplace efficiency (Gaurav et al., 2018). Generative AI, a subfield of AI, refers to computational methods that can create new and meaningful content—like text, images, or audio—by learning patterns from existing training data (Feuerriegel et al., 2023). This technology acts as a transformative force that can drive significant change. The technology replicates complex data distributions to produce outputs that closely resemble or surpass real-world data quality (Lehmann & Buschek, 2020; Tomczak, 2024). By modeling high-dimensional probability distributions, it creates seemingly new samples that reflect the underlying structure of the original data (Ruthotto & Haber, 2021; Tomczak, 2024; Weisz et al., 2023). Unlike traditional AI systems that map input features to output labels, generative AI focuses on understanding data structures to generate new and meaningful content (Jebara, 2004).

Generative AI stands out because of its unique characteristics, setting it apart from many historical technological advancements, like the internet, which have primarily been driven by government-led initiatives (Goldman Sachs Global Institute, 2023). Conversely, its development and growth are dominated by a few tech companies, including OpenAI, Alphabet (Google), and Microsoft, which control digital platforms (Birch & Bronson, 2022). Traditional AI has become ubiquitous in powering advertising algorithms, content recommendations, and social media targeting, typically functioning behind the scenes on platforms like Apple's Siri, yet generative AI has brought its capabilities to the forefront, making its influence more visible and directly impactful. In their intermediary roles, Generative AI tools also resemble social media platforms, such as Facebook and X, connecting users with service providers within a platform economy driven by network effects (Wörsdörfer, 2022). As users and service providers increase, these platforms become increasingly attractive, fostering monopolistic dynamics and consolidating technological power structures (Jullien & Sand-Zantman, 2021; Sharon & Gellert, 2024). By February 2024, 23% of adults in the United States reportedly used OpenAI's ChatGPT, up from 18% in July 2023 (Backlinko, 2024). This indicates the rapid adoption and increasing reliance on generative AI tools, even in the workplace. The reliance has resulted in markets dominated by a handful of firms that wield unparalleled power and resources. These firms further centralize their authority and operate beyond the reach of traditional government-led governance. The changes in power dynamics raise critical questions about accountability (Khanal et al., 2024).

Moreover, many businesses are increasingly implementing generative AI tools in their workplaces, leveraging their ability to enhance productivity by combining human beings with machine computational power. The tools facilitate task automation, streamline workflows, and support decision-making (Nakavachara et al., 2024; Rana et al., 2024). Empirical studies (Budhwar et al., 2023; Goldstein, 2023; Fauzi et al., 2023; Kumar, 2024; Peng et al., 2023) have shown the significant impact of generative AI tools on work performance. For instance, Brynjolfsson et al. (2023) found that generative AI tools enhanced employee productivity by 14%, while Noy and Zhang (2023) reported a 40% decrease in task completion time for writing-intensive work. Similarly, Dell'Acqua et al. (2023) demonstrated that consultants from the Boston Consulting Group, a profession known for demanding workload, completed tasks 25% faster with generative AI tools, showcasing their efficiency in high-intensity environments. Even job seekers have benefited from AI-driven automation in resume writing and portfolio creation, which has increased efficiency and reduced costs (Malhotra et al., 2021). Despite certain drawbacks (De Cremer et al., 2023; Morshidi et al., 2023), most literature has underscored generative AI's performance benefits across sectors. However, there is a limited understanding of who perceives the positive effects of these tools on their work performance and why, particularly in the context of the public sector. To address the gap, this study explores how civil servants' organizational power, and their two types of motivations influence their perceptions of generative AI-assisted work performance.

2.2 Generative AI Tools in Public Administration

AI has advanced unprecedentedly, transforming various industries, reshaping daily life for citizens, and redefining interactions with emerging technologies like generative AI. These tools analyze patterns in existing datasets and generate seemingly new and meaningful content (Dasborough, 2023; Hadi et al., 2023). This rapid evolution drives significant changes in working environments, where generative AI enhances performance by automating routine tasks and facilitating idea generation (Androniceanu, 2024; Castro & New, 2016; Hoffmann et al., 2024; Wirtz et al., 2018). While the private sector has effectively leveraged these tools to streamline operations, reduce staffing needs, and lower costs (Rana et al., 2024), the government faces distinct challenges as it prioritizes the public interest and ensures equitable access to services over efficiency-driven outcomes (Council of the European Union, 2023).

Accountability and equity, foundational principles of public administration, present opportunities and challenges in adopting and implementing generative AI (Erkkilä, 2020). These tools enhance decision-making by efficiently processing large datasets, identifying patterns humans may overlook, and automating routine tasks such as filing, scheduling, or data entry. This enables civil servants to relieve themselves of simple administrative burdens, such as drafting and reviewing documents, and focus more on highly valued activities and strategic priorities, fostering greater accountability and responsiveness to citizens' needs (Salah et al., 2023). However, their "black box" nature and lack of transparency in reasoning raise significant accountability concerns, as even software developers do not fully comprehend how these algorithms function (Bloch-Wehba, 2021; Radford et al., 2019). Equity challenges also emerge due to biases embedded in the training datasets of generative AI tools, often derived from culturally narrow, predominantly English internet sources. Such biases hinder fairness and exacerbate systemic disparities, affecting marginalized groups disproportionately (Bender et al., 2021; Faisal et al., 2021; Schramowski et al., 2023).

Despite challenges such as algorithmic bias, data privacy risks, and environmental concerns related to high energy consumption, generative AI has gained widespread adoption in the public sector, especially among civil servants, due to its ability to enhance efficiency and foster innovation (Bright et al., 2024). Civil servants, who allocate up to 30% of their time to paperwork and administrative duties, can utilize automation to focus more on higher-value activities and strategic priorities (Gmyrek et al., 2023; Viechnicki & Eggers, 2017). Like its transformative effect on other industries, generative AI has the potential to reshape public-sector operations, fundamentally redefining the roles and responsibilities of civil servants (Criado et al., 2020). The Boston Consulting Group (2024) also indicates that this technology could result in annual productivity improvements estimated at $1.75 trillion globally across all levels of government by 2033. Moreover, generative AI assists in policy development, decision-making, public service delivery, and citizen engagement, significantly transforming public administration and redefining the roles of civil servants (Salah et al., 2023). As governments encounter increasing pressure to transition to a digital society, the potential of generative AI is becoming clear in its ability to boost administrative efficiency, promote equitable and impactful public services, and provide vital support to less experienced and entry-level workers (Bright et al., 2024; Brynjolfsson et al., 2023).

Empirical studies on generative AI tools in public administration have been limited in recent years. Most research (Noonpakdee, 2024) focuses on adoption as the technology remains in its early development stages (Al Naqbi et al., 2024; Bright et al., 2024). These studies provide valuable insights into the government's adoption of technology. However, there is a limited understanding of how individuals perceive the benefits of their work performance and the factors that shape these perceptions. To address the gap, this study examines how civil servants' organizational power, and two types of motivations influence their perceptions of generative AI-assisted work performance. It is important to note that simply adopting generative AI tools—without exploring its effectiveness—may not ensure meaningful implementation in the public sector. Therefore, we draw on the extrinsic and intrinsic motivations and the reinforcement politics model as these frameworks provide complementary perspectives on how individual and organizational factors shape perceptions of work performance.

3. THEORETICAL FRAMEWORK

3.1 Motivation in Work Performance

Motivation in the workplace is crucial for clarifying differences in an employee's work performance. Motivation is an internal force that energizes, directs, and sustains behavior over time (Diefendorff & Chandler, 2011). Intrinsic motivation stems from a genuine interest in or enjoyment of an activity. It is linked to high-quality performance and improved employee well-being, even when applied to specific tasks (Ryan & Deci, 2000). Hawthorne studies (Mayo, 1949; Landsberger, 1968) suggested that work conditions can influence productivity, drawing attention to organizational psychological and social dynamics. These findings facilitated the development of core theories like Maslow's Hierarchy of Needs (1943), suggesting that employees are motivated to fulfill a sequence of needs, and Herzberg's Two-Factor Theory (1959), which differentiated between hygiene factors that prevent dissatisfaction and motivators that promote satisfaction. While these theories have faced methodological critiques (Hackman & Oldham, 1976), they laid the groundwork for understanding how external and internal motivations interact in the workplace. While motivation theories often emphasize intrinsic factors, extrinsic rewards are still important—particularly for attracting and retaining talent. Extrinsic motivation, influenced by external reward or pressure, is often effective in achieving short-term goals and meeting organizational expectations. A reward system combining material and psychological incentives has been shown to enhance employee satisfaction and performance, aligning each value and task goal (Gagné & Deci, 2005).

Maslow's Hierarchy of needs suggests that once fundamental needs are satisfied, psychological needs become more powerful motivators in the workplace than basic physiological ones. Employees pursue fulfillment by striving for higher-level needs like esteem and self-actualization. Similarly, Herzberg (1959) suggested that although monetary compensation can initially motivate employees, its effectiveness diminishes over time, redirecting the motivational focus toward psychological and social factors. In this context, McGregor (2002) reinforced this perspective through Theory Y, which emphasizes intrinsic motivations in contrast to the extrinsic motivations highlighted in Theory X. Nevertheless, extrinsic motivation remains a fundamental motivational tool for motivating employees, particularly in attracting and retaining talent, and it is embedded in many performance-based incentive systems (Taylor, 1919; Bishop, 1987). Some scholars often study two types of motivations to understand their impact on employee work performance (Moran et al., 2012).

Recent empirical studies (Baard et al., 2004; Rhoades & Eisenberger, 2002; Moran et al., 2012; Van den Broeck et al., 2016) have emphasized the key role of motivation in improving workplace performance. Motivation is generally divided into extrinsic and intrinsic types, with each playing a unique role in employee engagement and productivity (Deci et al., 2001). Intrinsic motivators, such as knowledge, accomplishment, and stimulation, significantly enhance employee engagement and task performance (Weinberg & Gould, 2023; Amabile et al., 1994). Similarly, Chintalloo and Mahadeo (2013) and Khan et al. (2014) observed that two types of motivations drive higher work performance, while Abdullatif (2016) mentioned that extrinsic factors provide a foundation for motivation and intrinsic factors, intrinsic motivation positively influencing employee performance. Although motivation has been widely studied concerning workplace performance across sectors, limited research has investigated who perceives the benefits of adopting emerging technologies, why, and what factors shape this perception—especially within the public sector. To address this gap, this study explores how civil servants' organizational power and motivational factors influence their perceptions of generative AI-assisted work performance. Furthermore, given the structural characteristics of public organizations—often more bureaucratic and centralized than their private-sector counterparts and focused on public interest (Perry & Rainey, 1988)—this study provides valuable insights into how two types of motivations influence employee performance in the context of advanced technology adoption.

3.2 Reinforcement Politics Model

Reinforcement politics model (Kraemer & Dedrick, 1997; Kraemer & King, 1986; Kraemer & King, 2006) provides a framework for understanding how the impact of computing technologies—such as mainframe computers in the 1980s and early 1990s and later e-government technologies—was significantly shaped by individuals in positions of power within government organization. Organizational power, defined as the authority to make decisions within a hierarchical structure (Pinsonneault & Kraemer, 1993), enables these individuals to influence the adoption and implementation of technologies in ways that reinforce existing power dynamics (Pinsonneault & Kraemer, 1997). Technologies play a key role in shaping how control over information is exercised, with information becoming a critical resource of power in decision-making. While information is not inherently powerful, those with access to and control of it can influence decisions and maintain authority in bureaucratic structures (Kraemer & King, 1986). Emerging technologies have the potential to either centralize or decentralize access to information, yet their actual use often reflects and reinforces pre-existing hierarchies. Furthermore, the allocation of critical resources, such as budgets and technical infrastructure, is typically managed by senior civil servants, further consolidating the power.

According to the reinforcement politics model, civil servants with organizational power are more likely to perceive greater benefits from supporting the adoption of generative AI tools. However, during the early stages of adopting and diffusing emerging technologies within government organizations, these individuals might face uncertainties surrounding implementation. Such uncertainties challenge the assumption that technological innovations serve the interests of those in power or reinforce existing hierarchies (Lee, 2008). Emerging technologies can disrupt established workflows, raise concerns about operational reliability, and complicate the process of decision-making. Bureaucrats used to traditional systems may resist adoption due to concerns about transparency, effectiveness, or the potential erosion of their authority. This resistance is often driven by a desire to maintain institutional stability, particularly when technological governance frameworks are designed to protect the interests of those already in power. In contrast, individuals with less organizational power may regard emerging technologies as opportunities to challenge the status quo. By acquiring specialized expertise and leveraging emerging tools to influence decision-making processes, individuals can reposition themselves as valuable contributors, potentially shifting the balance of authority and redefining organizational roles.

In recent years, several empirical studies (Burkhardt & Brass, 1990; Heintze & Bretschneider, 2000; Jasperson et al., 2002) have examined the political dynamics surrounding technology adoption, emphasizing that the success of emerging technologies depends not only on their technical features but also on organizational power structures and individuals' adaptability to change. Kraemer and King (1986) suggested that computing technologies will likely reinforce existing organizational arrangements: individuals favoring centralization use information technologies to strengthen control, while those advocating for decentralization employ them to promote autonomy. Similarly, Chelmis and Prasanna (2013) suggested that managers are more effective than peer pressure in encouraging the adoption of emerging microblogging platforms among their employees. However, Lee (2008) observed that lower-ranking civil servants in Korea were among the early adopters of electronic approval systems (EAS), suggesting that resistance to technological innovation—particularly in its early developmental stages—often originates from entrenched power hierarchies and concerns over potential threats to established roles. Lee's study also noted that high-ranking officials in the central government adopted such technologies more readily than their counterparts in local government. While much of the existing literature argues that adopting information technology influences organizational dynamics, relatively little research has investigated who perceives these tools as beneficial to their work performance and why, especially within the public sector. Heintze and Bretschneider (2000) are among the few scholars who suggest that the adoption of information technology may have a limited impact on organizational dynamics but can directly improve performance. To address this gap, this study examines how the organizational power of civil servants, alongside their extrinsic and intrinsic motivations, shapes their perceptions of generative AI-assisted work performance.

4. THEORETICAL MODEL & HYPOTHESIS

In Figure 1, the conceptual model demonstrates the relationships between two types of motivations and perceived work performance, with organizational power, as indicated by government level and organizational rank—acting as moderating factors. H1 assumes a relationship between extrinsic motivation and perceived work performance, whereas H3 posits that extrinsic motivation influences intrinsic motivation. Both extrinsic and intrinsic motivation were hypothesized to independently affect perceived performance (H1 and H2, respectively). The moderating role of organizational power was examined at the government level (H5a and H6a) and organizational rank (H5b and H6b), which may either strengthen or weaken these motivational effects. Additionally, H4a and H4b investigated the direct effects of government level and organizational rank on perceived work performance. Collectively, this model provides a comprehensive framework for understanding how two types of motivations and organizational power dynamics influence perceived work performance.

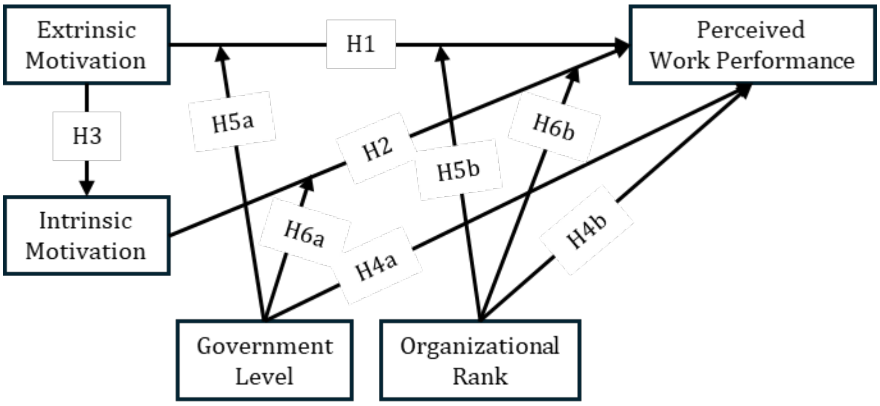

Fig. 1 – Research Model

H1: Civil servants with stronger extrinsic motivation are more likely to perceive improved work performance when utilizing generative AI tools than those with weaker extrinsic motivation

H2: Civil servants with stronger intrinsic motivation are more likely to perceive improved work performance when utilizing generative AI tools than those with weaker intrinsic motivation

H3: Civil servants' extrinsic motivation positively influences their intrinsic motivation when utilizing generative AI tools

H4a: Civil servants at higher levels of government are more likely to perceive improved work performance when utilizing generative AI tools than those at lower levels

H4b: Civil servants in higher organizational ranks are more likely to perceive improved work performance when utilizing generative AI tools than those in lower organizational ranks

H5a: Government level moderates the relationship between extrinsic motivation and perceived work performance when utilizing generative AI tools, such that the positive relationship is stronger for civil servants at higher levels of government

H5b: Organizational rank moderates the relationship between extrinsic motivation and perceived work performance when utilizing generative AI tools, such that the positive relationship is stronger for civil servants in higher organizational ranks

H6a: Government level moderates the relationship between intrinsic motivation and perceived work performance when utilizing generative AI tools, such that the positive relationship is stronger for civil servants at higher levels of government

H6b: Organizational rank moderates the relationship between intrinsic motivation and perceived work performance when utilizing generative AI tools, such that the positive relationship is stronger for civil servants in higher organizational ranks

5. METHODOLOGY

5.1 Data

This study utilized survey data collected by KIPA in April 2023 to test nine hypotheses. The survey targeted Korean civil servants from central, provincial, and local governments to explore their perceptions of generative AI-assisted work performance. The questionnaire consisted of five sections: (1) general perceptions of generative AI, (2) user experiences in work-related contexts, (3) perspectives of non-users, (4) views on adopting generative AI tools in government affairs, and (5) demographic information. The survey was not explicitly designed for the study; only a subset of relevant items was analyzed. Each questionnaire was translated from Korean to English using ChatGPT.

A total of 1,608 responses were collected using a Computer-Assisted Web Interviewing (CAWI) system between April 21 and April 27, 2023, when generative AI was still in its early stages of development. The participants were recruited by various channels, including an official cooperation letter from the Ministry of the Interior and Safety (MOIS), banners, and online panels, ensuring voluntary participation. The survey was conducted by Next Research and commissioned by KIPA. Among the respondents, 545 were from the central government, 416 from provincial governments, and 647 from local governments. The respondents included civil servants from a wide range of roles, ranging from rank three (senior officials) to rank nine (entry-level positions) within the Korean civil service system, with lower rank numbers indicating higher positions. At the time of the survey, generative AI tools were optional, with decisions left to individual discretion. Table 1 represents the demographic characteristics of the participants, such as gender, age, government level, and organizational rank.

Tab. 1 – Demographic Characteristics of the Participants

Demographics	*Category*	*Subjects (N = 1,608)*	
		Frequency	*Percentage*
Gender	Male	801	49.8
	Female	807	50.2
Age	20s	211	13.1
	30s	601	37.4
	40s	500	31.1
	50s	287	17.8
	60s and above	9	0.6
Government Level	Central	545	33.9
	Provincial	416	25.9
	Local	647	40.2
Organizational Rank	Rank 3 or above	6	0.4
	Rank 4	33	2.1
	Rank 5	165	10.3
	Rank 6	359	22.3
	Rank 7	487	30.3
	Rank 8	304	18.9
	Rank 9	254	15.8

5.2 Measurement

Dependent Variable

The study's dependent variable is perceived work performance, a latent construct evaluated utilizing the PLS-SEM method. Perceived work performance reflects employees' subjective evaluations of productivity, effectiveness, and quality of contribution (Deci & Ryan, 1985; Ryan & Deci, 2000). Initially, an item inquired where respondents had utilized generative AI tools in their work; however, it was excluded because of low Cronbach's alpha and composite reliability. Instead, it was measured using an item that evaluated how participants perceived the effectiveness of generative AI tools across five dimensions: reducing workload, improving work efficiency, generating new ideas, enhancing the quality of work outputs, and increasing client or stakeholder satisfaction. The item used a five-point Likert scale: 1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, and 5 = strongly agree. This approach offered a more robust measurement of participants' perceptions of work performance.

Independent Variable

The independent variables consist of two types of motivations: extrinsic and intrinsic. Extrinsic motivation, driven by external rewards or pressures, effectively achieves short-term goals and meets organizational expectations. In contrast, intrinsic motivation, derived from internal satisfaction and genuine interest in tasks, promotes creativity, problem-solving, and long-term commitment (Gagné & Deci, 2005). Extrinsic motivation was measured across two dimensions: superior directives and expectations of improved performance evaluations. However, the former was excluded due to low Cronbach's alpha and composite reliability. Therefore, extrinsic motivation was only assessed using the expectations of improved performance evaluations. Intrinsic motivation was also measured across two dimensions: capturing enjoyment and interest in using generative AI tools at work. As with the dependent variable, participants' responses were recorded on a five-point Likert scale. This refined approach ensured a more reliable assessment of the independent variables.

Moderator

The moderators represent the government levels and organizational ranks. Organizational power, or the authority to make decisions within a hierarchy, is commonly measured through the levels of government and organizational rank (Pinsonneault & Kraemer, 1993). Initially, organizational power was conceptualized as a single moderator; it was divided into two constructs after Cronbach's alpha and composite reliability fell below acceptable thresholds, indicating insufficient reliability. Government level was coded as central government (1), provincial government (2), and local government (3), demonstrating a hierarchy from higher to lower governance levels. Organizational rank reflects the civil system hierarchy in Korea, with ranks ranging from nine (1) to three or above (7), indicating a progression from lower to higher ranks. This study ensured the reliability and validity of organizational power as a moderating variable by treating government level and organizational rank as distinct constructs.

Control Variable

The control variables are gender and age. Gender was determined based on participants' responses. The item was pre-coded in the dataset as male (1) or female (2). Age was reported by respondents and categorized into groups on an ordinal scale: 20s (2), 30s (3), 40s (4), 50s (5), and 60s and above (6), indicating a progression from younger to older. This coding improved clarity and consistency in analyzing demographic controls.

5.3 Estimation Model

This study utilized the PLS-SEM model using Smart PLS 4.0 software (Ringle et al., 2015). This model is especially effective for predictive models and identifying key driving factors in complex relationships (Hair et al., 2011). This study utilized a sample of civil servants from central, provincial, and local governments to examine perceptions of generative AI-assisted work performance. These perceptions are influenced by extrinsic and intrinsic motivations, with organizational power measured by government level and organizational rank as moderating factors. In Korea, emerging technologies have historically been promoted and implemented mainly by the central government, while provincial and local governments tend to adopt these technologies at later stages (Lee, 2008). This gap highlights the potential role of organizational power in influencing civil servants' motivation to utilize generative AI tools. To analyze these dynamics, PLS was used to evaluate the relationships between motivation types and perceived work performance while considering the moderating effects of organizational power.

6. RESULTS

6.1 Measurement Model

Cronbach's alpha and composite reliability (CR) were calculated to assess reliability, and both values exceeded the recommended threshold of 0.7, as suggested by Hair et al. (2019) (Table 2). Factor loadings were well above 0.708, and the Average Variance Extracted (AVE) exceeded 0.5, indicating strong convergent validity (Bagozzi et al., 1991; Hair & Alamer, 2022). Discriminant validity was evaluated using two established criteria. First, the square root of the AVE for each construct was greater than its correlations with other constructs, satisfying Fornell and Larcker's (1981) criteria (Table 3). Additionally, the Heterotrait-Monotrait (HTMT) ratio of correlations was analyzed, with all constructs falling below the recommended threshold of 0.85 (Henseler et al., 2015) (Table 4). The results tested the measurement model's reliability and validity.

Tab. 2 – Reliability and Validity

Construct	*Item*	*Mean*	*Standard deviation*	*Factor loading*	*Cronbach's alpha*	*CR (rho_a)*	*CR (rho_c)*	*AVE*
Extrinsic Motivation	Q9-2	2.676	.599	1				
Intrinsic Motivation	Q9-3	3.788	.459	.913	.827	.837	.920	.852
	Q9-4	3.891	.406	.933				
Government Level	SQ4	2.063	.859	1				
Organizational Rank	Q22	3.000	1.303	1				

Gender	Q21	.502	.500	1				
Age	SQ1	3.553	.949	1				
Work Performance	Q7-1	3.679	.450	.832	.882	.886	.914	.681
	Q7-2	3.825	.428	.822				
	Q7-3	3.692	.434	.745				
	Q7-4	3.708	.430	.867				
	Q7-5	3.565	.453	.855				

Tab. 3 – Fornell-Larcker Scale Results

	Constructs	*1*	*2*	*3*	*4*	*5*	*6*	*7*
1	Extrinsic Motivation	1						
2	Intrinsic Motivation	.179	.923					
3	Government Level	-.008	.005	1				
4	Organizational Rank	-.036	-.036	-.227	1			
5	Gender	-.013	-.007	.126	-.139	1		
6	Age	-.012	-.031	-.064	.597	-.184	1	
7	Work Performance	.231	.440	.028	-.043	-.068	-.032	.825

Tab. 4 – HTMT Ratio

	Constructs	*1*	*2*	*3*	*4*	*5*	*6*	*7*
1	Extrinsic Motivation							
2	Intrinsic Motivation	.201						
3	Government Level	.008	.005					
4	Organizational Rank	.036	.038	.227				
5	Gender	.013	.007	.126	.139			
6	Age	.012	.033	.064	.597	.184		
7	Work Performance	.246	.510	.031	.046	.073	.034	

6.2 Structural Model

A bootstrap resampling method with 1,608 resamples was employed to evaluate the structural models. The results indicate that extrinsic motivation significantly positively affects perceived work performance ($\beta = .155$, $p < .05$), supporting H1. In addition, extrinsic motivation positively affects intrinsic motivation ($\beta = .179$, $p < .05$), supporting H3. Intrinsic motivation significantly influences perceived work performance ($\beta = .414$, $p < .05$), supporting H2. In contrast, government level ($\beta = .034$, $p > .05$) and organizational rank ($\beta = -.013$, $p > .05$) do not significantly affect perceived work performance, indicating that H4a and H4b are not supported. Furthermore, the moderating effects of government level and organizational rank on the relationship between extrinsic motivation and perceived work performance are not statistically significant (H5a: $\beta = -.032$, $p > .05$; H5b: $\beta = .002$, $p > .05$). Also, their moderating effects on the relationship between intrinsic motivation and perceived work performance are not significant (H6a: $\beta = .008$, $p > .05$; H6b: $\beta = -.036$, $p > .05$). Lastly, the model accounted for 23% of the variance in perceived workplace performance. Figure 2 presents a structural model summarizing the PLS-SEM results.

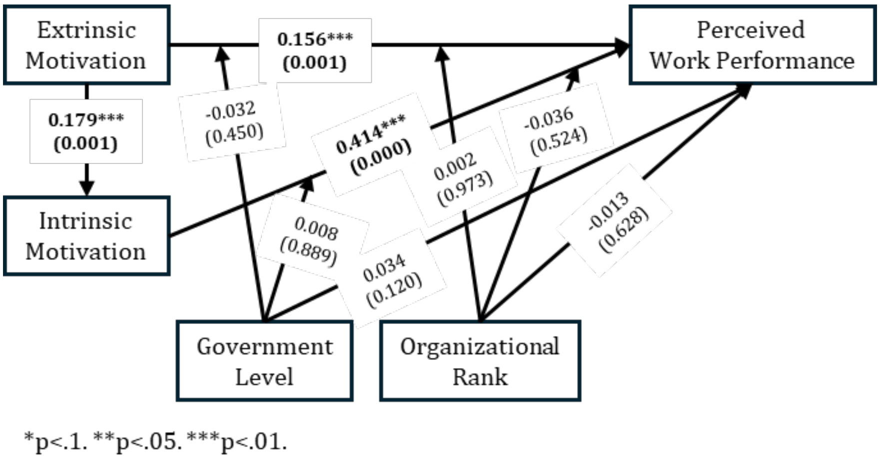

Fig. 2 – PLS-SEM Results

7. DISCUSSION

7.1 Theoretical Implications

This study provides empirical evidence supporting the idea that motivation affects work performance by showing the effectiveness of generative AI tools in public administration but challenging the reinforcement politics model regarding organizational power dynamics in technology adoption. This underscores the essential role of intrinsic motivation among civil servants in enhancing their perceived work performance when utilizing generative AI tools. Civil servants who enjoy these tools are likelier to perceive enhanced productivity and efficiency. Additionally, the positive relationship between the two types of motivation suggests that external incentives, such as recognition or improved evaluations, can enhance intrinsic motivation under certain conditions. However, this study challenges the basic assumption of the reinforcement politics model that organizational power dynamics significantly impact the adoption and effectiveness of new technologies. Contrary to expectations, organizational power did not directly impact perceived work performance or strengthen the relationship between two types of motivation and perceived work performance. This discrepancy may arise from how generative AI tools and computing technologies were developed. Information technologies have primarily been driven by government-led initiatives, which have made them compatible with government affairs (Goldman Sachs Global Institute, 2023). In contrast, generative AI has been primarily developed and advanced by a few major tech companies (Birch & Bronson, 2022). Furthermore, since the data was collected when the generative AI tool was still in its early development stages, its compatibility with government functions may not have been fully recognized.

7.2 Practical Implications

This study underscores the practical implications for the government as it aims to adopt and implement generative AI tools in the workplace. To enhance civil servants' intrinsic motivation, the government is introducing training programs demonstrating how these tools can streamline workflows, improve decision-making, and facilitate work productivity. Drawing on Singapore and Iceland, fostering an environment that encourages curiosity, innovation, and active participation is essential for maximizing the benefits and value of these technologies. The public sector faces high employee turnover, with many civil servants shifting to the private sector for more competitive salaries (Ciobanu & Androniceanu, 2015). The Korean civil service system has historically been rigid and based on seniority. Despite recent efforts to incorporate performance-based approaches, it still lags the private sector (Kim, 2005; Kim, 2014). Given this structure, automating administrative tasks with generative AI tools can help civil servants focus more on high-value activities and strategic priorities (Viechnicki & Eggers, 2017). Kim and Chung (2021) suggests that information technologies such as big data and cloud computing have had little impact on improving efficiency at the organizational level within Korean government institutions. However, this study emphasizes the need for a supportive infrastructure that facilitates the adoption of generative AI tools, as motivation—particularly extrinsic incentives—plays a crucial role in shaping individual perceptions of work performance. To leverage these tools in addressing public sector challenges, the government implements thoughtfully designed incentives encouraging adoption among civil servants. Moreover, aligning these incentives with external rewards, professional aspirations, and public service value is vital for ensuring long-term adoption and meaningful impact.

7.3 Limitations and Future Research

This study had several limitations. It relied solely on cross-sectional data collected through the CAWI system, which may introduce self-selection bias due to open participation via a publicly accessible government agency website. While utilizing a government platform helps mitigate this risk—since it is less accessible than commercial search engines like Google and Bing—there remains the possibility that individuals who are not government employees may misrepresent themselves as civil servants. Moreover, the data were collected in April 2023, when generative

AI was still in its early development stages. Consequently, the findings may not align with the current technological landscape or accurately reflect the evolving capabilities of generative AI. Methodologically, this study encountered limitations in its measurement model, as some latent variables were represented by fewer than the recommended three indicators, potentially affecting the robustness and reliability of the measurements. However, since the data were collected by KIPA rather than specifically for this study, it relied on a limited number of indicators for certain constructs due to data constraints. To address the issues, we employ PLS-SEM, which is well-suited for models with fewer indicators and complex relationships. By maximizing explained variance and enabling flexible modeling of latent constructs, PLS-SEM helped mitigate measurement limitations and enhance the validity of the results (Hair et al., 2017). Lastly, this study only focused on the Korean public sector, which may restrict the applicability of its findings to other contexts.

Future research should adopt a longitudinal approach to track changes over time to address the above limitations, providing a comprehensive understanding of how perceptions of generative AI-assisted work performance evolve. Expanding the scope beyond Korea by conducting comparative studies in various cultural and institutional settings could further enhance the applicability of the findings. Such studies would provide deeper insights into potential motivations and variations in organizational power dynamics, enabling a better understanding of how generative AI influences public sector performance across different governance structures and policy environments. Finally, additional indicators for each latent variable in future models would enhance the measurement's precision and reliability, leading to more robust and generalizable conclusions.

8. CONCLUSION

This study examines the factors influencing civil servants' perceptions of generative AI-assisted work performance, focusing on two types of motivations and the moderating effects of organizational power. The findings reveal that both types of motivation positively influence perceived work performance, with intrinsic motivation having a more significant impact. Furthermore, extrinsic motivation significantly enhances intrinsic motivation, underscoring the dynamic interplay between these two motivational constructs. However, contrary to expectations, organizational power—assessed by government levels and organizational ranks—did not significantly moderate the relationship between motivations and work performance. This indicates that traditional power structures have less influence on government adoption and its effects than earlier technological advancements.

Theoretically, this study empirically supports the idea that motivation affects work performance by demonstrating the effectiveness of generative AI tools in public administration while challenging the reinforcement politics model regarding organizational power dynamics in technology adoption. Intrinsic motivation plays a crucial role in civil servants' perceived work performance when utilizing generative AI tools, and external incentives can significantly enhance intrinsic motivation. However, organizational power did not directly impact perceived work performance. Practically, the government should boost motivation through training programs that promote curiosity, creativity, and problem-solving, fostering an innovation-friendly environment while using automation to enable greater focus on high-value activities and strategic priorities. Additionally, aligning external incentives with public service values and professional aspirations is essential for ensuring long-term adoption and maximizing the impact of generative AI in the public sector.

Despite its contributions, this study has several limitations. It relies on cross-sectional data collected via the CAWI system, which may introduce self-selection bias since a government website facilitated participation. While using a government platform mitigates their risk, non-civil servants still can misrepresent their identities. Additionally, data were collected in April 2023, when generative AI was still in its early development stages, meaning that the findings may not reflect its current capabilities. Methodologically, some latent variables were measured with fewer than the recommended three indicators due to data constraints; however, PLS-SEM was used to address this issue and enhance model validity. The study focuses on the Korean public sector, which limits its generalizability to other contexts. Future research should utilize a longitudinal approach to monitor the evolving perceptions of AI-assisted work performance, broaden its scope to encompass various cultural and institutional settings, and integrate more indicators to enhance measurement precision and model reliability.

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