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Harnessing Artificial Intelligence (AI) for Enhanced Organizational Performance in Public Sectors

Abstract: The increasing importance of artificial intelligence (AI)-driven activities in public organizations necessitates the development of digital transformation capabilities. This paper explores how public organizations can effectively harness AI to enhance organizational performance by driving change in key organizational activities. Through a survey-based study conducted in Vietnam, data were collected from 189 valid respondents. Structural equation modeling was employed to analyze the data. The results indicate that AI capabilities have a positive impact on workflow automation, novel insights generation, and interaction enhancement. Workflow automation and novel insights generation were found to positively influence organizational performance, while interaction enhancement had an insignificant negative effect. These findings shed light on the essential resources that constitute AI capabilities and demonstrate the effects of nurturing such capabilities on crucial organizational activities and, consequently, organizational performance.

Keywords: AI, AI capabilities, and organizational performance.

1. Introduction

In recent years, public organizations have embraced the process of digital transformation, utilizing innovative digital technologies, notably Artificial Intelligence (AI) (Mikalef et al., 2023). Governments have realized the importance of incorporating AI into the functioning of public organizations. This recognition stems from the understanding that AI can bring about substantial improvements in efficiency, effectiveness, and overall performance (Neumann et al., 2023). By harnessing the power of AI, public organizations can streamline processes, automate tasks, and make data-driven decisions, leading to better outcomes for citizens and stakeholders (Mikalef et al., 2023; Misuraca et al., 2020). In Vietnam, one notable illustration is the AI-powered legal virtual assistant implemented by the Supreme People's Court. This system integrates over 173,000 legal documents, 27,000 legal FAQs, and 1.4 million judgments, assisting judges with legal research and decision-making. Since its deployment in 2022, the assistant has facilitated 10,000 to 15,000 interactions daily, reducing judges' workload by 30% and enhancing the efficiency of the judicial process. Plans are underway to make this tool publicly accessible by the end of 2025, aiming to disseminate legal knowledge and support citizens in legal matters (Vietnamnet Global, 2025). In the broader Vietnamese public sector, AI is increasingly seen as a strategic lever to modernize service delivery, address resource constraints, and improve responsiveness to citizen needs. National policies such as Vietnam's "National Strategy on Research, Development and Application of Artificial Intelligence until 2030" emphasize the integration of AI into public governance, aiming to elevate Vietnam into the top 50 countries in AI R&D by 2030 (Vietnam Prime Minister, 2021). Several ministries and local governments have initiated pilot projects applying AI to areas such as traffic monitoring, public health surveillance, education platforms, and citizen feedback systems. However, these initiatives face significant contextual challenges, including uneven digital infrastructure, data silos across agencies, low digital literacy among civil servants, and limited funding mechanisms for sustained innovation (Pham et al., 2024).

Although the transformative potential of artificial intelligence (AI) in enhancing organizational productivity, innovation, and competitiveness has been widely acknowledged, most existing literature remains centered mainly on its application within private-sector enterprises (Sharma et al., 2022; Senadjki et al., 2023; Wang et al., 2023). In contrast, scholarly attention to the role of AI in public organizations is still relatively limited despite the sector's increasing reliance on digital technologies to improve public service delivery. Public sector institutions differ markedly from their private counterparts in that they must operate within complex legal frameworks, maintain transparency and public accountability, and uphold ethical standards in AI governance, particularly in areas related to data security and citizen trust (Gualdi & Cordella, 2024; Mishra et al., 2024). These factors introduce unique barriers that may hinder the effective adoption and utilization of AI technologies in government settings, necessitating context-specific strategies that both harness AI's benefits and mitigate its potential unintended consequences (Wirtz et al., 2019; Fatima et al., 2022). While AI capabilities—defined as an organization's ability to orchestrate and leverage AI-related resources (Mikalef & Gupta, 2021)—have been studied extensively in business contexts, there is a critical lack of understanding regarding how these capabilities translate into improved performance in public organizations. This knowledge gap is particularly pronounced in developing countries, where limited economic scale, institutional capacity, and technological maturity may further constrain the realization of AI's benefits (Van Noordt & Tangi, 2023; Chowdhury et al., 2023). Addressing this gap is essential to inform more inclusive and effective AI strategies tailored to the unique structural, cultural, and operational realities of public sector organizations in emerging economies.

To address this knowledge gap, this study develops and empirically tests a conceptual model of AI capability in the public sector, focusing on three resource categories: tangible, intangible, and human (Van Noordt & Tangi, 2023). The study draws on data collected from IT directors of public organizations across major Vietnamese cities, as they possess significant potential for harnessing the benefits of AI applications across a broad range of services, catering to individual citizens, businesses, and other stakeholders in the public sector (Jakob & Krcmar, 2018). This context provides a compelling empirical setting to explore how AI capabilities contribute to organizational outcomes in the public sector.

The rest of this paper is structured as follows. In the next section, we introduce the concept of an AI capability and review existing literature that examines its application within the context of public organizations. In Section 3 of this paper, we present our conceptual model and put forth hypotheses that establish the foundation for our study. Subsequently, we provide a comprehensive account of the methodology adopted to effectively operationalize our research objectives. In section 5, we present the findings derived from our study. In the final section, we engage in an in-depth discussion regarding the theoretical and practical implications of our work, while also acknowledging and addressing significant limitations that may have arisen throughout the research process.

2. Theoretical background

2.1. AI capabilities in the public sector

Public sector organizations worldwide are increasingly exploring the use of AI technologies to modernize operations, improve citizen services, and optimize decision-making processes. Unlike private firms, public institutions operate under greater scrutiny, face legal and ethical constraints, and prioritize public value over profit. These unique conditions create both opportunities and challenges for AI adoption, and necessitate a deeper understanding of how AI can be effectively integrated within public sector environments.

AI technologies and their usage distinguish themselves from other technological progressions due to their unique capability to imitate cognitive functions, execute tasks resembling human performance, and possess the capacity to acquire knowledge and rectify errors autonomously (Russell et al., 2015). These technologies encompass a broad spectrum of applications, including workflow automation, predictive analytics, virtual agents, recommendation systems, and speech analytics (Wirtz et al. 2019). The adoption of AI technologies offers numerous advantages, for example, optimizing resource allocation, enhancing accuracy, and reducing errors by leveraging data-driven insights and automating repetitive tasks. Additionally, AI technologies can help organizations reduce costs by improving efficiency, eliminating manual processes, and minimizing resource wastage (Carvalho et al., 2020). The adoption of AI technologies within the public sector is experiencing a gradual increase, even though it is currently in the initial phases of its development (Mikalef et al., 2019). Previous empirical research in this field has primarily concentrated on identifying the factors that influence the adoption or hindrance of AI technologies, with a particular focus on legal and policy-related aspects (Dennehy et al., 2023). However, there remains a noteworthy research gap in the literature regarding how various public organizations can strengthen their capacity to effectively implement these technologies and enhance their overall performance (Mikalef & Gupta, 2021; Dwivedi et al., 2021). So far, several studies have provided evidence indicating the beneficial effects of AI-based applications in the domain of public administration. These studies have found that AI technologies positively influence various aspects, including the perceived value of public services (Wang et al., 2021), decision-making processes (Dennehy et al., 2023; Nasseef et al., 2021) and resource allocation improvements (Mikalef et al., 2023).

While some scholars suggest that the application of AI in the public sector does not significantly diverge from its implementation in the private sector (Criado & de Zarate-Alcarazo, 2022), with similar challenges noted in extracting value from AI initiatives (Mikalef & Gupta, 2021; Shollo et al., 2022), a growing body of literature highlights critical differences between these sectors. Public institutions, unlike private enterprises, focus on generating public value rather than profit, which shapes their approach to adopting AI technologies (Fatima et al., 2022). Differences in institutional goals, personnel motivations, and organizational objectives further distinguish public sector dynamics (Schaefer et al., 2021). Additionally, unique institutional and regulatory barriers often impede AI adoption in government contexts (Madan & Ashok, 2022), contributing to the comparatively slower uptake of AI in public organizations (Zuiderwijk et al., 2021). Public agencies also face heightened expectations from citizens, particularly around fairness, transparency, and accountability (Gaozhao et al., 2023), as well as greater demands for explainable and auditable AI systems (de Bruijn et al., 2022; Janssen et al., 2020). These expectations not only apply to the functioning of AI technologies themselves (Criado & de Zarate-Alcarazo, 2022) but also to how public resources are allocated and justified (Fatima et al., 2022). Thus, although some operational challenges in AI deployment are shared across sectors, the institutional context in which public organizations operate introduces distinct constraints and priorities. As a result, frameworks and empirical insights derived from private-sector AI implementation cannot be straightforwardly transferred to public-sector settings without contextual adaptation. To navigate these complexities, scholars increasingly argue that public sector organizations require more than just traditional digital transformation capabilities. Instead, they must cultivate a new type of organizational capability tailored to the specific demands of AI adoption (Mikalef et al., 2023; Mikalef & Gupta, 2021). Among emerging concepts in this field, AI capability, as introduced by Mikalef & Gupta (2021), has been widely recognized and applied in recent studies (Almheiri et al., 2024; Van Noordt & Tangi, 2023; Chowdhury et al., 2023; Weber et al., 2023). Recent research emphasizes that conceptualizing AI capability in the public sector requires greater specificity. For instance, Wang & Zhang (2024a) highlight that technological capabilities must be tailored to sector-specific functions and goals. Applying this to the public sector, AI capability must encompass not only infrastructural and human resources but also the strategic ability to match appropriate AI tools to targeted service objectives, interpret and incorporate AI-generated insights into policy decisions, and address ethical concerns arising from algorithmic governance. Similar to the case of digital green supply chains, where context-specific capability mapping is essential (Wang & Zhang, 2024b), public organizations must build nuanced and context-sensitive AI capabilities that reflect both technological and institutional demands. Defined as an organization's ability to acquire, integrate, and utilize AI-related resources, AI capability identifies the core requirements for deriving value from AI technology (Mikalef & Gupta, 2021). While enthusiasm around AI adoption is high, many organizations still face difficulties in achieving tangible performance outcomes from these technologies (Shollo et al., 2022). Grounded in the Resource-Based View (RBV), AI capability highlights the need for strategic alignment and integration of IT resources, human expertise, and complementary organizational capacities (Madan & Ashok, 2022; Wade & Hulland, 2004). Previous literature has supported the applicability of RBV in turbulent, technology-intensive environments (Priem & Butler, 2001), where performance is contingent upon how well organizations cultivate distinctive capabilities (Pang et al., 2014). This has also been conceptualized in public sector studies as innovation capability—referring to the institutional capacity to adopt, adapt, and leverage innovations to improve public service delivery and create public value (Bekkers et al., 2011; Boukamel & Emery, 2017; Gieske et al., 2016). Drawing on both theoretical foundations in RBV (Barney, 2001; Grant, 1991) and empirical studies in information systems (Bharadwaj, 2000; Wade & Hulland, 2004), we conceptualize AI capabilities in public organizations as consisting of three interrelated resource types: tangible (technological infrastructure), intangible (data and knowledge), and human (skills and expertise). These combined resources determine the extent to which an organization can harness AI to foster innovation and deliver enhanced performance outcomes (Van Noordt & Tangi, 2023; Lal & Bharadwaj, 2020).

According to previous literature, tangible AI-capability resources refer to the physical and material assets that an organization possesses. In the context of AI capabilities, tangible resources may include hardware infrastructure, computing power, data storage facilities, and AI-specific tools and technologies (Chen et al., 2023). These resources provide the foundation for implementing and operationalizing AI initiatives within an organization. Human resources include the knowledge, skills, expertise, and capabilities of individuals within an organization. In the context of AI capabilities, human resources involve employees who possess AI-related competencies, such as data scientists, AI analysts, machine learning engineers, and AI strategists (Mikalef et al., 2019). These individuals contribute their expertise in developing, deploying, and managing AI technologies, thereby driving the organization's AI capabilities (Mikalef et al., 2019). Intangible resources encompass non-physical assets that contribute to an organization's competitive advantage. Within the realm of AI capabilities, intangible resources may include intellectual property, proprietary algorithms, patents, AI-related patents, algorithms, software, and organizational knowledge and culture (Maragno et al., 2023; Mikalef et al., 2023). These intangible resources are crucial for organizations to utilize AI technologies effectively and differentiate themselves from competitors. In practice, AI has been deployed in public organizations for a range of purposes, including intelligent virtual assistants to manage citizen inquiries, fraud detection in social welfare programs, traffic pattern prediction, and AI-supported healthcare diagnostics (OECD, 2019; Wirtz et al., 2019; Zuiderwijk et al., 2021). These applications illustrate the growing reliance on AI not just for operational efficiency, but for strategic governance and service personalization in the public sector.

Taken together, these institutional, ethical, and operational specificities suggest that AI implementation in public sector organizations cannot simply mirror strategies adopted in the private sector. Instead, there is a clear need to develop public-sector-specific conceptualizations of AI capability, ones that reflect the value-driven mandates, regulatory environments, and citizen-centered missions of government entities.

2.2. AI and organizational performance

Despite widespread claims about the potential value that AI can offer public sector organizations, there exists a scarcity of empirical research substantiating these assertions. Specifically, there is a notable knowledge gap concerning how public organizations effectively leverage AI. In a recent scholarly contribution, Mustak et al. (2021) elucidate a collection of AI-based applications that hold relevance for public organizations. In addition, the authors shed light on significant challenges associated with the implementation of AI in the public sector. Through these illustrative examples, it becomes evident that AI can instigate diverse forms of organizational change. According to Mikalef et al. (2023), it is proposed that AI can bring about three distinct categories of organizational impact.

Firstly, it can automate processes by automating routine and repetitive tasks, allowing organizations to streamline their operations and increase efficiency. By leveraging AI-powered automation, organizations can reduce manual efforts, minimize errors, and accelerate the speed of executing various processes. This can free up human resources to focus on more strategic and complex tasks, leading to increased productivity and cost savings (Young et al., 2019). Secondly, AI can facilitate improved engagement and interaction with both internal and external stakeholders. Internally, AI-powered tools and platforms can enable employees to collaborate more effectively, access information easily, and make data-driven decisions. Externally, AI-powered chatbots, virtual assistants, and personalized recommendation systems can enhance customer experiences, enabling organizations to engage with their customers in a more personalized and responsive manner (Androutsopoulou et al., 2019). This can result in increased customer satisfaction, loyalty, and positive brand perception. Lastly, AI technologies possess the ability to analyze vast amounts of data, identify patterns, and generate valuable insights that may not be readily apparent to humans. By processing and interpreting complex data sets, AI can uncover hidden correlations, trends, and predictive patterns. These novel insights can assist organizations in making informed decisions, identifying new opportunities, and developing innovative strategies (Kouziokas, 2021). By harnessing the power of AI, organizations can gain a competitive advantage by staying ahead of market trends and customer preferences.

Despite the initial promising findings in these research studies, the current body of work primarily relies on individual case studies or remains conceptual in nature. Furthermore, these studies often fail to analyze the various mechanisms of value generation simultaneously. Consequently, it becomes challenging to determine how public organizations should effectively structure themselves to AI and what the overall impact on organizational performance might be. Therefore, by harnessing AI capabilities, public organizations can transcend the limitations of employing single AI-based applications and instead embark on a comprehensive digital transformation of their operations, leading to enhanced overall performance.

3. Hypothesis Developments and Research Framework

In this section, we outline hypotheses and research framework, which propose that AI capabilities exert an indirect influence on organizational performance by driving changes in organizational activities. Building upon the findings of Davenport & Ronanki (2018), we identify three intermediary pathways that are conceptually and practically separable: workflow automation (focusing on routine task efficiency), novel insights generation (emphasizing data-driven decision making), and interaction enhancement (relating to communication quality with users and employees). Each of these pathways represents a unique set of technological affordances, organizational implications, and measurement dimensions. This approach is consistent with prior frameworks that highlight the multidimensional impacts of AI adoption in organizational contexts (Wirtz et al., 2019; Mikalef et al., 2023). Therefore, we treat them as separate mediating variables in our research framework, and we argue that AI catalyzes changes in the efficiency and effectiveness of utilizing digital technologies to support crucial operational activities. These organizational impacts, in turn, are hypothesized to enhance key performance indicators that hold significance for public organizations.

3.1. AI Capacities and Workflow automation

AI capabilities are increasingly recognized as essential enablers of workflow automation, particularly in complex organizational environments where manual processes are resource-intensive, error-prone, and inefficient. By cultivating the technical, human, and organizational resources necessary for AI deployment, organizations can identify and implement intelligent systems that automate repetitive tasks with greater speed, consistency, and accuracy (Wirtz et al., 2019). Notably, robotic process automation (RPA)—a key application of AI—allows software agents to mimic human interactions with digital systems, thereby accelerating routine processes such as form validation, document routing, and data extraction. For example, using AI tools in immigration processing has led to faster and more accurate decision-making by automating rule-based assessments (Chun, 2007). Similarly, AI-powered interfaces have significantly streamlined repetitive administrative functions such as data entry and requirements checking (Jefferies, 2016; Al-Mushayt, 2019). In healthcare, AI is increasingly applied to automated diagnostic imaging, where it can reduce analysis time and improve accuracy compared to manual interpretation. Although human oversight remains essential in certain edge cases, these systems have been shown to reduce the diagnostic gap between novice and expert practitioners, supporting faster and more standardized care (Collier et al., 2017; Gandhi et al., 2018). Beyond these sectoral applications, AI process automation systems can incorporate schema-based suggestions, case-based reasoning, and intelligent sensor technologies, enabling them to handle not only repetitive but also semi-structured tasks under varying conditions (Wirtz et al., 2019). These capabilities are particularly valuable in public administration, where processes such as licensing, permit issuance, or benefits processing often follow complex and context-dependent rules. However, the effectiveness of AI-based workflow automation is highly dependent on data quality and systems' resilience against misuse. AI systems trained on biased, outdated, or low-quality data may produce inaccurate or discriminatory outcomes, undermining trust and operational integrity (Mehr et al., 2017; EY, 2018). Moreover, as Conn (2017) warns, AI can "learn" unintended behaviors from flawed environments, and Bostrom & Yudkowsky (2014) emphasize the need to design AI systems that are robust against adversarial manipulation or intentional misuse by human actors. This is particularly critical in the public sector, where transparency, fairness, and accountability are paramount. These issues highlight the importance of combining AI capabilities with human oversight and governance mechanisms. In general, the overall impact of AI capabilities on workflow automation is largely positive when properly implemented. Organizations that invest in building technological, human, and organizational AI assets are more likely to benefit from faster service delivery, reduced process variability, and improved accuracy. Thus, AI capabilities not only enhance operational efficiency but also serve as a strategic enabler of digital transformation across sectors. Therefore, we propose the hypothesis as follows:

H1: AI capabilities will have a positive impact on workflow automation.

3.2. AI Capacities and Novel insights generation

AI capability is also anticipated to strengthen the data analysis capabilities of public organizations, enabling them to extract valuable insights. Utilizing techniques such as clustering, machine learning, and classification, public organizations can unveil latent patterns and knowledge that can inform decision-making processes (Singh et al., 2021). The potential applications of these techniques are diverse, encompassing areas such as improved forecasting and prediction for an event, and resource scheduling. Although AI capability plays a crucial role in supporting organizations in leveraging data for decision-making, recent studies have also pointed out that AI may, in some ways, hinder the process of generating new novel insights. First, AI systems tend to rely on existing patterns derived from historical data, which can lead to the reproduction of old knowledge rather than the discovery of novel or creative insights. AI-generated content often lacks the depth and originality typically found in human-generated ideas (Sternberg, 2024; Ma et al., 2023). Second, AI systems tend to filter out outliers during training and analysis, even though such anomalies can be the very sources of breakthrough thinking or innovative ideas (Ruef & Birkhead, 2024). Third, AI systems are heavily dependent on the data they are trained on; without diverse and representative datasets, the systems may produce flawed or biased results (Shams et al., 2023). Therefore, to ensure the effectiveness of such applications, public organizations must possess adequate data and technological resources, employ personnel with technical expertise in AI-based applications, and establish appropriate structures and processes to facilitate collaboration in this regard (Campion et al., 2022; Sun & Medaglia, 2019). In light of these considerations, we propose the hypothesis as follows.

H2: AI capabilities will have a positive impact on novel insights generation.

3.3. AI Capacities and Interaction enhancement

Interaction enhancement refers to the extent to which artificial intelligence (AI) technologies improve the quality, efficiency, and effectiveness of communication between public organizations and their stakeholders, particularly citizens. This construct captures how AI-enabled systems, such as chatbots, conversational agents, virtual assistants, and intelligent query routing platforms, facilitate more seamless, responsive, and scalable interactions in the delivery of public services. In recent years, AI capabilities have increasingly been leveraged not only to improve external communication with citizens (Pan et al., 2022; Wirtz et al., 2019) but also to enhance internal engagement by streamlining workflows and offering timely, personalized assistance to employees (Bickmore et al., 2020; Mikalef et al., 2023). These applications demonstrate the potential of AI to transform communication processes, enabling greater responsiveness, consistency, and efficiency in interaction. Advancements in natural language processing, gesture recognition, and context-aware systems have further broadened the scope of human–AI interaction, allowing machines to anticipate user needs and respond across multimodal channels (Cath et al., 2017; Ice, 2015). These developments have significantly elevated expectations around the role of AI in enhancing communication quality, particularly in complex public sector environments. However, realizing these benefits requires organizations to possess sufficient AI capabilities—that is, the ability to orchestrate and apply tangible, human, and intangible AI-related resources (Mikalef & Gupta, 2021). Such capabilities are crucial not only for selecting appropriate technologies but also for ensuring their effective integration into service processes in a way that respects contextual, cultural, and ethical considerations. When strategically developed, AI capabilities enable public entities to design and refine interaction tools that align with stakeholder needs and institutional goals. While the relationship between AI and interaction enhancement is nuanced and context-dependent (Lee & Sathikh, 2013), the overall balance of evidence supports a positive influence when AI capabilities are strategically managed. Accordingly, we propose the hypothesis as follows.

H3: AI capabilities will have a positive impact on Interaction enhancement.

3.4. Workflow automation and Organizational Performance

The introduction of AI capabilities in public organizations is posited to have an indirect impact on performance outcomes by enhancing workflow automation, novel insights generation, and interaction enhancement. Through the strategic prioritization and effective utilization of AI-based applications, organizations have the potential to enhance their performance, as the effectiveness of AI depends on its timely and relevant application. It is contended that the organizational impacts of AI will subsequently contribute to improvements in overall organizational performance.

The employment of AI in automating manual and repetitive processes has been posited to yield several benefits, including a significant reduction in the time required to complete processes, a decrease in human errors, and an enhancement in the transparency of activities (Hunt et al., 2022). In the context of public organizations, manual and repetitive processes constitute a considerable portion of daily operations, encompassing a wide range of tasks such as application processing, document management, and data entry and transfer. These processes are often time-consuming, prone to errors, and resource-intensive, which can hinder the efficiency and effectiveness of public services. Therefore, by automating such processes, public organizations can free up personnel to focus on more complex and high-value tasks that require human judgment, creativity, empathy, and problem-solving skills, thereby enhancing the overall effectiveness of public services (Wilson & Daugherty, 2019).

However, while these advantages are substantial, the literature also highlights certain risks that may hinder organizational performance if automation is not appropriately managed. Employee concerns over job security and role displacement can reduce morale and increase resistance to AI adoption (Bankins et al., 2024). Furthermore, integrating AI technologies often demands significant investments in training, system alignment, and process redesign, which may temporarily slow productivity and strain public sector resources (Tan et al., 2024). In labor-intensive settings, over-automation may inadvertently reduce opportunities for meaningful work and provoke social or organizational tension (Mukherjee, 2022). These findings suggest that the performance impact of AI-based workflow automation is highly contingent upon how well the implementation is managed, particularly in balancing technological efficiency with human and organizational factors. Nevertheless, when AI capabilities are strategically aligned with operational priorities and integrated with appropriate support mechanisms, they are expected to enhance public organizations' overall effectiveness and responsiveness. Therefore, we propose the following hypothesis:

H4: Workflow automation will have a positive impact on organizational performance.

According to the proposed hypotheses H1 and H4, it is posited that the introduction of AI capability will indirectly influence organizational performance by facilitating improvements in workflow automation. We suggest the hypothesis as follows.

Ha: AI Capabilities have a positive indirect impact on organizational performance through Workflow automation.

3.5. Novel insights generation and Organizational Performance

Public organizations encounter the challenges of optimizing resource utilization while addressing diverse societal needs. Within the constraints of limited resources, they must take well-informed actions to tackle emerging issues before they escalate. By harnessing AI capabilities, public organizations can extract actionable insights from extensive data sets, enabling them to proactively address potential problems, optimize resource allocation, and make data-driven decisions. These applications include predictive maintenance of public infrastructure, efficient utilization of financial, physical, and human resources, and informed decision-making based on previously inaccessible data (McBride et al., 2019). AI technology assists public organizations in navigating complex scenarios and maximizing resource utilization, ultimately leading to improved organizational performance and positive societal outcomes (Simay et al., 2023; Brandt et al., 2021; Reggi & Dawes, 2022). The utilization of AI technology to gain novel insights generation empowers public organizations to enhance their understanding of and response to the needs of previously marginalized or overlooked groups of citizens (Hoekstra et al., 2021; van Ooijen et al., 2019). This enables a more comprehensive comprehension of citizen service requirements, facilitating proactive support and personalized information dissemination. For instance, it allows for timely notifications to parents regarding school registration deadlines or reminders about important deadlines and applications. Recent scholarly investigations have demonstrated the substantial performance benefits of novel insights generation in the contexts of smart cities and public administration, where large volumes of rapidly changing data are often encountered. Based on the above discussions, we suggest the following hypothesis:

H5: Novel insights generation will have a positive Impact on Organizational Performance.

Based on the propositions stated in hypotheses H2 and H5, our proposition suggests that the presence of an AI capability within organizations will exert an indirect influence on organizational performance by augmenting the novel insights generation of organizations. Therefore, we hypothesize that:

Hb: AI Capabilities have a positive indirect impact on organizational performance through Novel insights generation.

3.6. Interaction enhancement and Organizational Performance

Interaction enhancement, particularly through AI-enabled tools, is increasingly considered a key driver of organizational performance. By enabling faster, more consistent, and more personalized communication with stakeholders—both internal and external—AI-based systems can reduce service delays, enhance employee support, and improve the overall user experience (Scupola & Mergel, 2022; de Bruijn et al., 2022). In public sector contexts, these technologies have been employed to improve citizen engagement by providing instant responses, guiding users through complex administrative procedures, and offering multilingual or inclusive access to services. Such interaction improvements have positively affected citizens' trust and satisfaction with government entities (Liu & Zowghi, 2023). Internally, AI-powered systems can also support employees by reducing repetitive communication tasks, improving task clarity, and alleviating stress, thus enhancing productivity and morale (Valle-Cruz & García-Contreras, 2023). Still, this potential is accompanied by notable obstacles. Several studies have cautioned that users may feel compelled to adapt to machine logic, resulting in frustration, confusion, or disengagement, especially in emotionally nuanced contexts (Ducatel et al., 2005). This is compounded by what has been described as the homogeneity problem, where standardized interaction protocols fail to reflect the diversity of user preferences and needs, thereby eroding trust and satisfaction (Tanaka & Kobayashi, 2015; Holmquist, 2017). Moreover, AI interaction tools may inadvertently introduce new stressors for employees, such as the burden of monitoring AI-generated outputs, dealing with system errors, or managing conflicting expectations from users and machines. If not properly implemented or supported, these systems can backfire, reducing service quality or employee resistance (Wirtz et al., 2019). Despite these concerns, it is important to emphasize that such negative effects are not inherent flaws of the technology itself but rather stem from the expectations of users (Hameed et al., 2016) or resistance to adopting these new tools (Wirtz et al., 2019; Aoki, 2020; Fast & Horvitz, 2017; Mehr et al., 2017). Nevertheless, when interaction enhancement tools are well-designed, contextually adapted, and supported by adequate training and feedback mechanisms, they can significantly improve communication quality, reduce service delivery friction, and foster stronger engagement with citizens and employees. In this sense, the benefits of AI-enabled interaction tools are not inherent in the technology alone but are largely determined by how effectively they are integrated into organizational processes and aligned with stakeholder needs. When these conditions are met, interaction enhancement can serve as a strategic enabler of organizational performance by increasing efficiency, trust, and satisfaction across multiple stakeholder groups. Taken together, while some short-term challenges may arise during the implementation of AI-based interaction tools—such as employee resistance, training needs, or technology misalignment—these barriers are largely transitional. In the long run, with appropriate organizational support, interaction enhancement is expected to yield substantial performance benefits. Therefore, we propose the following hypothesis:

H6: Interaction enhancement will have a positive impact on organizational performance.

Based on hypotheses H3 and H6, we put forward the proposition that the implementation of an AI capability will have an indirect impact on organizational performance by enhancing interaction enhancement facilitated by AI technology. Therefore, we hypothesize that:

Hc: AI Capabilities have a positive indirect impact on organizational performance through interaction enhancement.

Based on the above hypothesis developments, we propose the conceptual framework as the Figure 1:

Figure 1 (here)

4. Research Methodology

4.1. Surveyed Data and Summary Statistic

This study employed a survey-based methodology to gather data from 84 municipalities of the five largest cities in Vietnam, including Ho Chi Minh, Ha Noi, Da Nang, Hai Phong, and Can Tho. The decision to use a quantitative survey-based approach was influenced by its potential to enable confirmatory analysis and the concurrent evaluation of multiple factors. (Pinsonneault & Kraemer, 1993). Surveys are particularly effective in capturing general trends and identifying intricate relationships between key concepts in a study. Furthermore, while the study focuses only on five cities, these municipalities represent the five most socioeconomically developed urban areas in Vietnam and collectively account for approximately one-third of the country's total population. Due to their advanced levels of digital infrastructure and modernization in public administration, these cities are often early adopters of emerging technologies such as AI. Studying such contexts provides valuable insights and offers a meaningful foundation for other, less-developed regions that may follow similar digital transformation trajectories in the future. In this sense, although not fully representative of the entire public sector nationwide, the findings from this sample hold relevance and practical implications for broader digital governance strategies.

Before initiating the survey, we administered it to a group of highly experienced researchers to ensure the clarity and comprehension of its content. Next, the data collection process for this study involved the administration of an online questionnaire to a select group of key respondents in the five largest cities in Vietnam. The questionnaire was disseminated through email invitations sent to IT managers who are working in public organizations. A directory of mailing lists was created for each city or province, and public data was utilized to identify the most suitable respondents. After sending the first invitation email, we continued to send three prompts to enhance feedback rates. The data collection process commenced in late January 2023 and was completed in early June 2023, yielding a final sample of 252 responses, with 189 suitable for further analysis.

Our sample exhibited considerable variation in terms of population size, ranging from small municipalities with under 100,000 to large municipalities with over 700,000 citizens. The major respondents came from the two largest cities (Ho Chi Minh and Ha Noi), which account for 66.14% of the sample, followed by three smaller cities (Da Nang, Hai Phong, and Can Tho) at 33.86%. In addition, the survey results reveal that a notable proportion of municipalities in the sample have an average of more than three specialized employees engaged in IT projects. Furthermore, a significant number of municipalities exhibited substantial IT department sizes, with over six employees dedicated to IT-related responsibilities. As for employee qualifications, up to 97.35% of municipalities in the survey sample have a proportion of staff with post-graduate qualifications below 50%. Additionally, the majority of municipalities in the sample have a high percentage of employees aged 25-45, with only 2.65% of localities having a percentage of employees aged 25-45 below 25%. Regarding the adoption of AI technology, most municipalities reported implementing AI approximately six months to 2 years before the commencement of the study, accounting for about 77.25% (Table 1).

Table 1: Summary statistics of the sample

Factors	**Sample (N=189)**	**Proportion (%)**
Cities		
Ha Noi	70	37.04
Ho Chi Minh	55	29.1
Da Nang	15	13.22
Hai Phong	25	7.94
Can Tho	24	12.7
Municipality's Population		
<10000	2	1.06
10001-50000	2	1.06
50001-100000	12	6.35
100001-200000	62	32.8
200001-400000	72	38.1
400001-700000	35	18.51
>700000	4	2.12
Department's employees		
1-2	3	1.59
3-5	97	51.32
6-10	86	45.50
>10	3	1.59
Postgraduate employee ratio		
<25%	124	65.61
25- under 50%	60	31.74
50- under 75%	4	2.12
>75%	1	0.53
Employee ratio aged 25-45		

<25%	5	2.65
25- under 50%	44	23.28
50- under 75%	112	59.26
>75%	28	14.81
Experience using AI		
< 6 months	16	8.47
6 - less than 12 months	38	20.11
12- less than 18 months	64	33.86
18- less than 24 months	44	23.28
> 24 months	27	14.28

Source: Authors own work

Given that the data obtained for this study captured a momentary perspective and relied on the subjective viewpoints provided by the individual participants, we implemented two methods to mitigate possible biases. Initially, a Harmon one-factor test was performed on the five latent variables employed in the investigation. The outcomes of this test did not yield a single-factor outcome, as the maximum variance attributed to any single factor was 30.9%. Based on this finding, it can be inferred that there is no significant issue concerning common method bias. Secondly, in line with the recommendations of Lauro et al (2005), we assessed the goodness-of-fit of the research model using PLS path modeling. The results indicate that the model exhibits a satisfactory level of goodness-of-fit, surpassing the recommended lower threshold of 0.36 proposed by Wetzels et al. (2009). Therefore, this finding provides further confirmation that the presence of common method biases does not pose a concern in our research model.

4.2. Measurements

All items were assessed by using a 7-point Likert scale. The scale ranged from 1 (strongly disagree) to 7 (strongly agree), allowing for nuanced responses to each item. The AI capability construct was derived from the work of Mikalef & Gupta (2021) and modified to suit the context of Vietnam. The constructs of workflow automation, novel insights generation, and interaction enhancement were formulated based on the work conducted by Davenport & Ronanki (2018). These constructs were developed by adapting the authors' definitions and elaborating on the specific changes that occur within each category. To ensure the validity and refinement of the measurement items, a panel of seven experts was engaged in a series of activities, following the methodology outlined by Mackenzie et al. (2011). Organizational performance pertained to the extent to which public organizations perceived an improvement in efficiency and overall performance in their respective tasks. The assessment of organizational performance was derived from measurements utilized in prior published studies (Appendix A).

4.3. Data analysis

Partial least squares-based structural equation modeling (PLS-SEM) was employed in this study to investigate the proposed hypotheses, as well as to assess the validity and reliability of the model. PLS-SEM was selected for several reasons. First, it is well-suited for exploratory research, particularly when the theoretical framework is still evolving and includes formative constructs (Hair et al., 2019). Second, PLS-SEM can handle complex models with multiple constructs and indicators while maintaining robust performance with relatively small sample sizes and without strict assumptions about multivariate normality (West et al., 2016; Ahammad et al., 2017; Akter et al., 2017). Moreover, PLS-SEM provides the ability to calculate indirect and total effects, thereby facilitating the concurrent examination of relationships among multi-item constructs while minimizing overall error (Astrachan et al., 2014).

In comparison to the more traditional covariance-based structural equation modeling (CB-SEM), PLS-SEM was deemed more appropriate for the nature and objectives of this study. While CB-SEM is generally preferred for theory confirmation and goodness-of-fit testing in well-established models, the current research aims to explore and extend an emerging conceptual framework in the context of AI adoption in public sector organizations—an area where theoretical development is still in progress. Additionally, the presence of both formative and reflective constructs, along with the use of multiple mediation pathways, adds considerable complexity to the model, which PLS-SEM handles more flexibly than CB-SEM (Hair et al., 2021; Sarstedt et al., 2014). Finally, the sample size (n = 189), though acceptable, may be marginal for reliable estimation in CB-SEM, whereas PLS-SEM offers greater statistical power and stability under such conditions. Therefore, the choice of PLS-SEM aligns with both the theoretical orientation and practical constraints of the research design.

In this study, SmartPLS 4.0 software was employed to conduct the analysis. The dataset was carefully screened for accuracy and completeness before model estimation. Observations with any missing values were excluded from the final sample to ensure the reliability of the analysis. The study's sample of 189 responses satisfies the rule-of-thumb for PLS-SEM, which recommends a minimum sample size of ten times the largest number of formative indicators for any single construct or ten times the largest number of structural paths directed at a particular latent construct (Hair et al., 2011). In our model, the most complex construct has 14 indicators, and the largest number of arrows pointing at a construct is three, confirming that the minimum required sample is 140, well below our sample of 189.

Furthermore, the evaluation followed the two-step approach recommended by Hair et al. (2017), including (1) assessment of the measurement model (reliability, convergent validity, and discriminant validity) and (2) evaluation of the structural model (path coefficients, R^2 values, effect sizes, and predictive relevance). Bootstrapping with 5000 subsamples was performed to obtain robust standard errors and test the significance of path coefficients. To assess potential concerns related to common method bias (CMB), two techniques were applied. First, Harman's single-factor test was conducted to verify whether a single factor accounted for the majority of variance, and the results indicated that CMB was not a significant concern. Second, a full collinearity assessment was performed using variance inflation factors (VIFs), with all values falling below the conservative threshold of 3.3, providing further assurance that common method bias was not present. Although PLS-SEM served as the primary analytical approach, additional diagnostic assessments were conducted to evaluate model robustness. Specifically, model fit was assessed using multiple global fit indices such as SRMR, d_ULS, and d_G. Furthermore, the Gaussian copula approach proposed by Park and Gupta (2012) was applied to all key structural paths to address concerns regarding potential endogeneity.

5. Results

5.1. Measurement Model

We evaluate the measurement model involved in examining the statistical attributes of the first-order reflective latent constructs. Regarding the reflective constructs, the analysis included assessments of reliability, convergent validity, and discriminant validity. Firstly, reliability was evaluated at the construct-level as well as the individual-item level, utilizing measures such as Composite Reliability (CR) and Cronbach Alpha (CA), with the criterion of exceeding the minimum threshold of 0.70 as recommended by Nunnally (1978). We examined the construct-to-item loadings at the measurement item level to ensure that all values exceeded the minimum threshold of 0.70 (see Table 2).

Table 2: Evaluation of reliability and convergent validity

Constructs	**Code**	**Items**	**Factor loadings**	**α**	**CR**	**AVE**
AI Capabilities (AIC)				0.948	0.949	0.597
	AIC1	We can share big data across organizational units.	0.747			
	AIC2	We can facilitate high-value data to analyze the organizational environment	0.751			
	AIC3	We invest in enterprise networks to support the scale of applications.	0.710			
	AIC4	We adopt cloud-based services for performing machine learning	0.754			
	AIC5	We invest in storage infrastructure to support AI-based applications	0.759			
	AIC6	We have IT experts to support AI works	0.785			
	AIC7	Our data scientists are strong in data analysis	0.779			
	AIC8	Our data scientists have experience to complete their tasks	0.777			
	AIC9	Our technical team has a mutual understanding	0.783			
	AIC10	Our technical team has the same vision	0.805			
	AIC11	Our technical team has a collaboration	0.786			
	AIC12	Our team has a strong proclivity for high-risk projects	0.780			
	AIC13	Our team takes wide-ranging acts to achieve the company’s goal	0.815			
	AIC14	Our team maximizes the potential opportunities	0.777			
Workflow automation (WFA)				0.886	0.889	0.688

	WFA1	The utilization of artificial intelligence has helped us to automate operational activities	0.866			
	WFA2	The utilization of artificial intelligence has helped us to optimize information systems	0.802			
	WFA3	The utilization of artificial intelligence has helped us to automate financial activities	0.816			
	WFA4	The utilization of artificial intelligence has helped us to automate administrative tasks	0.785			
	WFA5	The utilization of artificial intelligence has helped us to automate human processes	0.875			
Novel insights generation (NIG)				0.906	0.908	0.681
	NIG1	The utilization of artificial intelligence has helped us to gain insight into citizens preferences	0.785			
	NIG2	The utilization of artificial intelligence has helped us to understand better about citizen needs.	0.809			
	NIG3	The utilization of artificial intelligence has helped us to detect hidden trends in citizen behavior.	0.812			
	NIG4	The utilization of artificial intelligence has helped us to uncover knowledge.	0.836			
	NIG5	The utilization of artificial intelligence has helped us to gain insight into key organizational activities.	0.848			
	NIG6	The utilization of AI has helped us to make more evidence-based decisions.	0.859			
Interaction enhancement (IE)				0.913	0.925	0.696
	IE1	The utilization of artificial intelligence has helped us to enhance responsiveness to citizen services	0.811			
	IE2	The utilization of artificial intelligence has helped us to improve the level of citizen satisfaction	0.853			
	IE3	The utilization of artificial intelligence has helped us to provide large volume of citizen queries	0.851			

	IE4	The utilization of artificial intelligence has helped us to increase the citizen engagement	0.767			
	IE5	The utilization of artificial intelligence has improved our ability to handle a variety of citizen inquiries	0.871			
	IE6	The utilization of artificial intelligence has made our interaction with citizens more seamless	0.849			
Organizational Performance (OP)				0.931	0.933	0.645
	OP1	The implementation of artificial intelligence has reduced operational costs.	0.769			
	OP2	The implementation of artificial intelligence has increased organizational efficiency.	0.799			
	OP3	The implementation of artificial intelligence has improved service quality.	0.748			
	OP4	The implementation of artificial intelligence has enhanced our innovation output.	0.816			
	OP5	The implementation of artificial intelligence has enabled the development of new citizen-facing solutions.	0.798			
	OP6	The implementation of artificial intelligence has improved knowledge generation across the organization	0.803			
	OP7	The implementation of artificial intelligence has improved IT system reliability.	0.804			
	OP8	The implementation of artificial intelligence has improved workflow synchronization across departments.	0.856			
	OP9	The implementation of artificial intelligence has reduced operational bottlenecks.	0.830			

Source: Authors own work

Secondly, convergent validity was verified by examining the Average Variance Extracted (AVE) values calculated by Smart-PLS software and confirming that each value surpassed the minimum threshold of 0.50 (See Table 2).

Table 3: Fornell–Larcker criterion

Construct	**AIC**	**WFA**	**NIG**	**IE**	**OP**
AIC	0.772				
WFA	0.470	0.829			
NIG	0.410	0.346	0.825		
IE	0.199	-0.105	-0.025	0.834	
OP	0.578	0.541	0.432	-0.078	0.803

Source: Authors own work

Lastly, discriminant validity was assessed using two established approaches: the Fornell–Larcker criterion and the Heterotrait–Monotrait (HTMT) ratio. Following the Fornell–Larcker approach (Fornell & Larcker, 1981), the square root of the average variance extracted (AVE) for each latent construct was compared to its correlations with other constructs. As shown in Table 3, all diagonal values (i.e., the square roots of AVE) are greater than the off-diagonal inter-construct correlations. For example, the square root of AVE for AI Capabilities (0.772) exceeds its correlations with Interaction Enhancement (0.199), Novel Insights Generation (0.410), Organizational Performance (0.578), and Workflow Automation (0.470). This satisfies the discriminant validity condition for all constructs.

Table 4: HTMT

Construct	**AIC**	**WFA**	**NIG**	**IE**	**OP**
AIC					
WFA	0.504				
NIG	0.440	0.383			
IE	0.208	0.127	0.091		
OP	0.616	0.589	0.464	0.119	

Source: Authors own work

In addition, we conducted HTMT analysis (Henseler et al., 2016) to further validate discriminant validity. The HTMT values between all construct pairs were below the conservative threshold of 0.85 (ranging from 0.091 to 0.616), indicating a clear distinction between the latent constructs (see Table 4). The highest HTMT value observed was between AI Capabilities and Organizational

Performance (0.616), which is well below the cutoff. These results collectively confirm that the constructs in the measurement model are empirically distinct. Therefore, based on both the Fornell–Larcker and HTMT criteria, the measurement model demonstrates adequate discriminant validity. We chose not to remove any items from the measurement model if their incorporation was strongly justified theoretically. Additionally, we examined the potential presence of multicollinearity among the elements of formative constructs. To evaluate this, we evaluated the variance inflation factor (VIF) values, ensuring that they remained under the more cautious threshold of 3.3, as suggested by Mikalef et al. (2022) (See Table 5).

Table 5: Construct Validation

Construct	Measure	Weight	Significant	VIF
AI Capabilities (AIC)				
	AIC1	0.090	P< 0.0001	2.130
	AIC2	0.076	P< 0.0001	2.221
	AIC3	0.088	P< 0.0001	1.931
	AIC4	0.095	P< 0.0001	2.221
	AIC5	0.086	P< 0.0001	2.193
	AIC6	0.090	P< 0.0001	2.327
	AIC7	0.101	P< 0.0001	2.294
	AIC8	0.098	P< 0.0001	2.261
	AIC9	0.086	P< 0.0001	2.371
	AIC10	0.105	P< 0.0001	2.487
	AIC11	0.101	P< 0.0001	2.340
	AIC12	0.091	P< 0.0001	2.353
	AIC13	0.092	P< 0.0001	2.628
	AIC14	0.094	P< 0.0001	2.363
Workflow automation (WFA)				
	WFA1	0.213	P< 0.0001	2.710
	WFA2	0.220	P< 0.0001	2.201
	WFA3	0.259	P< 0.0001	1.961
	WFA4	0.260	P< 0.0001	1.870
	WFA5	0.256	P< 0.0001	2.733
Novel insights generation (NIG)				
	NIG1	0.191	P< 0.0001	1.939
	NIG2	0.208	P< 0.0001	2.105
	NIG3	0.187	P< 0.0001	2.262
	NIG4	0.216	P< 0.0001	2.408
	NIG5	0.208	P< 0.0001	2.523
	NIG6	0.201	P< 0.0001	2.838
Interaction enhancement (IE)				
	IE1	0.213	P< 0.0001	2.186
	IE2	0.196	P< 0.0001	2.797

	IE3	0.170	P< 0.0001	2.770
	IE4	0.191	P< 0.0001	1.932
	IE5	0.259	P< 0.0001	2.639
	IE6	0.169	P< 0.0001	2.947
Organizational Performance (OP)				
	OP1	0.123	P< 0.0001	2.262
	OP2	0.143	P< 0.0001	2.540
	OP3	0.162	P< 0.0001	1.946
	OP4	0.139	P< 0.0001	2.470
	OP5	0.141	P< 0.0001	2.315
	OP6	0.137	P< 0.0001	2.344
	OP7	0.123	P< 0.0001	2.556
	OP8	0.144	P< 0.0001	3.233
	OP9	0.135	P< 0.0001	2.753

Source: Authors own work

5.2. Structural model

The results of the structural model evaluation, which underwent PLS analysis, are depicted in Figure 2. The figure displays important metrics, including the explained variance (R^2) of the dependent variables, the standardized path coefficients (β) representing the strength and direction of relationships, and the significance levels indicating the statistical significance of our hypothesized relationships. The significance of estimates, represented by t-statistics, was determined using the bootstrapping algorithm implemented in Smart-PLS. This analysis involved 5000 resamples to obtain robust and reliable results. As depicted in Figure 2, the results indicate that of the original six hypotheses examined, one hypothesis exhibited a negative and marginally significant relationship, while the remaining five hypotheses were found to be statistically significant and demonstrate a positive directional effect. The findings reveal that AI capabilities have a positive effect on all three organizational impacts: workflow automation ($\beta = 0.47$, $t = 8.979$, $p < 0.05$), novel insights generation ($\beta = 0.41$, $t = 7.993$, $p < 0.05$), and Interaction enhancement ($\beta = 0.198$, $t = 2.529$, $p < 0.05$). Moreover, the analysis indicates that workflow automation ($\beta = 0.442$, $t = 5.807$, $p < 0.05$) and novel insights generation ($\beta = 0.279$, $t = 4.137$, $p < 0.05$) have positive effects on organizational performance, respectively. However, the finding reveals an unexpected result, as interaction enhancement demonstrates an insignificant negative influence on organizational performance ($\beta = -0.025$, $t = 0.317$, $p > 0.1$).

Figure 2 (here)

The structural model also demonstrates that it accounts for a substantial amount of variance, explaining 22.1% for workflow automation (R^2= 0.221), 16.8% for novel insights generation (R^2= 0.168), and 3.9% for interaction enhancement (R^2 = 0.04). Moreover, the model explains 36.2% of the variance in organizational performance (R^2= 0.362).

Beyond testing the main structural relationships, the analysis also controls for contextual variation by incorporating variables such as municipality population size, number of IT department employees, postgraduate staff ratio, staff age composition, AI experience, and city-level characteristics. The analysis revealed that none of these variables had a statistically significant effect on organizational performance (all p-values > 0.05). These results indicate that demographic and institutional context had limited influence on the outcome variable compared to the core AI-related constructs.

To investigate whether the influence of AI capabilities on organizational performance is direct or mediated through other factors, we employed a bootstrapping approach. This nonparametric resampling technique, as recommended by Hayes (2017), does not assume normality in the sampling distribution. Initially, we verified the significance of the mediated paths from AI capabilities to organizational performance through potential mediators such as workflow automation, cost improvement, and customer experience, following the guidelines of Hair et al. (2021). Subsequently, we incorporated the direct path from AI capabilities to organizational performance in the model and observed that it retained partial significance, indicating the presence of partial mediation.

We assessed the proposed mediation pathways using bootstrapped parameter estimates based on 5000 subsamples generated within the PLS framework. This enabled us to calculate the standard error of each mediation effect and its corresponding t-statistic by dividing the indirect effect by the standard error. This approach offers several advantages, including the absence of distributional assumptions and the ability to simultaneously assess all indirect effects, even in the presence of multiple mediators, without isolating specific parts of the structural model. The results indicate that AI capabilities have substantive indirect influences on organizational performance through workflow automation, novel insights generation, and interaction enhancement, respectively.

Table 6: Summary of hypotheses, expected directions, and empirical results

Hypothesis	Proposed Relationship	Expected Direction	Result	p-value
H1	AIC→ WFA	Positive (+)	Supported	< 0.01
H2	AIC→ NIG	Positive (+)	Supported	< 0.01
H3	AIC→ IE	Positive (+)	Supported	< 0.05
H4	WFA→ OP	Positive (+)	Supported	< 0.01
H5	NIG→ OP	Positive (+)	Supported	< 0.01
H6	IE→ OP	Positive (+)	Unsupported	> 0.05
Ha	AIC→ WFA→ OP	Positive (+)	Supported	< 0.01
Hb	AIC→ NIG→ OP	Positive (+)	Supported	< 0.01
Hc	AIC→ IE→ OP	Positive (+)	Unsupported	> 0.05

Table 6 provides a summary of all structural hypotheses tested in the model. The table includes the hypothesized relationships between constructs, the expected direction of each effect based on theoretical rationale, and the empirical results derived from the PLS-SEM analysis. As shown, most of the hypothesized relationships were supported at statistically significant levels ($p<0.05$ or $p<0.01$), while a few exhibited marginal significance or were not supported. Notably, the unexpected negative effect of interaction enhancement on organizational performance, though only marginally significant, offers a compelling direction for further research.

Table 7: Model Fit Indices

Indicates	Model Type	Original sample (O)	Sample mean (M)	95% CI	99% CI
SRMR	Saturated model	0.055	0.047	0.053	0.056
	Estimated model	0.061	0.051	0.059	0.064
d_ULS	Saturated model	2.446	1.824	2.282	2.566
	Estimated model	3.094	2.168	2.874	3.35
d_G	Saturated model	0.97	0.979	1.217	1.345
	Estimated model	0.998	0.986	1.219	1.359

To evaluate the overall quality of the structural model, three global fit indices were examined: the Standardized Root Mean Square Residual (SRMR), squared Euclidean distance (d_ULS), and geodesic distance (d_G), as summarized in Table 7. The SRMR value for the estimated model was 0.061, which is well below the commonly accepted threshold of 0.08, indicating a good model fit (Henseler et al., 2016). Although the d_ULS value (3.094) for the estimated model slightly exceeds the upper bound of the 95% confidence interval of the saturated model (2.282), this alone does not invalidate the model fit. Importantly, the d_G value for the estimated model (0.998) falls comfortably within the 95% confidence interval of the saturated model (1.217), further supporting the structural model's adequacy. Overall, these results confirm that the proposed model demonstrates an acceptable level of global fit and is suitable for hypothesis testing.

5.3. Robustness checks

Potential endogeneity concerns were examined using the Gaussian Copula approach developed by Park & Gupta (2012), which aligns with recent methodological guidance from Hult et al. (2018). This technique is well-suited for detecting endogeneity in PLS-SEM models without requiring instrumental variables. We constructed copula terms for each potentially endogenous path—specifically for AI Capabilities and the three mediators (Workflow Automation, Novel Insights Generation, and Interaction Enhancement), as well as for the three mediators in relation to Organizational Performance.

Table 8: Endogeneity Test Using Gaussian Copula

	Original sample	**Sample mean**	**Standard deviation**	**T-statistics**	**P-values**
GC (AIC -> IE) -> IE	-0.173	-0.171	0.252	0.688	0.492
GC (AIC -> NIG) -> NIG	-0.463	-0.395	0.208	1.376	0.126
GC (AIC -> WFA) -> WFA	-0.501	-0.451	0.219	1.389	0.122
GC (AIC -> OP) -> OP	-0.282	-0.249	0.219	1.291	0.197
GC (IE -> OP) -> OP	-0.454	-0.328	0.475	0.956	0.339
GC (NIG -> OP) -> OP	-0.158	-0.129	0.212	0.743	0.457
GC (WFA -> OP) -> OP	0.593	0.475	0.34	1.745	0.081

As reported in Table 8, the copula terms corresponding to all structural paths are statistically insignificant at the 5% level (i.e., all $p > 0.05$), which suggests that endogeneity is unlikely to bias the estimation results. Although the copula term for the path Workflow automation (WFA) → Organizational Performance (OP) shows marginal significance ($p = 0.081$), this does not provide strong evidence of endogeneity. Therefore, we conclude that the relationships examined in our model are not substantively affected by reverse causality or omitted variable concerns.

6. Discussion

Public sector entities are increasingly adopting AI technologies. It is crucial to comprehend the profound impact of AI capabilities on how to utilize AI tools, particularly in automating processes, gaining novel insights generation, and engaging stakeholders. Our focus on organizational performance stems from its significance as a reliable metric for assessing the efficacy of AI transformations and capabilities (Wirtz et al., 2019). Emphasizing AI capabilities alone would not afford a comprehensive understanding of whether the organizational shift towards AI utilization will indeed yield the anticipated benefits.

6.1. Theoretical contribution

This paper contributes to the existing body of research on AI utilization within public entities by establishing a connection between AI capabilities and organizational performance. It underscores that, despite the positive influence of AI capabilities on the adoption of AI technologies, such capabilities do not universally translate into enhanced organizational performance. Specifically, our findings align with earlier research, such as that conducted by Mikalef & Gupta (2021), affirming the positive impact of AI capabilities on instigating organizational change through processes like automation, novel insights generation, and engagement. Nevertheless, it is noteworthy that this organizational change does not consistently result in enhancements in overall organizational performance. This observation aligns with analogous findings from the private sector, where previous research has indicated a limited impact of AI on organizational performance, as highlighted by Mikalef et al. (2023) and Brynjolfsson et al. (2018).

The study explores the intricate effects of different AI-based applications on organizational performance in the public sector. The findings reveal a distinct pattern: novel insights generation have a positive impact on performance, workflow automation leads to some improvements, while interaction enhancement has a negative influence.

One crucial factor influencing these varied outcomes is the inherent nature of each application. Workflow automation is known for enhancing value within existing processes, whereas novel insights generation have the potential to create entirely new pathways of value. Managers, especially those in higher-level positions, may find it easier to identify and appreciate these novel value paths facilitated by novel insights generation. For instance, in Vietnam, emerging applications of AI for workflow automation have been observed in administrative processes such as tax processing, judicial documentation, and e-permit handling—although most are still in pilot phases or fragmented deployments (Vietnamnet Global, 2025). These efforts show potential but highlight the need for stronger institutional support and strategic direction to ensure consistency across sectors.

The observed differences in the impact of these AI-based applications can also be attributed to prevailing trends in public sector organizations. The study highlights the current inclination of these organizations to focus on smaller-scale AI implementations. This approach may result in limited observable impact on organizational performance or, conversely, make it challenging to detect the effects due to the scale of implementation.

Notwithstanding these nuances, the study underscores a significant finding: organizations with sufficient AI capabilities can achieve improvements in organizational performance through strategic utilization of AI technologies. This holds particularly true for novel insights generation and workflow automation, emphasizing the importance of effective AI deployment for positive organizational outcomes. Consequently, the study contributes valuable insights into the complexities of AI-based applications in the public sector and their implications for organizational performance.

Nevertheless, our findings reveal a detrimental correlation between interaction enhancement and organizational performance, prompting the identification of multiple explanatory factors. One key explanation may lie in the misalignment between user expectations and the current maturity of AI solutions. As noted by Davenport & Ronanki (2018; Hameed et al., 2016), early-stage deployments such as AI-powered chatbots often create inflated expectations for immediate efficiency gains. In practice, however, these systems frequently require significant human oversight, iterative system training, and infrastructural support before yielding measurable benefits. This implementation burden is echoed by Wirtz et al. (2019), who emphasize that AI tools often suffer from a lack of intuitive human-computer interaction, causing miscommunication and increasing user frustration—especially when cognitive or emotional nuance is involved. In the Vietnamese public sector, provincial portals and smart city initiatives have experimented with virtual assistants to support public service delivery (Pham et al., 2024). However, challenges in language processing, limited personalization, and insufficient feedback loops often result in a poor user experience and distrust in these systems, dampening performance gains. Moreover, AI systems may inadvertently erode trust if they fail to meet social or contextual expectations. According to Fast & Horvitz (2017), concerns about job displacement and algorithmic opacity can fuel employee resistance, undermining the successful uptake of AI initiatives. This challenge is magnified when AI tools standardize responses without recognizing the diversity of user needs (Tanaka & Kobayashi, 2015), a phenomenon known as the homogeneity problem. Consequently, rather than improving communication and decision-making, these systems may introduce confusion and depersonalization (Holmquist, 2017), particularly in settings where human empathy is critical. Another critical factor is the organizational readiness to manage change. As suggested by Mikalef et al. (2023), the successful realization of AI-related benefits hinges not only on technical capability but also on the presence of cultural, strategic, and human capital support. In many public organizations, limited budgets, bureaucratic inertia, and insufficient training contribute to underdeveloped AI capabilities and slow diffusion of innovation (Wirtz et al., 2019). As a result, interaction enhancement projects are launched without the organizational capacity to integrate and sustain them effectively—leading to underutilization and potential inefficiencies. Additionally, low-quality or biased data may impair system performance and diminish user confidence. Mehr et al. (2017) and EY (2018) both warn that poorly curated datasets can lead to decision errors or unfair treatment, particularly in citizen-facing services. The perceived unreliability of these systems, in turn, can exacerbate resistance and reduce engagement, ultimately hindering organizational performance. In light of these considerations, our findings may reflect a broader tension in AI adoption—where technical potential outpaces the organizational, social, and cultural conditions required for its success. Therefore, while the negative association between interaction enhancement and performance appears paradoxical, it underscores the critical importance of aligning AI tools with human-centric design principles, stakeholder expectations, and institutional readiness (Ågerfalk, 2020).

The limited significance of control variables suggests that improvements in organizational performance are not primarily driven by structural factors such as city size, workforce composition, or prior AI experience. Instead, the core mechanisms associated with AI capabilities—particularly their role in enabling workflow automation and data-driven insights—appear to exert a more dominant influence. This implies that even municipalities with modest resources or smaller populations can achieve performance gains if AI systems are strategically deployed. It also reinforces the importance of internal organizational readiness and AI-specific resource alignment over contextual advantages.

6.2. Practical contribution

Our investigation also underscores several significant practical implications that hold particular salience and relevance for key stakeholder groups and decision-makers within public sector institutions.

First, public organizations should adopt a capability-driven approach to AI implementation by explicitly linking technology investments to identified process inefficiencies or performance gaps. Rather than adopting AI reactively or opportunistically, organizations should develop structured assessment frameworks that help match specific AI tools with operational contexts where they are most likely to generate value. Municipalities are encouraged to focus their early-stage AI investments on domains where operational complexity is relatively low but performance impact is high. These include administrative process automation, service request triage, and standard document handling such as form submissions, permit approvals, and data entry—where technologies like rule-based algorithms and robotic process automation (RPA) can immediately yield efficiency gains. By doing so, municipalities can free up human capital to focus on higher-value and citizen-facing activities.

Second, public organizations can enhance strategic decision-making by investing in data analytics capabilities. Managers should not only deploy advanced analytics tools but also foster analytical thinking and data literacy among staff to interpret AI-generated insights effectively. These capabilities are particularly vital in domains such as urban planning, resource allocation, and policy evaluation, where real-time data interpretation can lead to more responsive and impactful public service delivery.

Third, public organizations must recognize and address the potential disconnect between AI-driven interaction tools (e.g., chatbots, virtual agents) and user expectations or readiness. To mitigate these risks, designing and deploying AI-powered interaction systems should be user-centered and iteratively tested for usability, inclusiveness, and cultural fit. Public organizations must ensure that such systems are not only functionally efficient but also emotionally intelligent, capable of dealing with diverse user expectations and communication norms. This is especially critical in Vietnam, where citizens often prefer face-to-face contact for administrative procedures and may view AI agents as impersonal or unreliable. Additionally, the deployment of interaction-focused AI should be accompanied by human support systems, particularly in emotionally sensitive or high-stakes service contexts. Stakeholder feedback loops, co-design with citizens, and human oversight and fallback mechanisms should be incorporated by design to preserve service quality and trust.

Fourth, public organizations should consider developing capability roadmaps that balance technical infrastructure development with human capital enhancement. These include technical training, change management programs, and collaborative learning mechanisms that bridge the gap between technical teams and frontline service providers. In particular, technical training programs should emphasize data handling and ethical considerations, both of which are vital for maximizing the benefits of AI. AI-readiness should be viewed not only as a technological condition but as an organizational learning process.

Finally, ethical governance must be institutionalized as a core pillar of AI adoption. This includes establishing clear principles around transparency, algorithmic accountability, data privacy, and fairness. Public agencies should engage in regular audits of AI systems and ensure that decision-making processes involving AI remain comprehensible to citizens and subject to oversight. In contexts where algorithmic decisions affect public entitlements, grievance redress mechanisms must be proactively communicated, transparent, and accessible. This is especially important when deploying AI systems that influence public-facing services, where accountability and fairness are paramount (Janssen et al., 2020; Wirtz et al., 2019).

6.3. Contextual and institutional implications

In line with the theoretical and practical insights presented above, this section contextualizes the findings within the institutional setting of Vietnam's public sector. The findings of this study carry important institutional implications, particularly in the context of developing countries like Vietnam, where the digital maturity of public organizations remains uneven and policy coordination for AI implementation is still evolving. Despite a growing number of AI pilot projects, many public agencies operate without a unified national framework for AI governance, leading to fragmented applications and limited scalability (Pham et al., 2024). This underscores the need for cross-agency institutional coordination, strategic alignment with digital transformation agendas (Vietnam Prime Minister, 2021), and dedicated units to oversee AI ethics, interoperability, and long-term sustainability.

Moreover, public organizations in Vietnam face constraints related to procurement regulations, bureaucratic inertia, and talent retention, all of which affect their ability to adopt AI at scale. For instance, rigid public procurement systems often hinder timely acquisition and updating of AI technologies. Addressing such institutional bottlenecks will require policy reforms that encourage agile experimentation, public–private partnerships, and sandboxes for AI innovation.

Additionally, this study highlights the importance of building context-aware AI policies that are sensitive to local administrative culture, citizen expectations, and political accountability. The negative performance impact of interaction enhancement observed in this study, for example, may reflect deeper systemic gaps in digital trust, inclusive design, and co-production of public services. Therefore, institutional strategies must move beyond technical fixes to embrace human-centric design, participatory governance, and transparency mechanisms, especially when AI systems interact directly with the public.

Overall, these contextual realities reinforce the importance of adopting a fit-for-context approach to AI deployment in public sector settings. By highlighting the institutional, infrastructural, and human capital conditions in a developing country like Vietnam, our study extends current understandings of AI adoption beyond the private sector or developed economies, offering insights that are both globally relevant and locally actionable.

6.4. Limitations and further research

While this research contributes valuable insights to the existing literature on the intersection of AI and organizational value, it is not exempt from certain limitations. First, although the study employed data from five major cities in Vietnam—representing a significant proportion of the national population and leading regions in terms of digital innovation—the sample may still not fully capture the diverse contexts of municipalities across the country. In particular, variations in regulatory environments, infrastructure readiness, and organizational culture in less developed or rural regions may limit the generalizability of the findings. Nonetheless, given the advanced nature of these urban centers, the results serve as a valuable reference point for future technology diffusion in other localities. Second, due to limited research resources and logistical constraints, the sample size remained relatively modest. However, as discussed in the methodology section, the selected sample is methodologically appropriate for PLS-SEM and provides sufficient variation in demographic and organizational characteristics to uncover meaningful patterns. Future studies with expanded regional coverage and larger sample sizes would enhance the robustness and external validity of the findings. Third, despite the comprehensive data collection from numerous municipalities to capture effects, these outcomes only provide a static snapshot, lacking a longitudinal perspective on how AI capabilities induce organizational changes over time. Unforeseen internal and external contingencies could emerge as influential factors in value generation. Future investigations could benefit from longitudinal studies to discern the evolution and mechanisms of AI effects. Fourth, our analysis, although distinguishing between the three types of AI effects, lacks depth in elucidating how these effects are practically realized. Variances among municipalities in their approaches to achieving workflow automation and its relevance to different activities warrant further exploration. Consequently, future research could complement this study with more in-depth case analyses scrutinizing the intricate details of how organizational impacts unfold. Finally, despite employing various controls and providing detailed survey instructions, the evaluation of performance effects relies on subjective measures. This introduces potential bias, as perceptions of performance are derived from a single respondent. Although self-reporting is a common and accepted practice in organizational research (Podsakoff et al., 2003), it may not fully capture actual performance outcomes. With the growing prevalence of AI-based applications in municipalities, future investigations may explore their effects using objective performance metrics such as service processing times, cost savings, or citizen satisfaction scores. Alternatively, adopting a paired-responses survey method could mitigate potential biases in respondents' answers.

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Figures legends

Tables

Table 4	HTMT
Table 5	Construct Validation
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Table 7	Model Fit Indices
Table 8	Endogeneity Test Using Gaussian Copula

Data availability

The datasets analyzed during this study are not publicly available due to their involvement in ongoing related research. However, the datasets may be made available from the corresponding author upon reasonable request for academic purposes.

Competing interests

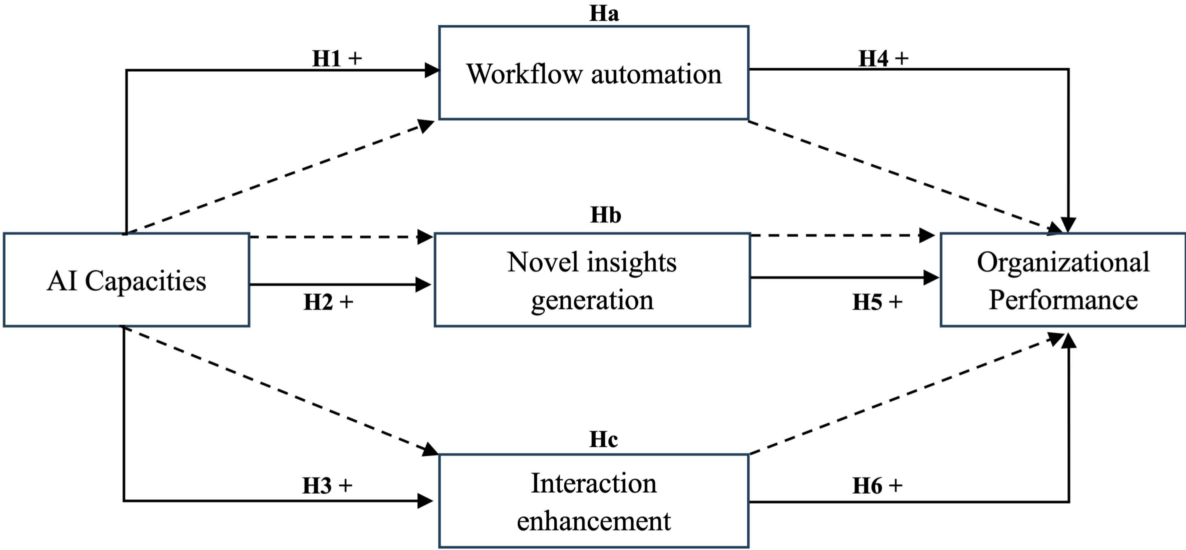
The authors declare no competing interests

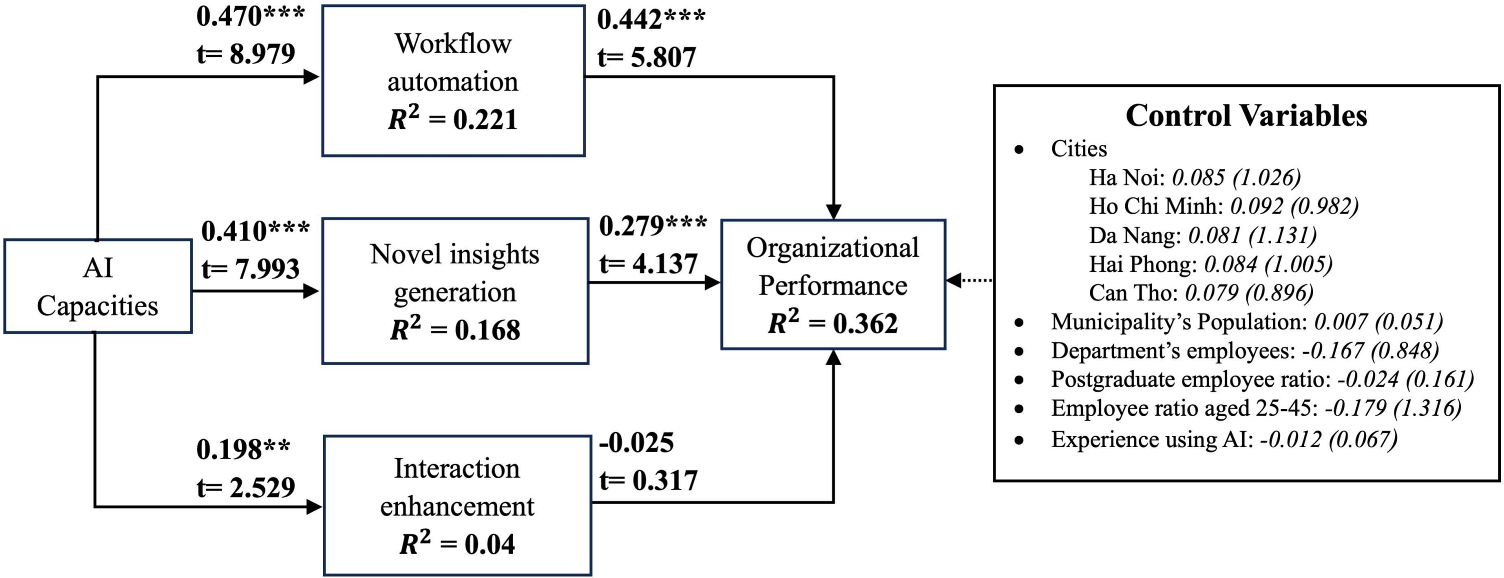
Ethical approval

This study was conducted in accordance with the ethical standards of the 1964 Declaration of Helsinki and its later amendments. It involved a voluntary, anonymous questionnaire targeting public sector employees and did not collect any sensitive, personal, medical, or biological information. There was no psychological intervention or foreseeable risk to participants. Based on the nature of the study, it fully meets the exemption conditions outlined in the Regulation on the Organization and Operation of the Research Ethics Committee (Decision No. 1228/QĐ-ĐHVL, dated August 12, 2022, Van Lang University). Accordingly, research that does not involve vulnerable populations, does not collect identifiable personal data, and poses minimal risk may qualify for automatic exemption from formal ethical approval. As such, this study was exempted from obtaining formal ethical clearance. No ethics approval number was issued.

Informed consent

Prior to participation, all respondents were informed about the purpose and scope of the study. Informed consent was obtained via a consent statement included on the introductory page of the questionnaire. Participants were explicitly informed that their involvement was voluntary, that they could withdraw at any time without consequence, and that all responses would remain confidential and anonymized. No personally identifiable data was collected, and all information was used solely for academic and research purposes. Informed consent was obtained during the data collection period from late January 2023 to early June 2023.


Ha
H1 +
Workflow automation
H4 +
Hb
AI Capacities
Novel insights generation
Organizational Performance
H2 +
H5 +
Hc
H3 +
Interaction enhancement
H6 +



0.470***
t= 8.979
Workflow automation
R^2 = 0.221
0.442***
t= 5.807
AI Capacities
0.410***
t= 7.993
Novel insights generation
R^2 = 0.168
0.279***
t= 4.137
Organizational Performance
R^2 = 0.362
0.198**
t= 2.529
Interaction enhancement
R^2 = 0.04
-0.025
t= 0.317
Control Variables
Cities
Ha Noi: 0.085 (1.026)
Ho Chi Minh: 0.092 (0.982)
Da Nang: 0.081 (1.131)
Hai Phong: 0.084 (1.005)
Can Tho: 0.079 (0.896)
Municipality's Population: 0.007 (0.051)
Department's employees: -0.167 (0.848)
Postgraduate employee ratio: -0.024 (0.161)
Employee ratio aged 25-45: -0.179 (1.316)
Experience using AI: -0.012 (0.067)