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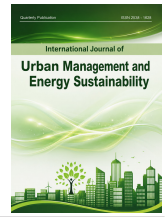

ORIGINAL RESEARCH PAPER

Artificial Intelligence Capabilities and Innovation Performance in Urban Management Organizations: The Mediating Roles of Organizational Learning and Decision-Making Agility

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ABSTRACT

Urban management organizations are under growing pressure to use artificial intelligence to deliver more responsive and innovative public services, yet investment in AI technologies does not translate automatically into innovation. The mechanisms through which organization-level AI capabilities create innovation value in public urban governance remain poorly understood. Drawing on the resource-based view and dynamic capabilities theory, this study examines how AI capabilities affect innovation performance in urban management organizations, and whether organizational learning and decision-making agility mediate this relationship. A cross-sectional survey of 312 managers and experts in five Iranian metropolitan municipalities was analyzed with partial least squares structural equation modeling, in which AI capabilities were specified as a higher-order construct comprising data and technology infrastructure, AI-related human skills, and AI governance and intangible resources. The results show that AI capabilities directly enhance innovation performance organizational learning and decision-making agility. Organizational learning and decision-making agility both carry significant indirect effects, including a serial path, and together account for 56.1% of the total effect, indicating complementary partial mediation. The model explains 29.1% of the variance in innovation performance and shows out-of-sample predictive power, while an importance–performance map analysis identifies AI governance and data resources as the priority areas for improvement. The study concludes that AI generates innovation in urban management mainly when it is converted into learning routines and faster, evidence-based decisions, and it offers municipal leaders a prioritized agenda for building these complementary capabilities.

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INTRODUCTION

Cities concentrate most of the world's population, economic activity and environmental pressure, and their administrations are expected to manage traffic, waste, land use, public safety and citizen services with constrained budgets and rising public expectations. Artificial intelligence (AI) has become one of the most promising tools for this task: machine-learning models forecast traffic and energy demand, computer vision supports infrastructure inspection, and conversational agents handle citizen requests (Allam & Dhunny, 2019; Yigitcanlar et al., 2020). Public-sector applications of AI are now documented across service delivery, policy analysis and internal administration (Dwivedi et al., 2021; Wirtz et al., 2019; Zuiderwijk et al., 2021). Yet the diffusion of AI in public administration remains uneven, and many initiatives stall at the pilot stage (Madan & Ashok, 2023; Neumann et al., 2024). A growing body of work argues that value does not come from AI technologies as such but from the organizational capability to combine data, technology, skills and governance arrangements into a coherent resource bundle (Mikalef & Gupta, 2021; Wamba-Taguimdje et al., 2020). In private firms, AI use has been linked to product and process innovation (Haefner et al., 2021; Rammer et al., 2022), and recent reviews identify innovation as a central outcome of AI adoption (Mariani et al., 2023). In the public sector, by contrast, evidence on how AI capabilities translate into performance is limited; the first studies of municipalities have examined the determinants of AI capabilities and their contribution to organizational performance (Mikalef et al., 2022, 2023), but not the innovation outcomes that city governments increasingly pursue.

Two gaps follow. First, the mechanisms that link AI capabilities to innovation are seldom theorized and tested. AI is expected to change how organizations learn from data and experience (Balasubramanian et al., 2022) and how quickly and on what basis they make decisions (Shrestha et al., 2019; Trunk et al., 2020), yet these mechanisms are rarely modeled together. Second, urban management organizations operate under public accountability, hierarchical decision structures and fragmented data ownership, conditions that may weaken the path from technological capability to innovation (Desouza et al., 2020; Selten & Klievink, 2024). Whether organizational learning and decision-making agility carry the effect of AI capabilities in this setting is therefore an open empirical question. This study addresses these gaps. Its aim is to explain how organization-level AI capabilities affect innovation performance in urban management organizations, and to test whether organizational learning and decision-making agility mediate this relationship, individually and in sequence. Three research questions guide the study. RQ1: To what extent do AI capabilities enhance the innovation performance of urban management organizations? RQ2: Do organizational learning and decision-making agility mediate this effect? RQ3: Which capability dimensions should municipal managers prioritize to improve innovation performance? The study makes three contributions. It extends the AI-capability perspective (Mikalef & Gupta, 2021) from firms to urban public organizations and links it to innovation rather than general performance. It specifies and tests a serial mediation model in which AI capabilities first strengthen organizational learning, which in turn enables more agile decisions, thereby integrating the learning (Huber, 1991) and decision-speed (Eisenhardt, 1989) traditions. Finally, an importance–performance map analysis translates the estimates into priorities for practice. Section 2 develops the theoretical framework and hypotheses, Section 3 describes the method, Section 4 reports the results, Section 5 discusses them and Section 6 concludes.

MATERIALS AND METHODS

Resource-based view and dynamic capabilities

The resource-based view holds that organizations outperform others when they control resources that are valuable, rare, difficult to imitate

and well organized (Barney, 1991). D
ynamic capabilities theory adds that, in changing environments, the decisive advantage lies in the capacity to integrate, build and reconfigure resources (Teece et al., 1997). Information-systems research has used this logic to explain why the same technology produces different outcomes across organizations: value arises when technical assets are combined with human skills and organizational routines (Mikalef & Gupta, 2021; Tallon & Pinsonneault, 2011). For public organizations, the relevant competitive outcome is not market share but the ability to create public value through new services, processes and policies (De Vries et al., 2016). This study therefore treats AI capability as a bundle of resources and examines the organizational processes learning and decision-making through which the bundle is converted into innovation.

AI capabilities in urban management organizations

AI capability is defined as an organization's ability to select, orchestrate and leverage its AI-specific resources (Mikalef & Gupta, 2021). Following this conceptualization, three complementary resource categories are distinguished: tangible resources (data, technology and basic infrastructure), human resources (technical and business skills for AI), and intangible resources (inter-departmental coordination, change capacity and governance of AI risk). In municipalities, these resources are often dispersed across departments and dependent on legal mandates, procurement rules and political support (Mikalef et al., 2022; Neumann et al., 2024). Data quality, interoperability and ethical safeguards are recurring obstacles (Wirtz et al., 2019; Zuiderwijk et al., 2021), and the organizational placement of AI units shapes whether solutions move beyond pilots (Selten & Klievink, 2024). Consistent with prior work, AI capability is modeled here as a higher-order construct formed from these three dimensions.

Organizational learning

Organizational learning refers to the processes through which an organization acquires, distributes, interprets and stores knowledge so that its range of potential behaviors changes (Huber, 1991). Learning capability comprises managerial commitment, a systems perspective, openness and experimentation, and knowledge transfer and integration (Jerez-Gómez et al., 2005). Learning-capable organizations are more innovative because they detect emerging needs, test new solutions and retain what works (Jiménez-Jiménez & Sanz-Valle, 2011). AI changes the learning process itself: algorithms codify patterns in large data sets, but substituting machine judgment for human judgment can also reduce the experiential learning on which organizations rely (Balasubramanian et al., 2022). Learning therefore emerges as a plausible, but not automatic, channel through which AI capability affects innovation.

Decision-making agility

Decision-making agility is the organization's capacity to sense relevant changes and to make and implement well-informed decisions quickly. Studies of high-velocity environments show that fast decision makers use more, not less, real-time information and consider more alternatives simultaneously (Eisenhardt, 1989). Information-technology capabilities support this agility when they are aligned with strategy (Tallon & Pinsonneault, 2011). In government, agile principles iterative development, user feedback and empowered teams are increasingly applied to policy and service design (Mergel et al., 2021). AI can strengthen decision agility by augmenting human judgment with predictions and scenario analysis, although the appropriate division of labor between humans and algorithms depends on the decision context (Jarrahi, 2018; Shrestha et al., 2019; Trunk et al., 2020).

Innovation performance in urban management

Public-sector innovation is the introduction of new services, processes, organizational forms

or governance arrangements that create public value (De Vries et al., 2016). Adoption depends on organizational capacity, managerial attitudes and environmental pressures (Damanpour & Schneider, 2009), and increasingly on collaboration among public, private and civic actors (Torfing, 2019). For city administrations, innovation performance includes new or improved citizen services, process redesign that reduces cost or delay, and technological solutions for urban problems. AI broadens the space for such innovation by enabling new data-driven services and by supporting the generation and evaluation of ideas (Haefner et al., 2021; Mariani et al., 2023; Yigitcanlar et al., 2020).

Hypotheses development

Direct effects. AI capabilities provide the data, analytical tools and skills needed to identify unmet citizen needs, design new services and automate processes. Firm-level evidence links AI use to innovation outcomes (Rammer et al., 2022; Wamba-Taguimdje et al., 2020), and AI capability has been associated with organizational creativity and performance (Mikalef & Gupta, 2021), including in public organizations (Mikalef et al., 2023). AI capabilities also equip organizations to capture, analyze and share knowledge, which strengthens learning (Balasubramanian et al., 2022), and to make faster, evidence-based decisions (Shrestha et al., 2019). Learning, in turn, enables innovation (Jiménez-Jiménez & Sanz-Valle, 2011); agile decisions shorten the cycle from idea to implementation (Eisenhardt, 1989; Mergel et al., 2021); and organizations that learn continuously can decide faster because they interpret new information more effectively (Huber, 1991). Hence: H1: AI capabilities positively affect innovation performance. H2: AI capabilities positively affect organizational learning. H3: AI capabilities positively affect decision-making agility. H4: Organizational learning positively affects innovation performance. H5: Decision-making agility positively affects innovation performance. H6: Organizational learning positively affects decision-making agility.

Mediating effects.

Capability theories imply that resources create value through the processes they enable (Teece et al., 1997). AI capabilities should therefore affect innovation partly by strengthening learning and decision agility, and partly through a sequence in which learning improves the quality and speed of decisions, which then accelerates innovation. Hence: H7a: Organizational learning mediates the effect of AI capabilities on innovation performance. H7b: Decision-making agility mediates the effect of AI capabilities on innovation performance. H7c: Organizational learning and decision-making agility sequentially mediate the effect of AI capabilities on innovation performance. Figure 1 summarizes the research model. (Fig. 1).

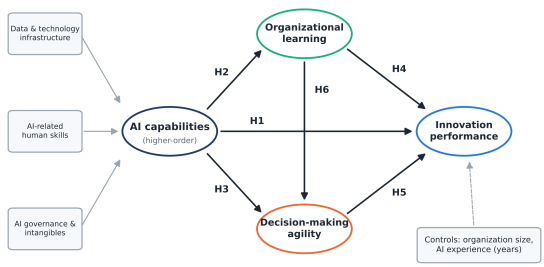

Figure 1: Research model and hypotheses

Population, sampling and data collection

The population comprises managers and experts in the municipalities of five Iranian metropolises Tehran, Mashhad, Isfahan, Shiraz and Tabriz cities, working in units that plan, procure or use data-driven and AI-based solutions. A stratified random sample was drawn proportionally to the size of each municipality and organizational unit. Of 420 questionnaires distributed between February and May 2025, 336 were returned (80.0%); 24 were excluded because of missing values above 10% or straight-lining, leaving 312 usable responses. This exceeds the minimum of 155 required by the inverse square root method to detect path coefficients of 0.20 at the 5% sig-

nificance level (Hair et al., 2022). Early and late respondents did not differ significantly on any construct (independent t-tests, $p > 0.05$), suggesting that non-response bias is unlikely. Table 1 reports the sample profile. (Tab. 1)

Table 1: Profile of respondents (n = 312).

Characteristic	Category	n	%
Gender	Male	221	70.8
	Female	91	29.2
Education	Bachelor	87	27.9
	Master	166	53.2
	PhD	59	18.9
Position	Senior manager	45	14.4
	Middle manager	120	38.5
	Expert/analyst	147	47.1
Tenure (years)	<5	47	15.1
	5–10	110	35.3
	11–20	108	34.6
	>20	47	15.1
Organizational unit	ICT & smart city	84	26.9
	Urban planning & development	68	21.8
	Urban services & environment	68	21.8
	Transport & traffic	46	14.7
	Finance & administration	46	14.7
Municipality	Tehran	111	35.6
	Isfahan	58	18.6
	Mashhad	55	17.6
	Tabriz	48	15.4
	Shiraz	40	12.8

Measures

All constructs were measured with multi-item reflective scales adapted from validated sources and rated on seven-point Likert scales (1 = strongly disagree, 7 = strongly agree). Items were translated into Persian and back-translated, reviewed for content validity by a panel of eight academics and senior municipal managers, and pilot-tested with 30 respondents who were excluded from the main sample. Table 2 summarizes the constructs; the full questionnaire is provided in the Supplementary Appendix. Organization size (log of staff) and years of AI experience were included as control variables for innovation performance. (Tab. 2)

Table 2: Constructs, definitions and measurement sources.

Construct	Dimension (items)	Operational definition	Source
AI capabilities (AIC; second-order)	Data & technology infrastructure, AID (4)	Availability, quality and integration of data and AI-ready computing and platforms	Mikalef and Gupta (2021)

AI capabilities (AIC; second-order)	AI-related human skills, AIS (4)	Technical and business skills of staff to develop, use and evaluate AI	Mikalef and Gupta (2021)
	AI governance & intangibles, AIG (4)	Inter-departmental coordination, change capacity and governance of AI risks	Mikalef et al. (2022)
Organizational learning (OL)	First-order (5)	Commitment, systems view, openness/ experimentation, knowledge transfer	Jerez-Gómez et al. (2005)
Decision-making agility (DMA)		Speed and quality of sensing, deciding and implementing in response to change	Eisenhardt (1989); Tallon and Pinsonneault (2011)
Innovation performance (INP)		New or improved services, processes and technological solutions and their adoption	Jiménez-Jiménez and Sanz-Valle (2011); De Vries et al. (2016)

Common method variance

Procedural remedies were applied: respondents were assured of anonymity, predictor and outcome items were placed in separate sections, and item wording avoided ambiguity (Podsakoff et al., 2003). Statistically, Harman's single-factor test showed that the first factor accounts for 36.3% of the variance, below the 50% threshold, and all full-collinearity variance inflation factors (1.39–1.57) are below 3.3 (Kock, 2015). Common method bias is therefore unlikely to threaten the results.

Data analysis

The model was estimated with the PLS-SEM algorithm (path weighting scheme, Mode A, stop criterion 10−7). The higher-order AI-capability construct was estimated with the disjoint two-stage approach: the construct scores of the three dimensions from the first stage served as indicators of the second-order construct in the second stage (Sarstedt et al., 2019). The measurement model was assessed through indicator loadings, Cronbach's α, ρA, composite reliability (ρC) and average variance extracted (AVE), and discriminant validity through the heterotrait–monotrait ratio (HTMT) and the Fornell–Larcker criterion (Fornell & Larcker, 1981; Henseler et al., 2015). The structural model was assessed through collinearity (VIF), path coefficients with 5,000 bootstrap subsamples and percentile 95% confidence intervals, effect sizes (f^2), R^2, the standardized root mean square residual (SRMR), and out-of-sample prediction with PLSpredict using 10 folds and 10 repetitions (Hair et al., 2019; Shmueli et al., 2019). Indirect effects were tested by bootstrapping and classified following Zhao et al. (2010). Finally, an importance–performance map analysis (IPMA) contrasted the total effects of the predictors with their average performance on a 0–100 scale (Hair et al., 2022).

FINDINGS AND DISCUSSION

Measurement model

Table 3 shows that all first-order indicator loadings range from 0.741 to 0.890, above the 0.708 threshold, and that indicator VIFs (1.60–2.90) are below 3. Cronbach's α (0.848–0.905), ρA (0.849–0.906) and composite reliability (0.898–0.929) exceed 0.70, and AVE values (0.677–0.737) exceed 0.50, establishing internal consistency and convergent validity (Hair et al., 2019). At the second order, the three dimensions' load strongly and significantly on AI capabilities (0.883, 0.822 and 0.822; all $p < 0.001$), with ρC = 0.880 and AVE = 0.710, which supports the higher-order specification (Sarstedt et al., 2019). Discriminant validity is supported. All HTMT ratios among first-order constructs (0.303–0.724) are below the conservative 0.85 threshold Table 4, the highest value occurring, as expected, between two dimensions of the same higher-order construct. At the second-order level, HTMT values range from 0.457 to 0.564, and the square root of each construct's AVE exceeds its correlations with all other con-

structs (Fornell & Larcker, 1981; Henseler et al., 2015). (Tab. 3 and 4)

Table 3: Measurement model: loadings, reliability and convergent validity.

Construct / indicator	Loading	VIF	α	ρA	ρC	AVE
Data & technology infrastructure (AID) - AID1	0.876	2.51	0.881	0.883	0.918	0.737
AID2	0.832	2.04				
AID3	0.890	2.70				
AID4	0.835	2.01				
AI-related human skills (AIS) - AIS1	0.868	2.30	0.850	0.873	0.898	0.689
AIS2	0.886	2.29				
AIS3	0.817	1.84				
AIS4	0.741	1.60				
AI governance & intangibles (AIG) - AIG1	0.844	2.01	0.848	0.849	0.898	0.688
AIG2	0.838	2.00				
AIG3	0.838	1.96				
AIG4	0.797	1.70				
Organizational learning (OL) - OL1	0.823	2.04	0.880	0.884	0.913	0.677
OL2	0.847	2.19				
OL3	0.821	2.07				
OL4	0.828	2.12				
OL5	0.794	1.90				
Decision-making agility (DMA) - DMA1	0.831	2.07	0.882	0.890	0.914	0.680
DMA2	0.845	2.31				
DMA3	0.870	2.48				
DMA4	0.804	2.03				
DMA5	0.768	1.73				
Innovation performance (INP) - INP1	0.860	2.55	0.905	0.906	0.929	0.724
INP2	0.863	2.53				
INP3	0.846	2.34				
INP4	0.884	2.90				
INP5	0.800	1.96				
AI capabilities (second order) - AID	0.883	1.97	0.795	0.801	0.880	0.710
AIS	0.822	1.72				
AIG	0.822	1.56				

Table 4: Discriminant validity: heterotrait–monotrait ratios (HTMT) and Fornell–Larcker criterion.

Construct	AID	AIS	AIG	OL	DMA	INP
Data & technology infrastructure (AID)	0.859	0.629	0.578	0.416	0.400	0.373
AI-related human skills (AIS)	0.724	0.830	0.486	0.316	0.412	0.273
AI governance & intangibles (AIG)	0.670	0.571	0.829	0.412	0.376	0.337
Organizational learning (OL)	0.471	0.358	0.474	0.823	0.506	0.457

Decision-making agility (DMA)	0.448	0.465	0.430	0.564	0.824	0.432
Innovation performance (INP)	0.418	0.303	0.383	0.512	0.479	0.851

Structural model and hypothesis testing

Inner VIF values (1.00–1.50) indicate no collinearity among predictors. The SRMR of the saturated model is 0.052, below the 0.08 threshold, indicating acceptable approximate fit (Hair et al., 2022). The model explains 20.7% of the variance in organizational learning, 32.8% in decision-making agility and 29.1% in innovation performance Figure 2. Table 5 shows that all six hypothesized direct paths are positive and significant. AI capabilities have the strongest effect on organizational learning (β = 0.455, t = 10.17; f^2 = 0.262, a medium effect), followed by the effects of organizational learning on decision-making agility (β = 0.369) and of AI capabilities on decision-making agility (β = 0.301). Innovation performance is driven by organizational learning (β = 0.257), decision-making agility (β = 0.219) and, to a smaller extent, directly by AI capabilities (β = 0.172, p = 0.004). Neither organization size nor AI experience has a significant effect. H1–H6 are therefore supported. (Fig. 2 and Tab. 5)

Table 5: Results of direct-effect hypothesis tests.

Hypothesis	Path	β	t	p	95% CI	f^2	VIF	Decision
H1	AIC → INP	0.172	2.84	0.004	[0.051, 0.287]	0.030	1.41	Supported
H2	AIC → OL	0.455	10.17	< 0.001	[0.369, 0.544]	0.262	1.00	Supported
H3	AIC → DMA	w0.301	6.10	< 0.001	[0.204, 0.395]	0.107	1.26	Supported
H4	OL → INP	0.257	4.13	< 0.001	[0.136, 0.378]	0.062	1.50	Supported
H5	DMA → INP	0.219	3.80	< 0.001	[0.108, 0.333]	0.045	1.49	Supported
H6	OL → DMA	0.369	7.46	< 0.001	[0.272, 0.465]	0.161	1.26	Supported
Control	Size → INP	−0.056	1.16	0.247	[−0.152, 0.039]	0.004	1.00	n.s.
Control	AI experience → INP	0.069	1.42	0.157	[−0.026, 0.166]	0.007	1.02	n.s.

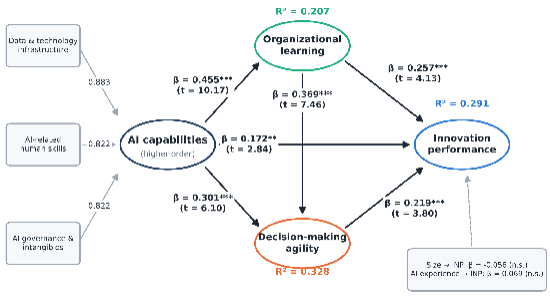

Figure 2: Structural model results: standardized path coefficients, t-values and R^2.

Mediation analysis

Table 6 reports the indirect effects. All three specific indirect effects are significant, because none of their bootstrap confidence intervals includes zero: through organizational learning (β = 0.117, 95% CI [0.059, 0.185]), through decision-making agility (β = 0.066, [0.028, 0.115]) and through the serial path from learning to agility (β = 0.037, [0.018, 0.061]). The total indirect effect (β = 0.220) is larger than the direct effect (β = 0.172), and both are significant and positive. Following Zhao et al. (2010), this pattern indicates complementary partial mediation; the variance accounted for (VAF) is 56.1%. H7a, H7b and H7c are supported. Organizational learning carries the largest share of the indirect effect. (Tab. 6)

Table 6: Specific, total indirect and total effects of AI capabilities on innovation performance.

Hypothesis	Effect	β	t	95% CI	Result
H7a	AIC → OL → INP	0.117	3.62	[0.059, 0.185]	Supported
H7b	AIC → DMA → INP	0.066	2.96	[0.028, 0.115]	Supported

H7c	AIC → OL → DMA → INP	0.037	3.30	[0.018, 0.061]	Supported
—	Total indirect effect	0.220	6.15	[0.158, 0.294]	Significant
—	Direct effect (AIC → INP)	0.172	2.84	[0.051, 0.287]	Significant
—	Total effect	0.392	7.89	[0.293, 0.488]	VAF = 56.1%

Predictive power and importance–performance map

PLSpredict shows that all Q²predict values for the innovation-performance indicators are positive (0.072–0.146), so the model outperforms the naïve mean benchmark. Prediction errors were approximately symmetric, so the RMSE was compared with the linear regression benchmark: the PLS-SEM model produces lower RMSE for all five indicators (Tab. 7), which indicates high out-of-sample predictive power (Shmueli et al., 2019).

Table 7: Explanatory and predictive power of the model.

Endogenous construct / indicator	R^2	R^2adj	Q²predict	RMSE (PLS)	RMSE (LM)	MAE (PLS)	MAE (LM)
Organizational learning (OL)	0.207	0.205	-	-	-	-	-
Decision-making agility (DMA)	0.328	0.324	-	-	-	-	-
Innovation performance (INP)	0.291	0.279	-	-	-	-	-
INP1	-	-	0.110	1.260	1.301	1.034	1.057
INP2	-	-	0.146	1.228	1.256	0.994	1.026
INP3	-	-	0.100	1.311	1.341	1.057	1.082
INP4	-	-	0.114	1.300	1.341	1.055	1.082
INP5	-	-	0.072	1.279	1.316	1.043	1.065

The IPMA Figure 3 shows that AI capabilities have the highest importance for innovation performance (total effect = 0.472) but the lowest performance among the constructs (56.9 on a 0–100 scale), whereas organizational learning combines high importance (0.351) with the highest performance (59.0). Among the AI-capability dimensions, AI governance and intangible resources show the lowest performance (56.5) with an importance (0.167) comparable to that of data and technology infrastructure (0.162). Improving AI capabilities particularly their governance and data dimensions, therefore offers the largest marginal gain in innovation performance. (Fig. 3)



Figure 3: Importance–performance map for innovation performance (construct and AI-capability dimension level).

RESULTS AND CONCLUSION

Theoretical implications

The findings answer RQ1 by showing that AI capabilities improve the innovation performance of urban management organizations, extending firm-level evidence (Mikalef & Gupta, 2021; Rammer et al., 2022) and recent municipal evidence on performance (Mikalef et al., 2023) to public innovation. The direct effect is modest, however, and most of the total effect (56.1%) passes through organizational processes. This supports the resource-based and dynamic-capabilities argument that resources create value

through the routines that deploy and reconfigure them (Barney, 1991; Teece et al., 1997), and it is consistent with reports that public AI initiatives often fail to scale when they remain technology projects (Madan & Ashok, 2023; Neumann et al., 2024). For RQ2, organizational learning is the dominant mediator. AI capabilities strengthen the acquisition, interpretation and transfer of knowledge, which in turn supports innovation (Huber, 1991; Jiménez-Jiménez & Sanz-Valle, 2011). This result qualifies the concern that algorithmic decision-making may crowd out human learning (Balasubramanian et al., 2022): in the studied organizations, AI appears to complement rather than substitute learning. Decision-making agility is a second, independent channel, consistent with arguments that AI augments human judgment and accelerates decisions (Jarrahi, 2018; Shrestha et al., 2019). The significant serial path shows that learning precedes agility; fast decisions are most valuable when they rest on accumulated organizational knowledge (Eisenhardt, 1989). Integrating the two mechanisms in one model is a contribution beyond studies that examine either learning or decision-making alone (Trunk et al., 2020).

Practical implications

Three implications follow for municipal leaders, answering RQ3. First, the IPMA identifies AI capabilities, and especially their governance and data dimensions, as the priority area: their importance is high but their performance is the lowest. Municipalities should invest in shared data platforms, interoperability standards and clear rules for AI risk, accountability and procurement (Desouza et al., 2020; Wirtz et al., 2019). Second, because learning carries the largest indirect effect, AI programs should be designed as learning programs: projects should include structured experimentation, after-action reviews and mechanisms that transfer insights across departments (Jerez-Gómez et al., 2005). Third, agile governance practices—cross-functional teams, iterative development and delegated decision rights—are needed so that AI-generated insights reach decisions quickly (Mergel et al., 2021; Selten & Klievink, 2024). Collaboration with universities, firms and citizens can further widen the innovation potential of urban AI (Torfing, 2019; Yigitcanlar et al., 2020).

This study examined how AI capabilities affect innovation performance in urban management organizations and the mediating roles of organizational learning and decision-making agility. PLS-SEM analysis of 312 managers and experts showed that AI capabilities, conceptualized as a higher-order bundle of data and technology infrastructure, human skills and governance resources, have a significant direct effect on innovation performance and stronger indirect effects through organizational learning, decision-making agility and the serial path linking them. Together, the mediators account for 56.1% of the total effect, and the model shows both explanatory and out-of-sample predictive power. The central conclusion is that AI creates innovation value in city administrations when it is embedded in learning routines and agile decision processes, not when it is deployed as a standalone technology. The study also has limitations. The cross-sectional, self-reported design limits causal inference, although procedural and statistical checks suggest that common method bias is not a serious concern. The sample covers five Iranian metropolises, so generalization to other administrative and cultural contexts requires caution. Future research should use longitudinal or multi-source designs, include objective innovation indicators, compare municipalities across countries with multigroup analysis, and examine moderators such as data governance maturity, political support and citizen trust.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used Claude (Anthropic) to improve the language and readability of the manuscript, to assist in structuring the text and drafting the graphical

abstract and highlights, and to write the Python scripts used to estimate the PLS-SEM model. After using this tool, the authors reviewed and edited the content as needed, verified all references and statistical results, and take full responsibility for the content of the publication.

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