

Determinants and Challenges of Artificial Intelligence Adoption in Public Sector Governance: A Systematic Review

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ABSTRACT

Governments continue to invest heavily in Artificial Intelligence, yet uptake across public sector organisations remains uneven and often stalls well short of policy targets. This review examines why, drawing on 68 empirical studies published between January 2020 and December 2025 and screened under PRISMA 2020. An integrated Technology-Organisation-Environment-Individual (TOE-I) framework, combining TOE with the Unified Theory of Acceptance and Use of Technology (UTAUT), was used to organise the determinants and challenges reported across this body of work. Data quality and availability, leadership commitment, and trust in AI systems emerged as the most consistently cited determinants, alongside system compatibility, digital literacy, and interoperability. On the challenges side, organisational barriers dominate the corpus, ahead of technological, individual, and environmental barriers with legacy system integration, bureaucratic inertia, algorithmic bias, cultural resistance, and regulatory uncertainty recurring across contexts. Read together, these patterns suggest that AI adoption in government is less a technology problem than an organisational and human one: the tools exist, but the institutional conditions to use them well often do not. The TOE-I structure developed here gives policymakers and public sector managers a shared vocabulary for diagnosing where their own agencies stand and where intervention would matter most.

Keywords: Artificial Intelligence Adoption; Public Sector Governance; Technology-Organisation-Environment Framework; Unified Theory of Acceptance and Use of Technology (UTAUT); Digital Government Transformation

INTRODUCTION

Artificial Intelligence (AI) is emerging as a transformative force with the potential to enhance operational efficiency, service delivery, and evidence-based policymaking in government sectors worldwide (Dwivedi et al., 2021; Wirtz et al., 2019). Governments globally are exploring AI applications for diverse purposes, including intelligent traffic management, automated fraud detection, predictive healthcare analytics, and citizen-centric virtual assistants (World Bank, 2021). These technological advancements align with national strategic initiatives that position AI as a cornerstone of governance excellence (Malaysian Administrative

Modernisation and Management Planning Unit, 2021; Ministry of Science, Technology and Innovation, 2021; Prime Minister's Office of Malaysia, n.d.).

Despite strong policy frameworks and strategic intentions, a persistent gap remains between the aspiration to adopt AI and its practical implementation in public sector organisations globally. The World Bank (2021) identifies this phenomenon as the "AI adoption lag," observed in both developed and developing countries, raising critical questions about the conditions necessary for successful AI uptake. In developing economies, this gap is compounded by lower baseline knowledge and readiness among the citizens and officials who interact with government-initiated AI services (Lartey et al., 2025). This implementation gap is particularly concerning given the substantial government investments in digital transformation initiatives.

The implementation challenge is intrinsically linked to the unique institutional setting of the public sector, which differs fundamentally from the private sector. Government adoption motivations extend beyond efficiency gains, profitability, and competitive advantage (Janssen et al., 2020). They encompass bureaucratic structures, strict accountability requirements, transparency imperatives, and a focus on creating public value rather than maximising profits (Janssen et al., 2020). Private sector models inadequately capture the distinctive characteristics of public sector adoption, which operates within complex, multi-stakeholder environments with emerging regulatory pressures and associated ambiguities.

Existing information systems research offers valuable insights into technology adoption processes within organisations. The Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) and the Technology-Organisation-Environment (TOE) model (Tornatzky & Fleischer, 1990) have been successfully applied to predict traditional technology adoption in government contexts (Liang et al., 2021; Wang & Shih, 2009). However, these established models require adaptation when applied to AI, which presents novel challenges distinct from traditional technology adoption, including algorithmic transparency, ethical governance, human-AI collaboration, and algorithmic accountability (Wirtz et al., 2019).

Recent academic research has increasingly addressed contextual issues and offers multidisciplinary assessments of AI's social impact (Dwivedi et al., 2021). While these contributions are valuable, the academic literature lacks a systematic and comprehensive aggregation of technological, organisational, environmental, and individual factors and their interrelationships within a coherent evidence base. This research gap is particularly significant because it leaves policymakers without a comprehensive, evidence-informed pathway to bridge the aspiration-implementation divide.

This systematic review aims to address this gap by synthesising empirical evidence on the determinants and challenges of AI adoption across public sector organisations worldwide. The review is organised around two research questions:

RQ1: What are the primary factors driving AI adoption in public sector governance?

RQ2: What are the main challenges to AI adoption?

Beyond its academic contribution, this review offers practical guidance for public sector policymakers and managers. By systematically mapping the current landscape of AI integration in public governance, it provides evidence-informed recommendations to overcome challenges and strategically allocate resources for AI adoption.

LITERATURE REVIEW

Theoretical Framework

Multiple complementary theoretical frameworks inform the understanding of technology adoption in organisational contexts. The Technology-Organisation-Environment (TOE) framework, proposed by Tornatzky and Fleischer (1990), offers a holistic perspective on adoption decisions from three angles: technological attributes, organisational resources and capabilities, and environmental pressures and

opportunities. This framework has been extensively adopted in studies of technology use in the public sector (Liang et al., 2021; Wang & Shih, 2009).

The **technological dimension** refers to innovation characteristics, including compatibility, complexity, relative advantage, and observability. In the context of AI, technological factors also encompass data quality, system interoperability, algorithmic reliability, and scalability, which influence AI systems' ability to operate effectively within government infrastructures.

The **organisational dimension** reflects internal features affecting adoption decisions, such as leadership commitment, financial resources, organisational culture, and technical expertise. Public sector organisations often face constraints in this dimension due to budgetary limitations, hierarchical decision-making structures, and cultures resistant to innovation.

The **environmental dimension** incorporates external factors including regulatory requirements, stakeholder expectations, competitive pressures (including the influence of other jurisdictions), and interorganisational relationships. For public sector organisations, environmental factors include policy mandates, citizen expectations, and partnerships with technology vendors and research institutions.

The Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) complements the TOE framework by emphasising individual-level factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions that influence technology acceptance. UTAUT has demonstrated strong predictive capability across multiple technologies and settings but requires adaptation for AI to address psychological concerns specific to AI systems, including trust in automation, job displacement anxiety, and confidence in algorithmic judgment (Dwivedi et al., 2021).

Recent theoretical extensions have incorporated constructs such as perceived intelligence, anthropomorphism, and trust in automation to capture the distinctive nature of human-AI interaction dynamics (DePietro et al., 1990). These extensions acknowledge AI systems' unique capabilities to learn, adapt, and make autonomous decisions, which fundamentally shift user expectations and usage patterns.

Recent scholarship has recognised the need for an integrated framework that combines TOE and UTAUT to address both organisational and individual dimensions of AI adoption in the public sector (Hržica et al., 2025). This integrated Technology-Organisation-Environment-Individual (TOE-I) framework provides a more comprehensive lens for understanding the multi-level nature of AI adoption, acknowledging that technological, organisational, and environmental factors interact with individual-level psychological and behavioural factors to shape adoption outcomes.

Distinctive Public Sector Context

The public sector presents a unique and complex environment for AI regulation and use, differing significantly from the private sector, where profit and market competition are primary drivers. The public value mandate for public organisations calls for balancing the drive for technology efficiency with other core values in governance, such as accountability, openness and equity (Cordella & Tempini, 2015; Janssen & van den Hoven, 2015). These inherent pressures shape the adoption process. Furthermore, selecting and implementing is always a lengthy exercise due to the multi-centric nature of public sector decision-making in which many actors with different agendas are involved (Mergel et al., 2019).

Legacy information systems are often monolithic and are not so interoperable as to be able to be used by today's data-driven AI systems, which are a serious technical challenge and integration problem (Giest, 2017). A prevailing culture of risk aversion exists because public managers face direct political and public scrutiny for errors, making them reluctant to experiment with novel approaches (Klievink et al., 2017). These challenges are compounded by the rapidly evolving regulatory environment for algorithmic governance, including emerging standards for ethics and equity. This requires legal and technical skills, something that is generally not available in government bodies (European Commission, 2019; Wirtz et al., 2019).

The public sector also differs from the private sector in terms of accountability structures. Public organisations are accountable to citizens, elected officials, and multiple oversight bodies, creating complex layers of approval and scrutiny that can slow adoption processes. Additionally, public sector procurement processes are often rigid and slow-moving, making it difficult to acquire and implement cutting-edge AI technologies in a timely manner.

Review Methods

Research Design and Protocol

This systematic review followed the PRISMA 2020 guidelines (Page et al., 2021) that have been widely acknowledged to be the most accepted framework for systematic reviews and are highly transparent, rigorous and comprehensive. Before carrying out the study, the protocol for the systematic review was devised, defining the goals of the research, inclusion and exclusion criteria, searching strategy, data extraction and analysis techniques. The protocol development has helped to reduce any possible researcher bias in conducting the research.

The systematic approach was particularly suited to this study's interdisciplinary nature, spanning public administration, information systems, computer science, and policy studies, enabling integration of evidence from across these fields to identify the diverse factors contributing to AI adoption in public sector governance.

Search Strategy and Information Sources

Four databases were searched: Scopus, Web of Science, IEEE Xplore, and the ACM Digital Library, selected for their complementary coverage of artificial intelligence adoption and public sector research across multidisciplinary, technical, and human-computer interaction perspectives. The search string, adapted to each database, was: TITLE-ABS-KEY (("artificial intelligence" OR "machine learning" OR "AI system" OR "algorithm governance" OR "smart government") AND ("public sector" OR "government" OR "public administration" OR "ministry" OR "public service") AND ("adoption" OR "implementation" OR "diffusion" OR "acceptance" OR "challenges" OR "determinant" OR "factor")). The search was limited to peer-reviewed journal articles published between January 2020 and December 2025. An additional 18 records were identified through reference-list snowballing. The search returned 1,214 records; after duplicate removal, records proceeded to title and abstract screening.

Eligibility Criteria and Study Selection

Inclusion and exclusion criteria were carefully developed to guarantee methodological rigour and to limit the scope of studies to those most relevant to the research goals. Studies were eligible if they:

1. Presented empirical research on AI adoption in public sector organisations (central ministries, local authorities, public agencies).
2. Were published in peer-reviewed journals between January 2020 and December 2025.
3. Were written in English.
4. Presented original research (not theoretical or opinion pieces).
5. Addressed adoption factors rather than focusing exclusively on technical implementation aspects

Studies were excluded if they:

1. Addressed private sector adoption exclusively.
2. Lacked empirical validation (conceptual papers only).

3. Analysed AI applications without discussing adoption processes.
4. Were conference papers, book chapters, or grey literature.
5. Focused exclusively on citizen adoption of AI-based services rather than organisational adoption in government.

Records retrieved from database searches (n=1,214) were imported into Zotero reference management software for deduplication. Automatic duplicate detection was supplemented by manual verification to address metadata variations. After deduplication, 780 unique records remained. Initial screening based on titles and abstracts removed 568 irrelevant records. Two reviewers independently screened each record, with disagreements resolved through discussion. Inter-rater agreement for this stage was 94%. Full-text review was conducted for 212 articles. Of these, 144 were excluded for reasons including: not focusing on the public sector (n=45), not addressing AI/ML technology (n=38), not focusing on adoption factors (n=28), lacking empirical data (n=20), language limitations (n=8), or being irretrievable (n=5). A final corpus of 68 studies satisfying all criteria was included in the qualitative synthesis.

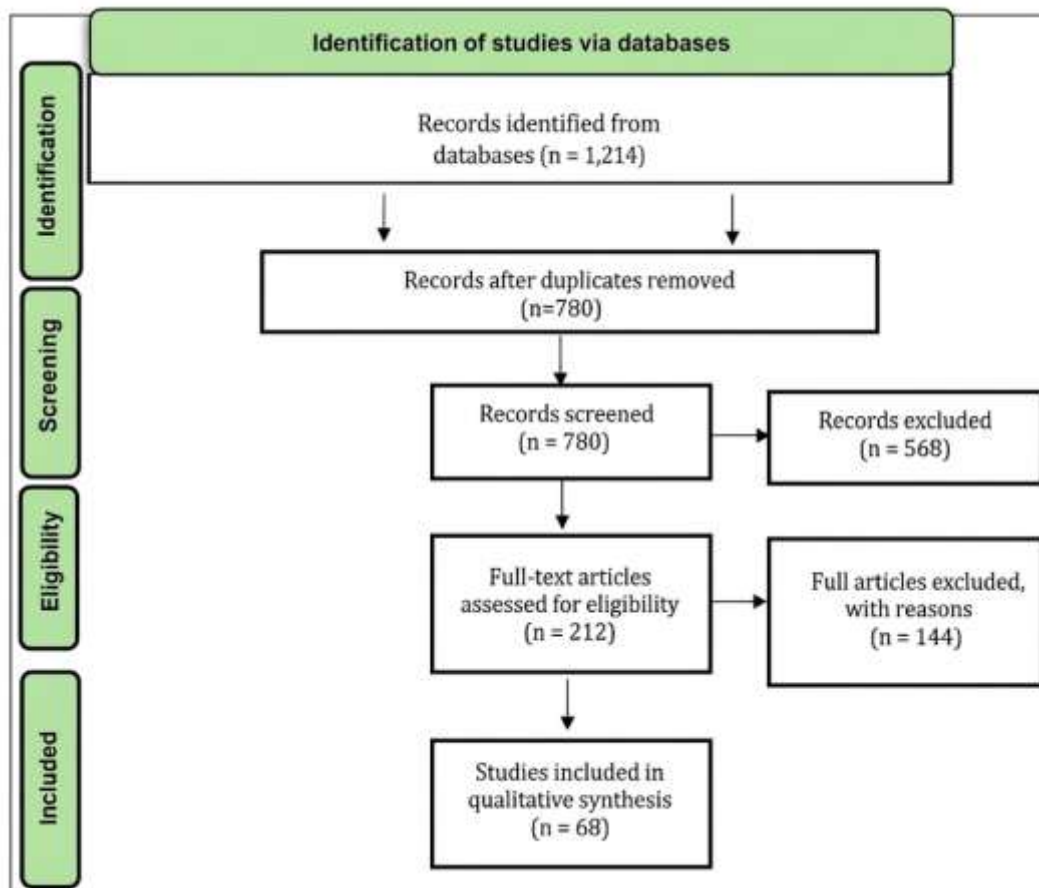


Figure 1: PRISMA Flow Diagram of the Study Selection Process

Data Extraction and Synthesis Methods

A customised data extraction form was developed to ensure consistency and rigour. The form captured: (1) bibliographic information (authors, year, journal, country); (2) methodological aspects (design, sample size, data collection and analysis methods); (3) contextual aspects (organisation type, AI application, development context); (4) adoption determinants and challenges, organised according to the TOE and UTAUT frameworks; (5) theoretical models applied; and (6) key findings and recommendations.

To ensure reliability, two researchers independently extracted data from a randomly selected pilot sample of 20 studies (29.4% of the corpus), achieving 92% agreement. Inter-rater agreement was calculated using Cohen's

kappa ($\kappa = 0.87$), indicating strong agreement beyond chance. Disagreements were resolved through discussion and refinement of extraction criteria before proceeding with full data extraction.

Thematic analysis was conducted following the procedures outlined by Braun and Clarke (2006): familiarisation with data, initial coding, theme generation, theme refinement, and theme finalisation. Deductive coding was guided by the TOE and UTAUT frameworks, while sub-themes were identified inductively from recurring patterns in the data. A determinant was counted as present if it was explicitly discussed as influencing AI adoption in the study's findings or discussion section. Multiple determinants could be coded from a single study. For challenges, each study was classified according to its most salient reported challenge, with exclusive categorisation resulting in proportions summing to 100%. Memos were maintained throughout the research process to capture theoretical insights and emerging concepts. Comparative analyses were conducted across methodology and study characteristics.

RESULTS

Overview of Included Studies

The synthesis is based on 68 empirical studies spanning diverse geographical and methodological contexts. Studies originated from 34 countries across six continents, with the majority from developed countries (42 studies, 61.8%) and the remainder from developing countries (26 studies, 38.2%). Methodologically, studies comprised 32 quantitative designs (47.1%, primarily surveys), 28 qualitative designs (41.2%, mainly case analyses, interviews, and document analysis), and 8 mixed-methods designs (11.8%).

The public sector contexts studied were national ministries ($n=24$, 35.3%), municipal governments ($n=18$, 26.5%), specialised agencies ($n=16$, 23.5%) and cross-sectoral activities ($n=10$, 14.7%). The applications of AI included in the responses were predictive analytics ($n=22$, 32.4%), chatbots or virtual assistants ($n=15$, 22.1%), computer vision ($n=10$, 14.7%), automated decision systems ($n=12$, 17.6%) and other specialised tools ($n=9$, 13.2%). This variety of contexts and applications supports a synthesis that provides a variety of perspectives on adoption dynamics in different implementation contexts.

Table 1. Characteristics of included studies ($n=68$).

Characteristic	Category	Number	Percentage
Geographical Focus	Developed Countries	42	61.80%
	Developing Countries	26	38.20%
Research Method	Quantitative	32	47.10%
	Qualitative	28	41.20%
	Mixed Methods	8	11.80%
Public Sector Context	National Ministries	24	35.30%
	Local Governments	18	26.50%
	Specialised Agencies	16	23.50%
	Cross-sectoral	10	14.70%
AI Application Type	Predictive Analytics	22	32.40%
	Chatbots/Virtual Assistants	15	22.10%

	Automated Decision Systems	12	17.60%
	Computer Vision	10	14.70%
	Other	9	13.20%

Determinants of AI Adoption in Public Sector Governance

Table 2 presents the key determinants of AI adoption by category, reporting frequency of mention across the 68 included studies. It is important to note that these frequencies reflect how often a determinant was mentioned as a factor influencing AI adoption in the included studies. Multiple determinants could be coded from a single study, and these figures represent presence in literature, not necessarily effect magnitude or importance. A determinant was counted as present if it was explicitly discussed as influencing AI adoption in the study's findings or discussion section.

Technological Determinants:

Data quality and availability was the most frequently cited technological determinant, mentioned in 89.7% of studies (61/68), underscoring the critical importance of high-quality, accessible, and well-governed data for AI system performance (Mikalef et al., 2022). System compatibility followed at 85.3% (58/68) (Neumann et al., 2024), indicating the necessity of AI products functioning within existing technical infrastructure. Interoperability is the ability of AI systems to share and understand data across different government databases, legacy systems, and departmental information systems, and was identified as a key dimension in 79.4% of studies (54/68) (Giest, 2017; Janssen et al., 2020). Demonstrated reliability was cited in 76.5% of studies (52/68) (Mikalef et al., 2023), highlighting the need for consistent and accurate AI performance to foster institutional trust. Scalability was mentioned in 69.1% of studies (47/68) (Mikalef et al., 2022), reflecting concerns about extending pilot projects to enterprise-wide implementations.

Organisational Determinants:

Leadership commitment emerged as the most frequently cited organisational determinant (88.2%, 60/68) (Selten & Klievink, 2024), indicating the vital role of executive buy-in in shaping strategic priorities and resource allocation. Dedicated funding for AI initiatives was emphasised in 80.9% of studies (55/68) (Andersson et al., 2025). Internal expertise development was cited in 77.9% (53/68) (van Noordt & Tangi, 2023), reflecting the clear need to build technical capacities within public sector workforces. Structured change management approaches addressing organisational transition and employee resistance were noted in 70.6% of studies (48/68) (Maragno et al., 2023), highlighting the importance of change management strategies.

Individual Determinants:

Trust in AI systems was the most frequently cited individual determinant (86.8%, 59/68) (Selten et al., 2023), indicating concerns about algorithmic reliability, transparency, and accountability. Digital literacy followed at 82.4% (56/68) (Kumar et al., 2025), highlighting the digital skills and confidence required for public servants to effectively engage with AI technologies.

Environmental Determinants:

Policy mandates were identified as influential in 73.5% of studies (50/68) (European Commission, 2023). Public-private partnerships were also prominent (66.2%, 45/68) (Horani et al., 2023), demonstrating the importance of collaboration with technology providers and research institutions. Citizen expectations (61.8%, 42/68) (Geske & Leyer, 2022) and peer influence from other jurisdictions (57.4%, 39/68) (Rodriguez Müller et al., 2025) showed significant variation across studies.

Table 2. Key determinants of AI adoption by category.

Category	Determinant	Frequency	Exemplar Study
Technological	Data Quality & Availability	61/68 (89.7%)	Mikalef et al. (2022)
	System Compatibility	58/68 (85.3%)	Neumann et al. (2024)
	Interoperability	54/68 (79.4%)	Giest (2017); Janssen et al. (2020)
	Demonstrated Reliability	52/68 (76.5%)	Mikalef et al. (2023)
	Scalability	47/68 (69.1%)	Mikalef et al. (2022)
Organisational	Leadership Commitment	60/68 (88.2%)	Selten and Klievink (2024)
	Dedicated Funding	55/68 (80.9%)	Andersson et al. (2025)
	Internal Expertise	53/68 (77.9%)	van Noordt and Tangi (2023)
	Change Management	48/68 (70.6%)	Maragno et al. (2023)
Individual	Trust in AI Systems	59/68 (86.8%)	Selten et al. (2023)
	Digital Literacy	56/68 (82.4%)	Kumar et al. (2025)
Environmental	Policy Mandates	50/68 (73.5%)	European Commission (2023)
	Public-Private Partnerships	45/68 (66.2%)	Horani et al. (2023)
	Citizen Expectations	42/68 (61.8%)	Gesk and Leyer (2022)
	Peer Influences	39/68 (57.4%)	Rodriguez Müller et al. (2025)

Challenges to AI Adoption

Table 3 summarises the primary challenges to AI adoption reported across the four TOE-I dimensions, alongside their relative share of the 68 included studies.

Table 3. Primary challenges to AI adoption by category.

Dimension	Share of Studies	Key Challenges Reported	Representative Sources
Organisational	24/68 (35.3%)	Bureaucratic inertia; resource limitations; cultural resistance to change; change-management capacity constraints	Andersson et al. (2025); Maragno et al. (2023); Selten and Klievink (2024)
Technological	19/68 (27.9%)	Legacy system integration; data quality challenges; interoperability issues	Giest (2017); Mikalef et al. (2022); Neumann et al. (2024)
Individual	15/68 (22.1%)	Trust deficits; digital literacy gaps; resistance to change among public servants	Kumar et al. (2025); Selten et al. (2023)
Environmental	10/68 (14.7%)	Regulatory uncertainty; ethical concerns (incl. algorithmic bias); external pressures	European Commission (2023); Horani et al. (2023); Rodriguez Müller et al. (2025)

Figure 2 presents the same distribution of primary AI adoption challenges across the four TOE-I categories graphically. Each study was classified according to its most salient reported challenge, with exclusive categorisation resulting in proportions summing to 100%.

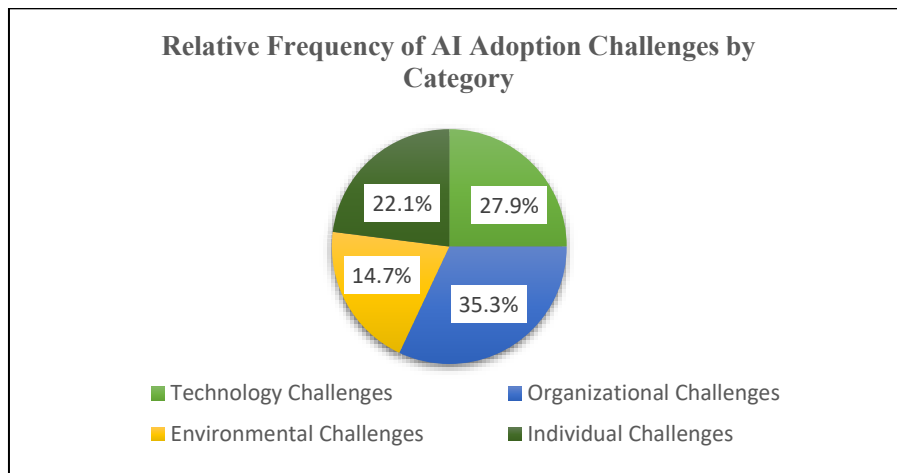


Figure 2. Relative frequency of AI adoption challenges by category.

Organisational challenges constituted the largest proportion of primary challenges (35.3% of studies, n=24). These challenges encompass bureaucratic inertia, resource limitations, cultural resistance to change, and capacity limitations in change management (Andersson et al., 2025; Maragno et al., 2023; Selten & Klievink, 2024).

Technological challenges followed as the primary category in 27.9% of studies (n=19), including legacy system integration, data quality challenges, and interoperability issues (Giest, 2017; Mikalef et al., 2022; Neumann et al., 2024).

Individual challenges accounted for 22.1% (n=15), relating to trust in AI systems, digital literacy deficits, and resistance to change among public servants (Kumar et al., 2025; Selten et al., 2023).

Environmental challenges represented the smallest category at 14.7% (n=10), including regulatory uncertainty, ethical concerns, and external pressures (European Commission, 2023; Horani et al., 2023; Rodriguez Müller et al., 2025).

This distribution indicates that institutional and cultural factors typically present greater challenges in the adoption process than technical factors alone. The substantial proportion of individual challenges highlights the pivotal role of human factors, including trust, digital literacy, and public officials' capacity for organisational change.

DISCUSSION

Key Determinants and Challenges

The findings from this systematic review reveal a multifaceted landscape of factors influencing AI adoption in public sector governance across technological, organisational, environmental, and individual dimensions. The consistently emphasised importance of data quality (Mikalef et al., 2022), system compatibility (Neumann et al., 2024), and system interoperability (Giest, 2017; Janssen et al., 2020) as enablers of AI adoption aligns with prior research on technology implementation in complex organisational settings. Data quality and availability emerged as the most frequently cited technological factor (89.7%), underscoring the foundational importance of high-quality, accessible, and well-managed data for AI system implementation (Mikalef et al., 2022). System compatibility (85.3%) (Neumann et al., 2024) and interoperability (79.4%) (Giest, 2017; Janssen et al., 2020) followed closely.

However, technological readiness alone does not ensure successful implementation. Leadership commitment (88.2%) (Selten & Klievink, 2024), dedicated funding (80.9%) (Andersson et al., 2025), change management approaches (70.6%) (Maragno et al., 2023), and internal expertise development (77.9%) (van Noordt & Tangi, 2023) emerged as consistently critical organisational components of successful adoption. This reflects the resource-intensive nature of AI implementation and the importance of strategic prioritisation at the highest levels of public sector organisations. The prominence of policy mandates (73.5%) (European Commission, 2023) and public-private partnerships (66.2%) (Horani et al., 2023) as environmental drivers suggest that external pressures and collaborative arrangements significantly influence adoption decisions.

The analysis of human dimensions of AI adoption identified two critical individual-level determinants: trust (86.8%) (Selten et al., 2023) and digital literacy (82.4%) (Kumar et al., 2025). This emphasis on individual-level factors, reflected in the 22.1% of studies identifying individual challenges as primary (Figure 2), underscores that human readiness and confidence in AI technologies are integral to any adoption strategy. This finding has important implications for capacity-building efforts. Targeted training programmes integrating technical skills with ethical awareness addressing algorithmic accountability, bias mitigation, and appropriate scope of automated decision-making are essential to prepare public servants for AI adoption (Kumar et al., 2025; Selten et al., 2023).

Organisational challenges constituted the largest proportion of challenge mentions (35.3%), encompassing bureaucratic inertia, resource limitations, and cultural resistance to change. This predominance indicates that institutional constraints may be more critical than technical issues in the adoption process (Maragno et al., 2023; Selten & Klievink, 2024). This connects to the concept of institutional 'embeddedness' with the ways organisational structures, risk-averse cultures, and complex change management requirements within public sector environments shape adoption trajectories. Environmental issues (14.7%), while less frequently identified as primary challenges, remain important, with policy mandates (73.5%) (European Commission, 2023) and public-private partnerships (66.2%) (Horani et al., 2023) emerging as significant environmental drivers that both pressure organisations to adopt and present regulatory challenges to overcome.

Theoretical Implications

This review has several theoretical implications for AI adoption in public sector governance. First, the need to extend existing adoption models with AI-specific constructs is evident. Traditional models such as UTAUT (Venkatesh et al., 2003) and TOE (Tornatzky & Fleischer, 1990) require adaptation to account for AI-specific challenges, including algorithmic accountability, trust in automation, explainability, and human-AI collaboration dynamics (Dwivedi et al., 2021; Wirtz et al., 2019). Interoperability as a distinct technological determinant (79.4% of studies) (Giest, 2017; Janssen et al., 2020) indicates that the technological dimension of the TOE framework should distinguish between general system compatibility and specific interoperability requirements of public sector AI systems. This distinction arises because government data silos, legacy systems, and departmental platforms introduce integration challenges qualitatively different from those found in the private sector.

The need for a dual-level analytical approach is clear (Hržica et al., 2025). The Technology-Organisation-Environment-Individual (TOE-I) framework, integrating TOE with UTAUT, provides a more comprehensive lens for understanding AI adoption. Individual-level factors (trust, digital literacy) interact with organisational determinants (leadership, resources, culture) and environmental pressures (policy mandates, partnerships) in ways that cannot be fully understood at any single level but require multi-level analysis (Selten & Klievink, 2024; Selten et al., 2023).

Second, the value of institutional theory in accounting for regulatory, normative, and cultural aspects of AI adoption is highlighted. Institutional theory, focusing on coercive (regulatory), mimetic (peer influence), and normative (professional standards) pressures (European Commission, 2023; Horani et al., 2023; Rodriguez Müller et al., 2025), offers a useful perspective on technology adoption. This is particularly relevant given the role of policy mandates (73.5%), peer influences (57.4%) in adoption decision-making.

Third, the need to conceptualise adoption as a continuum rather than a binary choice is evident. The literature reveals different levels of AI integration, ranging from pilot projects and specific applications to enterprise-wide adoption and institutionalisation (Mikalef et al., 2022; Neumann et al., 2024). This perspective helps organisations identify their current stage in the adoption process and appropriate strategies for progression.

Limitations

Two methodological boundaries of this review should be acknowledged, as they shape how the findings ought to be interpreted and applied.

First, the eligibility criteria restricted inclusion to peer-reviewed journal articles, deliberately excluding conference papers, book chapters, and grey literature such as government white papers, consultancy reports, and agency implementation reports (Section 3.3). This decision was made to preserve the methodological consistency and quality-control standards associated with peer review, which is particularly important given that AI adoption is a fast-moving practice area where non-peer-reviewed sources vary widely in rigour.

Second, the synthesis reports the *frequency* with which each determinant or challenge was identified across the 68 included studies (Table 2; Figure 2), rather than a pooled *effect size* or a statistically validated measure of each factor's impact on public sector performance outcomes. This descriptive, vote-counting approach was adopted because the corpus is methodologically heterogeneous: the majority of included studies employ qualitative or mixed-methods designs with differing operationalisations of the same construct (for example, "trust" is measured through survey scales in some studies and through interview coding in others), which precludes a formal meta-analysis of standardised effect sizes.

Future Research Directions

Building on the determinants, challenges, and limitations identified above, three directions appear particularly well positioned to advance both the theoretical and the practical value of this line of research.

First, comparative empirical studies that examine AI adoption across different administrative cultures and political systems, particularly contrasting developing and developed nations, would help establish which determinants identified in this review are context-general and which are context-specific. The present corpus is drawn predominantly from institutional settings in developed economies; emerging evidence suggests that adoption dynamics in developing-country public sectors are shaped by additional constraints around baseline digital readiness and institutional capacity (Lartey et al., 2025), and cross-national comparative designs are needed to test whether the TOE-I determinants identified here generalise across federal versus unitary systems, and across varying levels of civil service digitalisation.

Second, longitudinal qualitative case studies that track the long-term effectiveness of change management strategies and internal AI expertise development within specific agencies would address a gap that cross-sectional survey and interview designs, which dominate the current corpus, cannot close. Such case studies could follow individual public sector organisations through successive stages of AI adoption, from pilot to institutionalisation (Mikalef et al., 2022; Neumann et al., 2024), to clarify which change-management interventions (Maragno et al., 2023) and capability-building approaches (van Noordt & Tangi, 2023) produce durable improvements in staff trust and system use, as opposed to short-term compliance that fades once initial implementation pressure subsides.

Third, there is a clear opportunity to develop and psychometrically validate a quantitative AI-readiness measurement scale grounded in the TOE-I framework proposed in Section 5.2, building on preliminary dual-level readiness models that combine TOE and UTAUT constructs (Hržica et al., 2025). A validated instrument spanning the technological, organisational, environmental, and individual dimensions identified in this review would allow public sector organisations to empirically benchmark their internal AI readiness prior to deployment, track readiness over time, and compare readiness across agencies or jurisdictions in a standardised way, directly addressing the descriptive-to-diagnostic gap noted in Section 5.3.

CONCLUSION

This systematic review synthesises evidence from 68 empirical studies to identify key determinants and challenges influencing AI adoption in public sector governance. The literature reveals a multi-dimensional landscape shaped by technological, organisational, environmental, and individual factors. Key facilitators of adoption include leadership commitment (reported in 88.2% of studies), trust in AI systems (86.8%), data quality and availability (89.7%), system compatibility (85.3%), digital literacy (82.4%), and interoperability (79.4%). Key challenges encompass legacy system integration, resource constraints, bureaucratic inertia, ethical concerns, algorithmic bias, cultural resistance to change, and regulatory uncertainty.

The predominance of organisational challenges (35% of studies) indicates that institutional and cultural challenges often pose more significant impediments than technical limitations during the adoption process. These findings underscore that successful AI implementation requires addressing not only technical integration but also the organisational, cultural, and ethical dimensions of change.

Key priorities for public sector organisations include: fostering multi-layered trust through transparent governance and explainable AI systems (Selten et al., 2023); investing in human capital development through training programmes combining technical proficiency with ethical awareness (Kumar et al., 2025); establishing robust ethical standards and regulatory frameworks that balance innovation with public value protection (European Commission, 2023); prioritising interoperability and data governance to overcome legacy integration challenges (Giest, 2017; Janssen et al., 2020); building strong leadership commitment and dedicated funding mechanisms (Andersson et al., 2025; Selten & Klievink, 2024); and implementing comprehensive change management strategies that address employee resistance and cultural adaptation (Maragno et al., 2023).

By adopting a multi-dimensional approach that integrates technological, organisational, individual, and environmental considerations, governments can more effectively navigate the complexities of AI implementation to enhance governance efficiency and improve public service delivery.

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