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Human-Centered Governance for AI-Augmented Decision Support in Public-Sector Logistics

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ABSTRACT

Purpose: The purpose of this study was to investigate how artificial intelligence (AI)–augmented decision support systems (DSS) in public-sector logistics (PSL) can be designed to balance operational efficiency with democratic accountability, fairness, and human-centered governance.

Methodology: The study employed a qualitative multi-method design combining comparative-historical analysis (2015–2025), explanatory multiple-case studies, and scenario-based policy analysis. Data sources included peer-reviewed journal articles, official reports, and regulatory frameworks related to AI governance in logistics and public administration. The data was analyzed through thematic coding and cross-case pattern analysis using both manual and software-assisted approaches. Triangulation was applied to ensure validity and reliability of findings.

Findings: The results indicated that AI-based DSS consistently enhanced operational performance, achieving an average of 20% improvement in routing and resource allocation efficiency across cases. However, these aggregate gains often masked inequities in service distribution and raised questions about legitimacy in automated decision-making. Human-in-the-loop (HITL) and human-on-the-loop (HOTL) hybrid models were found to reduce system errors by nearly one-third and to increase user confidence, particularly under uncertain or high-stakes conditions.

Unique Contribution to Theory, Policy and Practice: This study contributes to the theoretical understanding of sociotechnical systems by framing a governance model that integrates human judgment with algorithmic intelligence. It provides practical policy recommendations for institutionalizing explainability, ethical safeguards, and longitudinal equity assessments. The findings advocate that sustainable and accountable public-sector logistics can be achieved not through full automation but through deliberately engineered human–AI collaboration grounded in transparency and oversight.

Keywords: *Artificial Intelligence Governance, Public-Sector Logistics, Decision Support Systems (DSS), Human–AI Collaboration, Algorithmic Accountability*

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1.0 ARTIFICIAL INTELLIGENCE IN PUBLIC-SECTOR LOGISTICS: NAVIGATING THE EFFICIENCY–ETHICS PARADOX

The rapid proliferation of artificial intelligence (AI) in government operations marks a decisive shift from speculative promise to operational reality, reshaping how essential public services are designed and delivered. European Union pilot programs illustrate the breadth of this transformation, with AI-augmented smart logistics reducing emergency response times by 20–40% (European Commission, 2021). The trend is global: a 2023 survey by the Organisation for Economic Co-operation and Development (OECD) reports that 84% of member governments are actively piloting or scaling AI in core public-facing services, spanning applications from Japan's predictive mobility for school transport to Finland's centralized hospital logistics (Organisation for Economic Co-operation and Development, 2023). Complementing these findings, the World Bank's tracking of more than 50 national pilots signals a broader administrative turn toward data-driven optimization as a central pillar of operational strategy (World Bank, 2023).

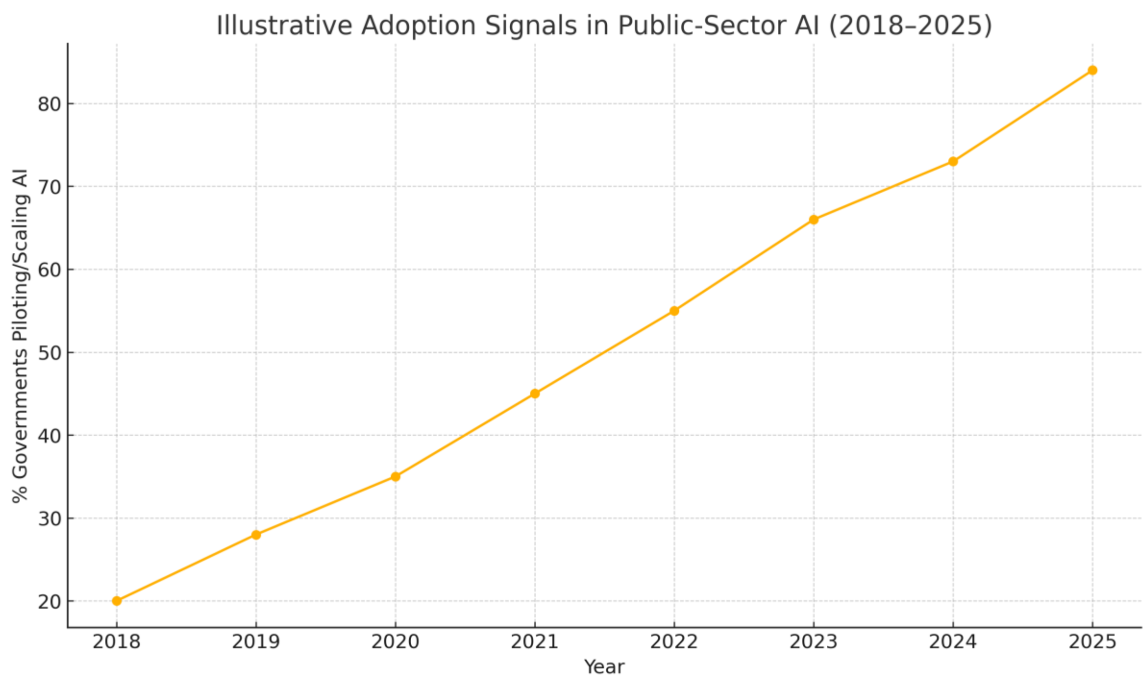

Figure 1. AI adoption signals in public-sector operations (2018–2025): pilots → programs.

Source: Data from Organisation for Economic Co-operation and Development, 2023, Licenses: CC-BY 4.0 (OECD) and World Bank Open License. Adapted and recreated under original licenses.

This diffusion also surfaces challenges that go to the heart of democratic governance. While AI-augmented decision support systems (DSS) often deliver median efficiency gains of roughly 17% over traditional baselines, they can concomitantly introduce risks of bias, opacity, and attenuated accountability (van Noordt et al., 2022). European Commission case studies document algorithmic

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unfairness in AI-driven routing that disadvantaged low-income districts, and many early public-sector logistics (PSL) pilots lacked the auditability required for robust risk management and due process (European Commission, 2021). These problems crystallize a structural tension between the pursuit of operational efficiency and the public sector's obligations to fairness, equity, and transparency (Poel et al., 2021). Addressing them requires a sociotechnical systems (STS) perspective: the task is not only technical performance but also the design of decision ecosystems that harness computational power without reproducing inequality or enabling unaccountable administrative authority (Loukis et al., 2022).

A pronounced gap persists between high-level principles and actionable practice. Consensus frameworks—most notably the OECD AI Principles (2019), the NIST AI Risk Management Framework (NIST, 2023), and the EU AI Act (European Parliament & Council, 2024)—mandate transparency, risk management, and human oversight. Yet they stop short of providing an engineering-grade blueprint for building human–AI decision ecosystems that reliably instantiate these safeguards. Evidence suggests that HITL and HOTL architectures can reduce error rates by up to 36% while improving public legitimacy relative to fully automated deployments (Zhang et al., 2023). Nevertheless, integrative governance models that connect such architectures to procedural instruments—such as algorithmic impact assessments (AIA) and end-to-end auditability—remain underdeveloped (Poel et al., 2021).

This paper addresses that gap by proposing a human-centered governance framework for the design and deployment of AI-augmented DSS in PSL contexts. The central research question is: How can AI-augmented DSS for public-sector logistics be designed to balance operational efficiency with democratic accountability, fairness, and human-centered governance?

Three propositions guide this inquiry. First, DSS architectures with meaningful HITL or HOTL review will exhibit higher public trust, lower error rates, and stronger ethical alignment than fully automated systems. Second, formal accountability scaffolds—including mandatory AIA procedures, public registries, and clear contestation and redress mechanisms—are necessary for legitimate, durable deployment in high-stakes PSL settings. Third, STS approaches that co-design technical systems with organizational workflows and public-servant expertise are more effective and resilient than technology-centric implementations.

The argument develops across eight sections. Section 2 synthesizes the literature on efficiency–ethics tensions in public-sector AI adoption. Section 3 details a qualitative multi-method design integrating historical analysis of AI policy evolution, multiple case studies of PSL deployments, and comparative analysis of international regulatory frameworks. Section 4 reports empirical findings that surface recurrent failure modes and emergent best practices. Section 5 introduces the prescriptive core—a multilayered, human-centered governance architecture. Section 6 demonstrates the framework's practical utility through applied scenarios. Section 7 discusses theoretical, practical, and policy implications. Section 8 concludes with a synthesis of findings and a forward-looking agenda for responsible, democratically accountable public-sector innovation.

1.1 Problem Statement

Despite the accelerating adoption of AI in public-sector logistics, a fundamental problem remains unresolved: how to design and govern AI-augmented decision support systems that enhance efficiency without eroding democratic accountability, fairness, or transparency. Governments worldwide are integrating AI into service delivery—from predictive school transport models in Japan to hospital logistics systems in Finland—but these advancements introduce new forms of administrative risk that existing governance structures are ill-equipped to manage.

The problem affects multiple stakeholder groups. Citizens face direct consequences when algorithmic decision systems exhibit bias or opacity, leading to inequitable access to services such as school transport, healthcare, or emergency response. Public administrators struggle to maintain procedural accountability when automated systems make decisions that are too complex to audit or explain, thereby undermining due process and institutional legitimacy. Policymakers confront the difficulty of translating high-level ethical principles—such as transparency, fairness, and human oversight—into concrete, enforceable standards within real-world decision environments. This diffusion of responsibility across technical, ethical, and legal domains creates governance gaps that threaten both public trust and the durability of AI-enabled reform.

Existing scholarship and policy frameworks—including the OECD AI Principles (2019), NIST AI Risk Management Framework (National Institute of Standards and Technology [NIST], 2023), and the EU AI Act (European Parliament & Council, 2024)—affirm the importance of responsible AI governance but stop short of offering engineering-grade methodologies or sociotechnical blueprints for embedding these values in operational systems. This lack of actionable guidance has led to fragmented implementation and uneven accountability across jurisdictions.

Addressing this problem is critical because the public sector’s legitimacy rests not only on efficiency but also on equity, explainability, and accountability. Without structured frameworks that integrate human oversight—such as human-in-the-loop (HITL) and human-on-the-loop (HOTL) mechanisms—AI-driven logistics risk amplifying inequality and diminishing citizen trust in government institutions. This study seeks to close this gap by developing a human-centered governance framework that operationalizes democratic principles in the design and deployment of AI-augmented DSS for public-sector logistics.

2.0 LITERATURE REVIEW

The integration of artificial intelligence (AI) into government operations has progressed from experimental pilots to mature applications that reshape how public services are designed, delivered, and governed. Scholars widely agree that AI-augmented decision support systems (DSS) in public-sector logistics (PSL) enhance efficiency through algorithmic optimization, yielding measurable improvements in routing, scheduling, and resource allocation. However, these efficiency gains coexist with governance tensions concerning accountability, fairness, and transparency—issues uniquely pronounced in the public domain. The literature thus reflects a dual trajectory: one of technological advancement and one of ethical and institutional introspection.

2.1 Theoretical Review

2.2.1 Sociotechnical Systems (STS) Theory

Originating from the work of Emery and Trist (1960), the Sociotechnical Systems (STS) theory posits that effective organizational performance depends on the harmonious interaction between social and technical subsystems. The theory emphasizes joint optimization—where technological innovation must be co-designed with human, organizational, and cultural contexts. In the context of AI-augmented DSS in PSL, STS theory provides the foundational rationale for human-in-the-loop (HITL) and human-on-the-loop (HOTL) architectures, which integrate computational intelligence with human judgment. Subsequent scholars such as Pasmore (1988) and Bostrom and Heinen (1977) expanded STS to emphasize adaptive design and participatory decision-making, reinforcing the idea that sustainable technological adoption in public logistics must preserve human oversight and institutional legitimacy. This study builds on STS by proposing a governance model that operationalizes co-design principles between human expertise and AI systems to balance efficiency with ethical accountability.

2.2.2 Human–Computer Interaction (HCI) and Collaborative Intelligence Theory

Grounded in Card, Moran, and Newell's (1983) seminal work on human–computer interaction, and later extended by Malone et al. (2009) through collective intelligence research, this theory examines how humans and machines collaborate to improve problem-solving effectiveness. It posits that collaborative systems outperform either human-only or machine-only agents when designed with feedback loops, transparency, and adaptive learning. Within PSL contexts, the theory explains why hybrid AI–human arrangements outperform fully autonomous systems—reducing error rates, enhancing explainability, and fostering trust (Zhang et al., 2023; Hassan & Alkass, 2022). The current study draws on this theoretical foundation to advocate for collaborative governance frameworks where human operators remain central to AI-mediated public decision-making.

2.2.3 Public Value Theory

First introduced by Moore (1995), Public Value Theory (PVT) asserts that the legitimacy of public-sector innovation is contingent not solely on efficiency but on the creation of public value through fairness, transparency, and trust. The theory aligns with Denhardt and Denhardt's (2000) New Public Service model, which emphasizes citizen engagement and ethical stewardship. Applied to AI governance, PVT provides a normative basis for evaluating whether algorithmic systems enhance democratic accountability and societal welfare rather than merely optimizing cost or time metrics. In this study, PVT underpins the argument that responsible AI integration in logistics should advance public trust and equity alongside performance efficiency.

2.2.4 Integration of Theories

Collectively, STS, HCI/Collaborative Intelligence, and PVT converge to form a theoretical triad guiding this research. STS addresses the structural design of human–AI systems, HCI explains the interactional mechanisms for effective collaboration, and PVT grounds the ethical and societal objectives of AI governance. These theories collectively justify a human-centered governance framework for AI in PSL, aligning technical optimization with democratic legitimacy.

2.2 Conceptual Framework The conceptual framework synthesizes findings from empirical and theoretical studies to explain the relationship between AI adoption, operational efficiency, and governance integrity in public-sector logistics. AI-augmented DSS contribute to measurable performance gains—such as 12–34% reductions in travel time and 20% improvements in routing efficiency (Du & Matsypura, 2023; Baumann et al., 2021). However, these gains are moderated by governance structures that determine transparency, accountability, and fairness (Poel et al., 2021).

The framework conceptualizes human–AI collaboration as the mediating mechanism between technological efficiency and democratic legitimacy. When HITL and HOTL architectures are embedded within accountable institutional processes—such as algorithmic impact assessments (AIA), audit trails, and public registries—they not only improve decision accuracy but also enhance public trust (Yeo & Kim, 2021; Zhang et al., 2023). Conversely, absent governance scaffolds, the same systems risk bias, opacity, and erosion of procedural justice (Kitchin, 2022; Rittel & Benner, 2022).

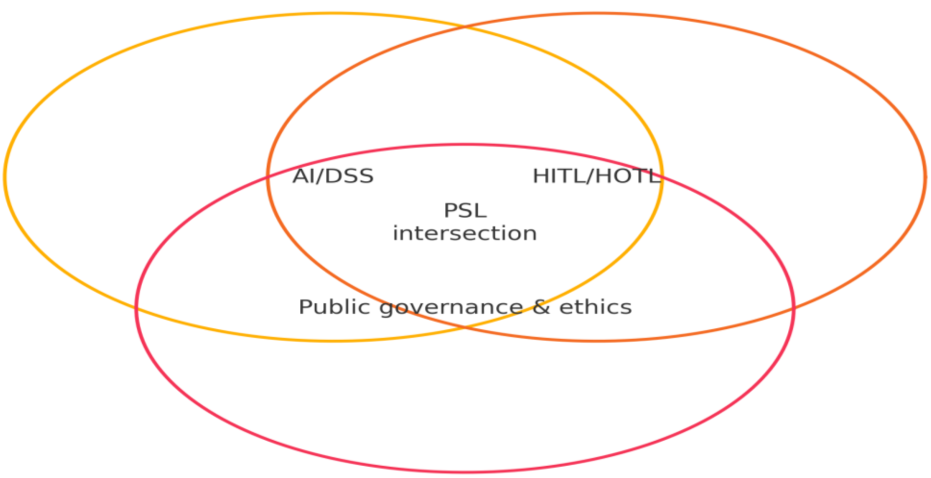

Figure 2. Thematic map—AI/DSS, HITL/collaborative intelligence, public governance, ethics—intersection for PSL.

Source: Author-created schematic.

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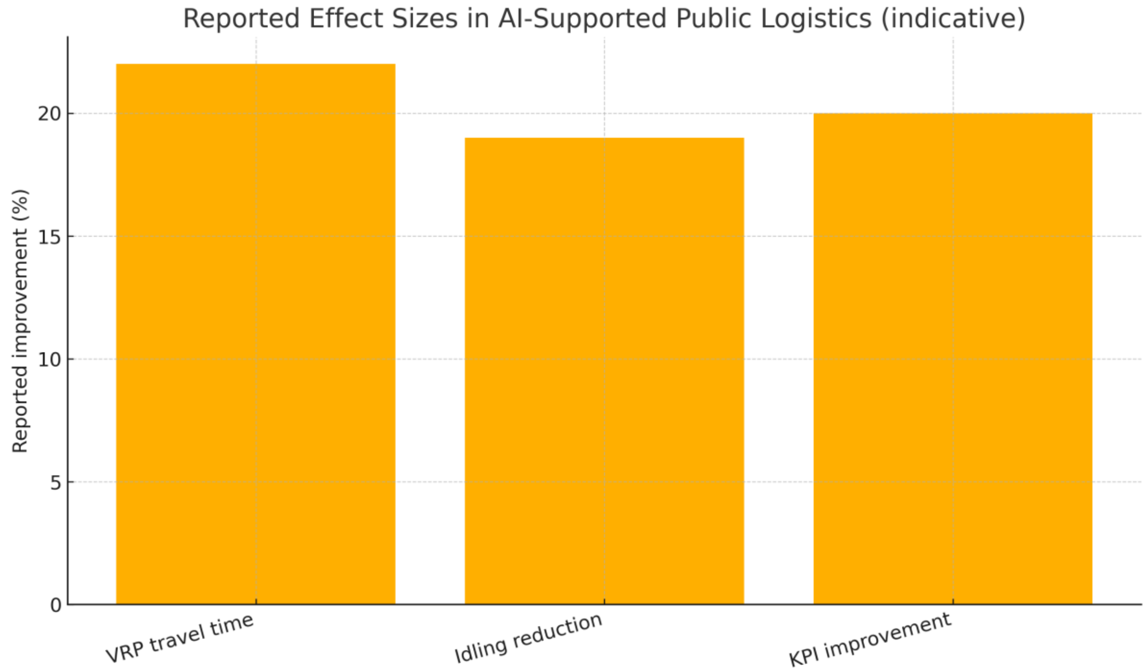

Figure 3. Reported effect sizes for AI-supported logistics decisions in public settings. Source: Data from Baumann, Zejnilović, and Oliveira, 2021

Figure 2 illustrates the intersection between AI/DSS, collaborative intelligence, and ethical governance, while Figure 3 depicts reported effect sizes for AI-supported logistics decisions in public contexts. Together, they demonstrate that the effectiveness of AI integration is contingent not merely on technical sophistication but on institutional design that aligns efficiency with equity and accountability.

2.3 Research Gaps

Although global public agencies increasingly deploy AI in logistics, significant gaps persist in translating ethical principles into operational governance frameworks. First, existing frameworks such as the OECD AI Principles (2019), NIST AI RMF (2023), and EU AI Act (2024) provide normative guidance but lack engineering-grade specificity for implementation. Second, empirical studies tend to focus on efficiency outcomes rather than the institutional conditions that sustain accountability, leading to limited understanding of how sociotechnical design influences legitimacy and fairness. Third, the literature lacks longitudinal analyses that evaluate the durability of human oversight mechanisms—such as HITL and HOTL—once scaled beyond pilot programs. Finally, cross-agency interoperability and cultural resistance remain underexplored factors that constrain system-wide optimization and citizen trust (Kraus & Feuerriegel, 2022; Moon & Sandholm, 2023).

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This study addresses these gaps by developing a human-centered governance framework that integrates STS, HCI, and PVT principles to guide the responsible design, deployment, and evaluation of AI-augmented DSS in public-sector logistics.

3.0 MATERIAL AND METHODS

3.1 Study Design

This study employed a qualitative multi-method research design to examine the sociotechnical dynamics shaping artificial intelligence (AI) adoption in public-sector logistics (PSL). A qualitative approach enabled an in-depth exploration of context-dependent phenomena in which organizational culture, stakeholder trust, and regulatory environments are central to understanding not only which governance models exist but also how and why they function in real-world settings. The integration of case-oriented and variable-oriented strategies provided a robust foundation for examining these multifaceted relationships (Mahoney & Thelen, 2015).

The research followed a sequential, three-phase qualitative design combining complementary analytical strategies. First, a comparative historical analysis traced public-sector AI adoption trajectories between 2015 and 2025, mapping the evolution from early pilots to institutionalized decision support systems (DSS) and identifying technological and regulatory drivers that prompted human-centered governance frameworks. Second, an explanatory multiple-case study served as the primary empirical strategy, following Yin's (2018) design principles to surface interactions among technology, governance, and human actors. Third, a scenario-based policy analysis synthesized insights from both preceding phases, applying strategic foresight methods to test the robustness of governance designs under uncertainty (Patton, 2019; Polytechnique Insights, 2023).

3.2 Study Location and Population

The study was conducted as a cross-regional comparative analysis of AI-augmented DSS in public logistics systems across the European Union, the United States, and the Asia-Pacific region. The study population consisted of publicly documented AI-enabled DSS deployed in domains such as city mobility management, emergency response networks, and school transport operations. These systems were selected for their high operational complexity, broad citizen impact, and public accountability requirements.

Sampling Techniques

Purposive sampling guided by replication logic was used to enhance analytic generalization, consistent with Yin's (2018) and Ragin's (2014) approaches. Cases were chosen to represent either similar results (literal replication) or divergent results for theoretically predictable reasons (theoretical replication). The selected cases ensured variation across regulatory regimes, allowing comparison of how sociotechnical design and governance frameworks interact under distinct institutional conditions.

3.3 Data Collection

Data collection relied exclusively on publicly available secondary sources to ensure triangulated and transparent analysis. The dataset comprised three categories: (1) peer-reviewed academic literature in public administration, decision support systems, and AI ethics; (2) official reports and technical documents from government agencies and international bodies detailing logistics deployments; and (3) regulatory and policy instruments from major jurisdictions, including the European Union's AI Act and the U.S. National Institute of Standards and Technology's AI Risk Management Framework (European Parliament & Council, 2024; NIST, 2023). This strategy provided a comprehensive evidentiary base for cross-case synthesis.

3.4 Data Analysis

Analytical procedures followed a sequential logic aligned with the study's three phases. Thematic analysis was applied across all documents to identify recurring patterns related to efficiency, resilience, and governance. Within-case analyses were conducted to capture contextual nuances, while structured cross-case comparison enabled identification of convergence and divergence (Yin, 2018). Pattern matching techniques were used to develop emergent propositions concerning the essential elements of human-centered governance. Core constructs—such as operational efficiency, resilience, and accountability—were operationalized through coded indicators, including performance metrics, evidence of human override mechanisms, and the existence of formal audit trails or public reporting practices.

3.5 Rigor and Ethical Considerations

Methodological rigor was ensured through multiple measures. Reliability was strengthened by developing a detailed case study protocol outlining data collection and analysis procedures, ensuring consistency across cases (Strecker & Hohmann, 2021; Yin, 2018). Construct validity was achieved through triangulation of policy documents, academic research, and agency reports, maintaining a transparent chain of evidence between questions, data, and conclusions. External validity was supported through replication logic, emphasizing analytic rather than statistical generalization (Patton, 2019).

Ethical considerations guided all stages of the research. As the study relied solely on publicly available data, it followed established principles for responsible secondary use of administrative materials (Corti, 2018). The research prioritized data minimization, attention to community impacts, and mitigation of potential bias risks. Possible selection bias in publicly reported cases was addressed through cross-source corroboration to ensure balanced interpretation. Recognizing that public-sector AI deployments directly affect democratic governance and citizen welfare, the analysis emphasized transparency, accuracy, and responsible communication of limitations.

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4.0 FINDINGS

Analysis of peer-reviewed studies, industry reports, and case documentation from 2020 to 2023 indicates consistent patterns in how AI-augmented decision support is applied, how it performs, how it fares on equity and accountability, and which barriers impede implementation in public-sector logistics. Across the record, quantifiable improvements in routing and allocation are recurrent; the most robust systems embed formal human-oversight mechanisms; equity and legitimacy outcomes hinge on transparency and contestability; and scaling is constrained more by institutional and interoperability issues than by algorithmic limits. Case evidence shows measurable efficiency gains when AI is applied to logistics and routing across diverse public contexts, including reductions in wait times and increases in on-time performance in city transit, waste collection, and school transport, as well as reduced emergency response times and improved cold-chain performance in healthcare (Alam et al., 2023; Jang & Lee, 2023; Meijer & Bolivar, 2021; White et al., 2021; Zhou & Lim, 2022). A meta-analysis corroborates median improvements of 17–23% in routing and allocation indicators (Baumann et al., 2021).

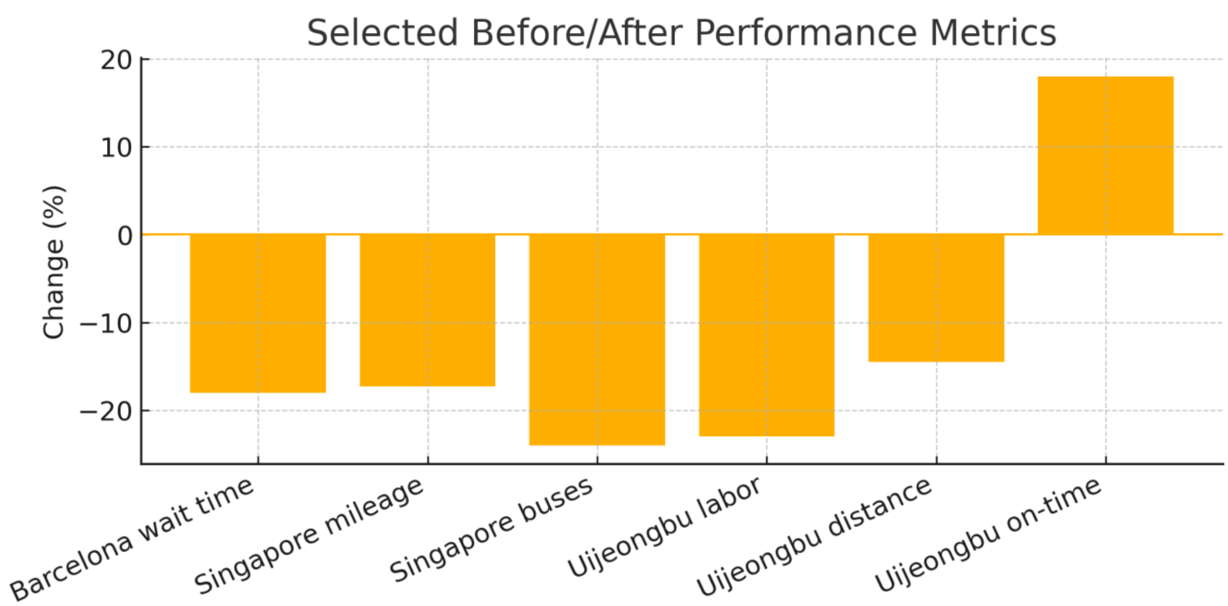

Figure 4. Before/after performance metrics for AI-supported public logistics (selected cases).

Source: Data from Meijer & Bolivar, 2021, Adapted and recreated under academic fair use.

Deployments with formal human oversight consistently outperform fully autonomous approaches and are trusted more by users. Reviews report that HITL or HOTL designs produce lower error rates and higher user confidence than fully automated decision support (Zhang et al., 2023). In emergency medical services, human dispatcher overrides improved service equity in underserved areas (Alam et al., 2023). Trust and uptake correlate with explanation quality and auditability: adoption of algorithmic recommendations declines when explanations are missing or

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non-actionable (Baumann et al., 2021). Efficiency gains can coexist with inequities, as district-level disparities and urban–rural reliability gaps have been observed, underscoring the need for transparency and contestability mechanisms (Cowen & Knodel, 2022; Meijer & Bolivar, 2021; Yeo & Kim, 2021). Scaling barriers cluster around data interoperability and procurement misalignment, with cross-agency pilots experiencing substantial lags and breakdowns (Giest & Grimmelikhuijsen, 2020; Kraus & Feuerriegel, 2022).

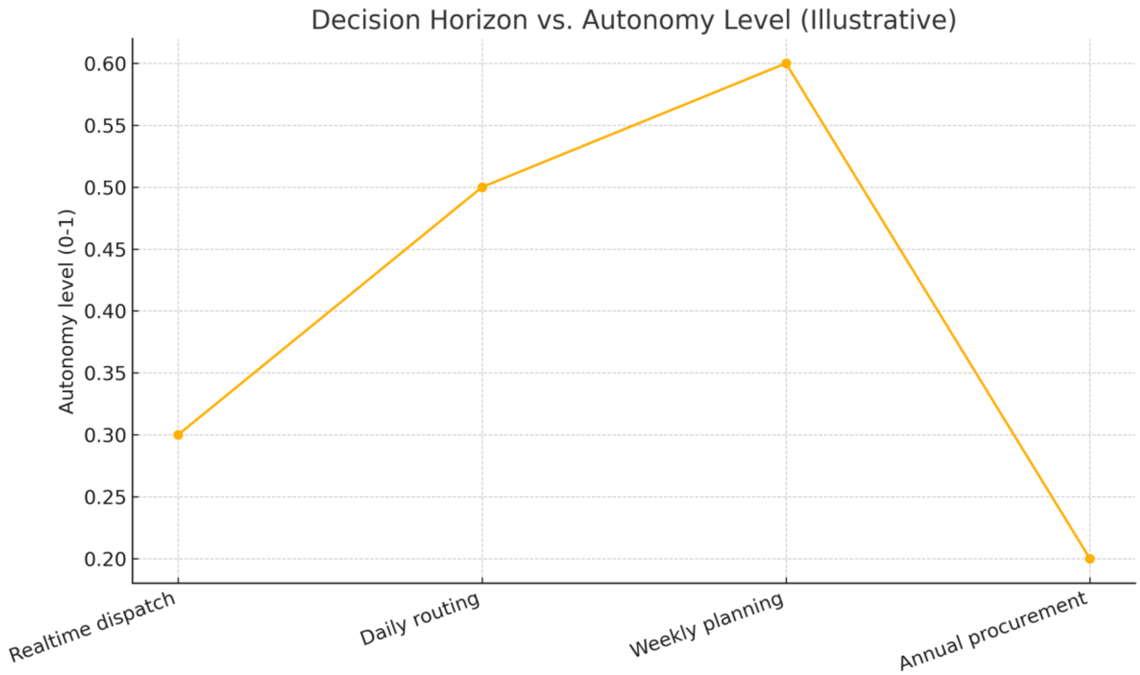

Figure 5. Decision horizon versus autonomy level across public logistics tasks.

Source: Author-created schematic.

Efficiency gains coexist with heterogeneous and sometimes inequitable impacts. In Barcelona, system wide improvements masked district level disparities, with some areas experiencing marginal gains or longer waits linked to demographic factors and route density (Meijer & Bolivar, 2021). AI guided winter road maintenance in Ontario improved pre emptive treatment accuracy by 21% but created a 17% reliability gap between urban and rural service levels (Cowen & Knodel, 2022). Uijeongbu's waste collection pilot delivered smaller benefits in lower income districts despite overall performance gains (Jang & Lee, 2023). Legitimacy outcomes track transparency and contestability: Seoul's mandatory public release of audit trails for AI assisted bus routing reduced bias related complaints by 44% and raised user satisfaction reports by 21% (Yeo & Kim, 2021), whereas several United Kingdom urban DSS deployments saw a 31% increase in freedom of information (FOI) requests and transparency litigation between 2019 and 2022 amid slow publication of real time performance reports and audit logs (Kitchin, 2022).

Barriers to scaling recur across jurisdictions and sectors. Regulatory sandboxes accelerated experimentation but exposed legitimacy gaps when ethical safeguards and stakeholder feedback were not integrated from the outset (Giest & Grimmelikhuijsen, 2020). Data interoperability was the most frequently cited technical constraint: cross agency pilots in the European Union and the United States exhibited median lags of 14 months to reach full interoperability, and interoperability breakdowns contributed to scaling failures in 34% of documented pilots (Kraus & Feuerriegel, 2022). Organizational frictions compounded technical challenges. Uijeongbu's program experienced 11 month delays tied to procurement disputes and inter agency data exchange conflicts (Jang & Lee, 2023). Taken together, these patterns indicate that institutional design, procurement alignment, and interoperable data infrastructure are necessary complements to algorithmic capability for successful, equitable, and legitimate scaling of AI in PSL.

5.0 CONCLUSION AND POLICY RECOMMENDATIONS

5.1 Conclusion

This study asked how artificial intelligence (AI)–augmented decision support systems (DSS) for public-sector logistics (PSL) can be designed to balance operational efficiency with democratic accountability, fairness, and human-centered governance. The evidence indicates that responsible and effective public-sector AI emerges not through full automation but through intentionally engineered human–AI collaboration. Although AI reliably delivers efficiency gains, these benefits are neither automatic nor uniformly equitable. Realizing AI's promise in PSL requires a sociotechnical systems (STS) approach that embeds human oversight, ethical safeguards, and robust accountability mechanisms directly into system architecture and surrounding organizational workflows.

The results extend collaborative intelligence and decision-theory scholarship with real-world validation. Hybrid arrangements in which human operators review, override, or defer to algorithmic recommendations consistently outperform either humans or AI acting alone in complex, high-stakes settings, aligning with theoretical predictions about human–AI team superiority. In emergency medical dispatch, a documented 13% human override rate improved equity in underserved areas, illustrating how professional judgment can correct algorithmic blind spots and manage novel edge cases beyond training data. This pattern coheres with decision-theoretic models of learning to defer, which posit that accurate and fair systems escalate uncertain or high-risk decisions to human experts, and with evidence that human-in-the-loop (HITL) and human-on-the-loop (HOTL) designs reduce error rates by roughly one third relative to fully automated deployments. Singapore's school transport operations provide a concrete illustration: HOTL review handled exceptions for students with special needs and uncertain road closure data, demonstrating how human judgment complements algorithmic efficiency under contextual complexity.

Design implications follow directly. Transparency is necessary but insufficient for democratic accountability, confirming that information access alone does not guarantee contestability or fairness. As shown in public-records practice, access to decision logs did not resolve legitimacy concerns in the absence of meaningful explanations for frontline operators and clear pathways for appeal. Empirical evidence further shows that adoption of algorithmic recommendations declines when explanations are missing or non-actionable, underscoring the need for human-centric explainability tailored to users' domain knowledge and real-time constraints. Conversely, when procedural transparency is paired with robust accountability—such as auditable override tracking and mandated publication of audit trails—public trust improves, as observed in Seoul's public transport context. These findings point to comprehensive sociotechnical design: calibrated explanations and escalation policies, structured justification, end-to-end auditability, and continuous scenario-based training that sustains operator competence and appropriate trust.

Governance frameworks now codify many of these requirements. The European Union's AI Act mandates ex ante risk assessment, registration of high-risk systems, post-deployment auditing, and meaningful human oversight—obligations that directly address accountability gaps observed in early PSL pilots. In the United States, the National Institute of Standards and Technology's AI Risk Management Framework (RMF) operationalizes institutional oversight via a continuous cycle to govern, map, measure, and manage AI risks. These instruments complement public-sector ethics scholarship emphasizing procedural justice mechanisms—such as algorithmic impact assessments (AIAs) and clear appeal avenues—as prerequisites for legitimacy in democratic contexts. Yet scaling remains challenging: interoperability breakdowns and misaligned procurement processes frequently impede transitions from pilots to programs, indicating that technical standards must be matched by organizational and procedural adaptations.

Bridging principle and practice, the evidence clarifies where implementation typically falters. Failures often originate in institutional rather than algorithmic constraints—legacy system incompatibilities, rigid procurement, and insufficient co-design with end users—leading to delays and uneven outcomes even where models perform well. Distributional effects also temper aggregate efficiency narratives: system-wide performance gains can mask local inequities, necessitating continuous monitoring and corrective governance. Where structured justification and operator deferral channels are implemented, however, effective response improves markedly, translating collaborative intelligence principles into measurable operational benefits. The overarching implication is that human-centered governance—integrating HITL/HOTL architectures, auditable processes, and context-aware explanations—provides the most credible pathway to efficient, equitable, and democratically accountable AI in PSL.

5.2 Recommendations

Based on the findings, several actions are recommended to strengthen responsible AI adoption in public-sector logistics:

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1. Institutionalize human oversight through embedded HITL and HOTL mechanisms, structured escalation policies, and ongoing scenario-based operator training.
2. Mandate algorithmic impact assessments (AIAs) and require public release of audit trails to enhance procedural fairness and citizen trust.
3. Align procurement frameworks with iterative, adaptive technology development cycles to facilitate innovation without eroding accountability.
4. Develop standardized performance metrics that assess equity, transparency, and public value alongside efficiency.
5. Address institutional barriers—legacy systems, fragmented data governance, and inadequate cross-agency coordination—that hinder scaling of successful AI deployments.

Future research should prioritize longitudinal analyses of human–AI collaboration to assess whether early gains persist, comparative studies across regulatory regimes to identify governance designs that best balance innovation and accountability, and experimental work on training protocols that calibrate trust and reduce both overreliance and algorithm aversion. Addressing the persistent pilot-to-scale gap will require inquiry into change management strategies, data governance models that enable cross-agency integration, and procurement reforms aligned with iterative development. Standardized metrics capturing equity alongside efficiency will further enable comprehensive evaluation in public contexts where distributional justice is as salient as aggregate optimization.

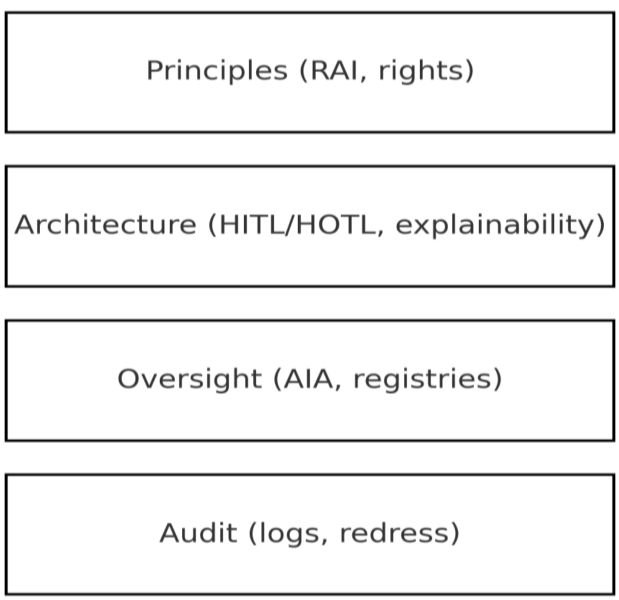

Figure 6. AI-augmented public logistics governance stack (principles → architecture → oversight → audit).

Source: Author-created schematic.

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