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INTEGRATING ARTIFICIAL INTELLIGENCE IN PENTAHELIX COLLABORATIVE GOVERNANCE: ADDRESSING POVERTY TARGETING GAPS IN DKI JAKARTA

INTEGRAÇÃO DA INTELIGÊNCIA ARTIFICIAL NA GOVERNANÇA COLABORATIVA DO PENTAHELIX: COMBATE À POBREZA E SUBLIMINAÇÃO DAS LACUNAS NA ATUAÇÃO EM DKI JACARTA

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Abstract
Urban poverty in rapidly urbanizing metropolitan areas requires coordinated, data-driven interventions involving multiple stakeholders. Although DKI Jakarta has achieved poverty rates below the national average (declining from 4.44% to 4.28% in 2024–2025), inequality remains high (Gini ratio 0.441), accompanied by targeting gaps in which 5.5% of priority beneficiaries are not reached due to data fragmentation and weak inter-agency coordination. This study explores the strategic integration of artificial intelligence (AI) within collaborative governance frameworks to improve poverty targeting accuracy and multi-stakeholder coordination in DKI Jakarta, focusing on the operationalization of the pentahelix model. Using a qualitative descriptive approach, data were collected through semi-structured interviews, focus group discussions, and document analysis involving government, private sector, academia, civil society, and community actors. Data analysis employed NVivo 12 with first-level coding based on

Resumo
A pobreza urbana em áreas metropolitanas em rápida urbanização requer intervenções coordenadas e baseadas em dados, envolvendo múltiplas partes interessadas. Embora a Região de Jacarta (DKI Jakarta) tenha alcançado taxas de pobreza abaixo da média nacional (diminuindo de 4,44% para 4,28% em 2024–2025), a desigualdade continua elevada (índice de Gini de 0,441), acompanhada por lacunas na identificação dos beneficiários, nas quais 5,5% dos beneficiários prioritários não são alcançados devido à fragmentação dos dados e à fraca coordenação interagências. Este estudo explora a integração estratégica da inteligência artificial (IA) em quadros de governação colaborativa para melhorar a precisão da identificação da pobreza e a coordenação entre múltiplas partes interessadas na DKI Jacarta, com foco na operacionalização do modelo penta-hélice. Utilizando uma abordagem descritiva qualitativa, os dados foram recolhidos através de entrevistas semiestruturadas, discussões em grupos focais e

Hymes' SPEAKING model and second-level thematic analysis. The findings indicate that AI-enabled poverty governance functions as a complex sociotechnical system, where AI applications primarily support data infrastructure through deduplication and inter-agency synchronization. Targeting precision emerges from the integration of algorithmic analytics with community-based validation rather than automation alone. However, implementation faces challenges related to data governance, human resource capacity, infrastructure limitations, and digital inequality. The study proposes an AI-Enhanced Pentahelix Collaborative Governance Model, emphasizing that effective AI use depends on institutional capacity building and sustained collaborative processes, with AI serving as an augmentative tool rather than a replacement for human decision-making.

Keywords: Artificial Intelligence. Collaborative Governance. Pentahelix Model. Urban Poverty. Targeting Precision. Data Integration. Metropolitan Governance. Sociotechnical Systems.

análise de documentos envolvendo atores do governo, do setor privado, do meio académico, da sociedade civil e da comunidade. A análise de dados utilizou o NVivo 12 com codificação de primeiro nível baseada no modelo SPEAKING de Hymes e análise temática de segundo nível. Os resultados indicam que a governação da pobreza habilitada pela IA funciona como um sistema sociotécnico complexo, onde as aplicações de IA apoiam principalmente a infraestrutura de dados por meio da deduplicação e da sincronização interagências. A precisão na identificação de alvos resulta da integração da análise algorítmica com a validação baseada na comunidade, em vez de apenas da automação. No entanto, a implementação enfrenta desafios relacionados com a governança de dados, a capacidade de recursos humanos, as limitações de infraestruturas e a desigualdade digital. O estudo propõe um Modelo de Governança Colaborativa Pentahelix Aprimorado por IA, enfatizando que o uso eficaz da IA depende da capacitação institucional e de processos colaborativos sustentáveis, com a IA a servir como uma ferramenta de reforço, em vez de um substituto para a tomada de decisões humanas.

Palavras-chave: *Inteligência Artificial. Governação Colaborativa. Modelo Pentahelix. Pobreza Urbana. Precisão na Identificação. Integração de Dados. Governação Metropolitana. Sistemas Sociotécnicos.*

1 INTRODUCTION

Urban poverty remains one of the most persistent and multidimensional challenges confronting metropolitan governance in the 21st century, particularly in rapidly urbanizing regions of the Global South. The complexity of poverty in urban settings extends beyond mere economic deprivation, encompassing restricted access to basic services, inadequate housing, limited employment opportunities, and systemic social vulnerabilities that demand coordinated, data-driven interventions across multiple stakeholder domains. As articulated in Indonesia's Constitutional mandate under Article 34 of the 1945 Constitution and reinforced through Law No. 13/2011 on Poverty Alleviation, governmental responsibility for addressing poverty transcends moral obligation to become a constitutional imperative requiring systematic, evidence-based implementation.

DKI Jakarta, as Indonesia's capital and most densely populated province with 10,672,100 inhabitants and a population density of 16,146 persons/km², presents a paradoxical case study in urban poverty governance. Despite achieving poverty rates below the national averagedeclining from 4.44% (464,930 individuals) in March 2024 to 4.28% (464,870 individuals) in March 2025the province continues to grapple with persistent inequality, as evidenced by its Gini Ratio increasing from 0.423 in 2024 to 0.441 in 2025, substantially above the national average. This juxtaposition of declining poverty headcount alongside rising inequality underscores a fundamental governance challenge: the effectiveness of poverty interventions is constrained not merely by resource availability, but critically by the precision of targeting mechanisms and the coordination capacity of implementing institutions.

Figure 1

Human Development Index, Percentage of Poor Population, and Gross Regional Domestic Product in DKI Jakarta in 2024

Kab/Kota	IPM	Presentase Penduduk Miskin (%)	Laju Pertumbuhan PDRB Atas Dasar Harga Konstan	Distribusi Persentase PDRB Atas Dasar Harga Berlaku (%)
(1)	(2)	(3)	(4)	(5)
Kepulauan Seribu	75,91	13,13	-7,85	0,24
Jakarta Selatan	86,71	3,10	5,32	22,84
Jakarta Timur	84,26	4,20	5,15	17,07
Jakarta Pusat	83,29	4,68	5,10	24,79
Jakarta Barat	83,85	4,09	5,30	16,87
Jakarta Utara	81,85	6,78	4,16	18,20
DKI Jakarta	83,55	4.44	4,96	16,77

Sumber: Provinsi DKI Jakarta Dalam Angka 2024

The emergence of artificial intelligence (AI) technologies has catalyzed transformative possibilities for urban governance, shifting paradigms from reactive to predictive and from fragmented to integrated decision-making systems. Recent advances in federated learning, multi-agent reinforcement learning (MARL), and knowledge graphs have demonstrated substantial potential for enhancing resource allocation efficiency, beneficiary identification accuracy, and cross-sectoral coordination in social welfare programs. As Lartey and Law (2025) observe, AI adoption in urban planning governance enables collaborative models that integrate technical innovation with ethical values, facilitating data-driven decision-making while maintaining democratic accountability. Similarly, Ghazinoory et al. (2025) systematically document AI's contribution to poverty alleviation through enhanced transparency, improved targeting mechanisms, and optimization of resource distribution across healthcare, education, and social protection sectors.

However, the integration of AI technologies into poverty governance frameworks faces substantial institutional, ethical, and operational challenges. Metropolitan managers frequently lack the technological familiarity and AI literacy necessary for effective implementation (Demirkol, 2025), while concerns regarding data privacy, algorithmic bias, and the digital divide persist as critical barriers to equitable AI adoption (Sanchez et al., 2025; Velmurugan et al., 2025). These challenges are compounded in contexts characterized by fragmented data ecosystems, limited interoperability across governmental agencies, and insufficient capacity for continuous data verification and validationconditions prevalent in DKI Jakarta's current poverty management infrastructure.

The collaborative governance paradigm offers a conceptual framework for addressing these multifaceted challenges by emphasizing cross-sectoral partnerships, shared accountability, and participatory decision-making processes. The pentahelix modelintegrating government, private sector, academia, civil society, and community actorshas emerged as particularly salient for urban poverty interventions, enabling co-creation of solutions that reflect diverse stakeholder perspectives and local contextual realities (Zolkafli & Salleh, 2025; Chougule, 2026). Empirical evidence suggests that multi-stakeholder partnerships enhance transparency, foster public trust, and mitigate the risks of technological determinism by embedding human-centered values within AI-driven governance architectures (Nizamani et al., 2025).

Despite these theoretical advances, significant research gaps persist at the intersection of AI-enabled governance and collaborative poverty alleviation in metropolitan contexts. First, while substantial literature examines AI applications in urban planning and smart city development, limited empirical research addresses the specific mechanisms through which AI technologies can be integrated into collaborative governance frameworks for poverty targeting and intervention coordination. Second, existing studies on collaborative governance in poverty alleviation predominantly focus on conventional coordination mechanisms, with minimal attention to how AI-driven data integration, predictive analytics, and intelligent resource allocation systems can augment multi-actor collaboration. Third, the practical challenges of institutional readiness, capacity building, and ethical AI deployment in resource-constrained metropolitan governments remain underexplored, particularly in Southeast Asian contexts where digital infrastructure, regulatory frameworks, and stakeholder capacities exhibit considerable heterogeneity.

The case of DKI Jakarta exemplifies these tensions with particular acuity. In 2024, the Provincial Government established the Tim Koordinasi Penanggulangan Kemiskinan (TKPKPoverty Alleviation Coordination Team) pursuant to Governor Decree No. 35/2024, implementing dual programmatic streams: household-based integrated social assistance and community empowerment targeting micro and small enterprises. The coordination mechanism relies on the Integrated Social Welfare Data (Data Terpadu Kesejahteraan Sosial/DTKS) as its primary targeting instrument, operationalized through Governor Decree No. 580/2024 which identified 495,272 individuals as priority beneficiaries for extreme poverty elimination efforts. However, monitoring conducted in 2024 revealed that 27,298 individuals within the target population had not received any program interventiona 5.5% coverage gap attributable to data synchronization failures, inadequate cross-agency coordination, and limited real-time verification capabilities.

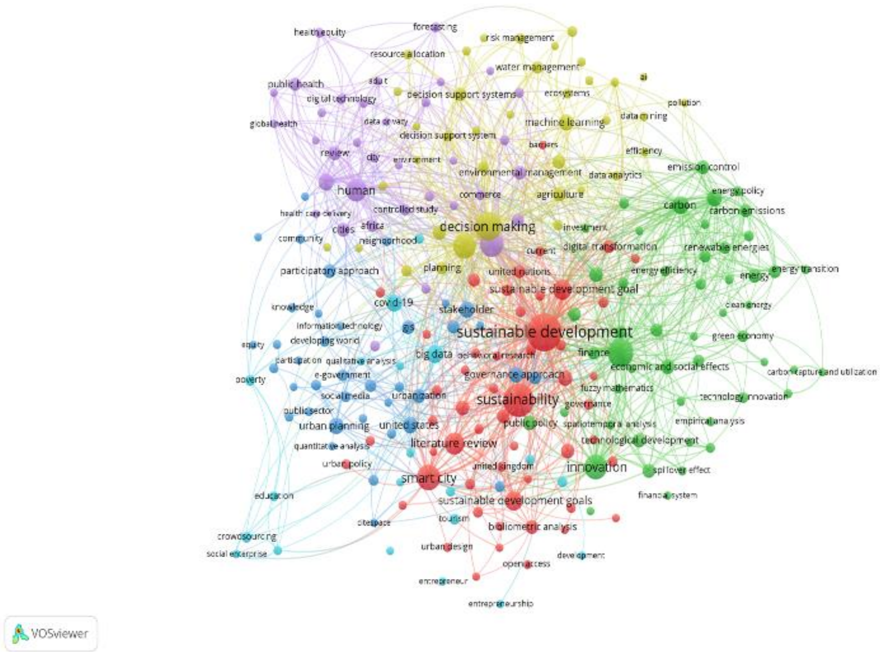
This targeting deficit illuminates a critical governance dilemma: despite substantial budgetary allocations for poverty programs (with 94 programs, 133 activities, 259 sub-activities, and 140 supporting action plans identified in the 2023-2026 Regional Poverty Alleviation Plan), the fragmented nature of data management across multiple agency-level data centers (Pusdatin Bappeda for planning, Pusdatin Sosial for social services, Pusdatin Dukcapil for population administration, and Pusdatin Keluarga for family welfare) impedes the systematic identification of service gaps and the dynamic reallocation of resources to unserved populations. This fragmentation persists despite the implementation of the One Data Indonesia initiative at the provincial level (Governor

Regulation No. 37/2022), which mandates data standardization, metadata harmonization, interoperability, and common reference codes across all governmental agencies.

The convergence of these challenges with recent technological advances presents both an imperative and an opportunity for governance innovation. AI-enabled systemsparticularly those leveraging federated learning for privacy-preserving data integration (Banala et al., 2024), MARL for optimizing multi-objective resource allocation under uncertainty (Wang & Pan, 2025), and knowledge graphs for contextual information structuring (Vakaj et al., 2024)offer potential pathways for addressing Jakarta's poverty targeting gaps while maintaining ethical standards of transparency, accountability, and inclusivity. Furthermore, the integration of blockchain technologies for secure data sharing and auditability (Khan et al., 2024; Bansal & Bhattacharya, 2025) could address prevailing concerns regarding data integrity and inter-agency trust.

Figure 2

Network Visualization



Nevertheless, technological solutions alone are insufficient without corresponding institutional adaptations and collaborative governance mechanisms. As Saxena et al. (2025) demonstrate through comparative analysis of public sector AI implementations, participatory design processes that engage vulnerable populations in system development are essential for fostering trust, ensuring cultural responsiveness, and avoiding the reproduction of existing inequalities through algorithmic decision-making. Similarly, Islam et al. (2026) emphasize the necessity of digital citizen hubs as interfaces between AI-enabled governance systems and community stakeholders, facilitating both service uptake and continuous feedback loops that enable system refinement.

The strategic significance of this research extends beyond Jakarta's immediate context. As metropolitan areas across the Global South confront similar tensions between rapid urbanization, resource constraints, and governance fragmentation, the development of replicable frameworks for AI-enabled collaborative poverty governance assumes broader policy relevance. Juárez-Merino (2025) notes that Latin American governments increasingly recognize AI's potential for enhancing citizenship services and welfare targeting, yet face comparable challenges in institutional capacity, ethical frameworks, and stakeholder coordination. The synthesis of technological innovation with collaborative governance principleswhat Robles and Mallinson (2025) term "adaptive AI governance frameworks"represents a critical frontier for sustainable urban development and social equity.

This study addresses these converging imperatives by examining how artificial intelligence can be strategically integrated within collaborative governance architectures to enhance poverty targeting precision and multi-stakeholder coordination in DKI Jakarta. Specifically, it investigates the mechanisms through which AI-driven data integration, predictive analytics, and intelligent resource allocation systems can augment the operational capacity of the pentahelix model, while identifying the institutional enablers and barriers that condition successful implementation. By developing an empirically grounded framework that synthesizes technological capabilities with participatory governance principles, this research contributes to both theoretical advancement in collaborative governance scholarship and practical innovation in metropolitan poverty alleviation strategies.

2 LITERATURE REVIEW AND THEORETICAL BASIS

The theoretical foundations of this study are anchored in three interconnected domains: the nature of governance in contemporary public administration, the conceptual architecture of collaborative governance as a response to complex policy challenges, and the multidimensional characteristics of urban poverty. These theoretical pillars are further augmented by emerging frameworks addressing AI-enabled governance and intelligent systems integration in metropolitan contexts.

2.1 The nature of contemporary governance

Contemporary governance theory has shifted from hierarchical, state-centered models toward networked and participatory governance arrangements that better address complex policy challenges or "wicked problems," characterized by uncertainty, multiple causal factors, and contested values (Peters & Pierre, 1998; Koppenjan & Klijn, 2004). This transition from government to governance emphasizes horizontal coordination among diverse actors—government agencies, private sector, civil society, academia, and communities—who contribute complementary resources, expertise, and legitimacy to public value creation (Rhodes, 1997; Osborne, 2010). Such collaborative governance frameworks are increasingly essential in policy domains including poverty alleviation, environmental sustainability, and urban development, where effective outcomes depend on shared knowledge and distributed implementation capacity.

The integration of artificial intelligence (AI) into governance represents a further evolution toward predictive and data-driven policy processes. AI enhances governance capacity by enabling large-scale data integration, pattern recognition, and optimized resource allocation across multiple objectives (Lartey & Law, 2025). However, the adoption of AI also introduces governance challenges related to democratic accountability, algorithmic transparency, and the safeguarding of human agency in decision-making (Velmurugan et al., 2025). Consequently, effective AI-enabled governance requires institutional designs that balance technological innovation with ethical standards, participatory legitimacy, and contextual adaptability, positioning AI as a supportive instrument within collaborative governance rather than a substitute for human judgment.

2.2 Collaborative governance: theoretical foundations and operational frameworks

Collaborative governance has become a key framework for addressing complex policy problems that cross organizational and sectoral boundaries. Defined by Ansell and Gash (2008) as a formal, consensus-oriented process involving public and non-state actors, collaborative governance emphasizes shared decision-making and collective responsibility for public outcomes. Emerson, Nabatchi, and Balogh (2012) further conceptualize this approach through an integrative framework highlighting the importance of system context, collaborative dynamics, and joint actions. Their model underscores that effective collaboration relies not only on institutional structures but also on trust, shared motivation, and the capacity for collective action among participating stakeholders.

The pentahelix model expands earlier helix frameworks by incorporating community actors alongside government, industry, academia, and civil society, recognizing the necessity of engaging affected populations directly in policy processes (Carayannis & Campbell, 2012). In poverty alleviation contexts, this model is particularly relevant due to poverty's multidimensional nature, which requires coordinated contributions from diverse actors, including regulatory authority, innovation, research expertise, advocacy, and local knowledge. Recent studies demonstrate that artificial intelligence (AI) can enhance pentahelix collaboration by improving coordination, targeting accuracy, and resource optimization across stakeholder domains (Ghazinoory et al., 2025; Zolkafli & Salleh, 2025).

Despite its potential, collaborative governance faces significant challenges related to power imbalances, institutional design limitations, and the need for sustained trust-building and adaptive learning (Ansell & Gash, 2008; Emerson et al., 2012). The integration of AI introduces both opportunities and risks: while AI-enabled systems can strengthen coordination through real-time data integration and predictive analytics, they also raise concerns regarding democratic legitimacy and the reproduction of existing power asymmetries. Consequently, recent literature emphasizes human-centered and participatory approaches to AI governance, positioning AI as an augmentative instrument that supports deliberation and joint decision-making rather than replacing human agency (Saxena et al., 2025; Nizamani et al., 2025).

2.3 The multidimensional nature of poverty and urban poverty specificities

Traditional poverty measurement in Indonesia, as applied by the Central Bureau of Statistics (BPS), relies on a unidimensional poverty line based on household expenditure thresholds. Although this approach facilitates quantitative monitoring of poverty trends, it inadequately captures the complexity of poverty by excluding non-monetary dimensions. Contemporary poverty theories, particularly Sen’s capabilities approach and the Multidimensional Poverty Index, conceptualize poverty as multidimensional deprivation encompassing health, education, living standards, empowerment, security, and political participation. Firdausi’s ECOPOS framework further integrates these perspectives by emphasizing powerlessness, capability deficits, limited opportunities, environmental vulnerability, economic constraints, and restricted political freedoms as interconnected elements of poverty.

This multidimensional understanding is especially relevant in urban contexts, where poverty is shaped by labor market precarity, housing insecurity, environmental risks, and social fragmentation. Urban poor populations often depend on unstable informal employment, face limited access to formal housing, and experience heightened exposure to pollution, inadequate sanitation, and disaster risks. Empirical studies in Jakarta’s informal settlements show that spatial marginalization intensifies deprivation by restricting access to essential services such as healthcare and education, creating self-reinforcing “poverty traps” in which disadvantages accumulate across multiple life domains. These conditions underscore the inadequacy of isolated, sectoral interventions in addressing urban poverty.

Given the systemic and interconnected nature of urban poverty, integrated and collaborative governance approaches are required. The application of artificial intelligence (AI) in poverty governance offers potential to manage this complexity through multidimensional data integration, predictive modeling, and adaptive policy optimization. Studies demonstrate that AI-based reinforcement learning can improve policy effectiveness by simultaneously addressing household-level and structural interventions. However, the use of AI also raises concerns regarding data quality, algorithmic bias, and equity. Consequently, effective AI-enabled poverty governance must adopt a sociotechnical approach that ensures transparency, accountability, and participatory validation to prevent the reproduction of existing inequalities.

2.4 AI-enabled governance and intelligent systems integration

The integration of artificial intelligence (AI) into collaborative governance represents an emerging theoretical frontier that combines computational capacity with participatory decision-making. Robles and Mallinson's (2025) Unified AI Governance Framework emphasizes balancing technological innovation with ethical standards, legal accountability, and democratic legitimacy through cross-sectoral coordination and adaptive learning mechanisms. This framework highlights key governance dimensions, including technical infrastructure, institutional arrangements, participatory processes, ethical safeguards, and system adaptability. Foundational technologies such as federated learning, knowledge graphs, and blockchain support AI-enabled collaboration by enabling privacy-preserving data integration, transparent reasoning, and secure, auditable information sharing across organizational boundaries, which are particularly critical in multidimensional poverty governance.

Advanced AI approaches, including multi-agent reinforcement learning (MARL), further enhance collaborative governance by optimizing coordinated actions among multiple stakeholders under uncertainty, improving efficiency, fairness, and policy stability. However, effective AI adoption depends not only on technological sophistication but also on institutional readiness, human capital, and organizational learning. Empirical studies indicate that limited AI literacy and insufficient capacity building remain major barriers in public administration. Consequently, participatory AI design is increasingly recognized as essential for ensuring legitimacy, contextual relevance, and public trust, despite its higher resource demands and implementation complexity. Synthesizing these insights, the literature underscores that AI-enabled collaborative governance requires an integrated framework combining multidimensional poverty understanding, pentahelix collaboration, advanced AI tools, participatory processes, and sustained institutional capacity development to support equitable and adaptive urban poverty alleviation.

3 RESEARCH METHODOLOGY

This study employs a qualitative descriptive approach to examine the integration of artificial intelligence within collaborative governance frameworks for poverty alleviation in DKI Jakarta. The research design is structured to capture the complexity of multi-stakeholder interactions, institutional arrangements, and technological implementation processes through systematic data collection and analysis procedures.

3.1 Research design and approach

The study adopts an interpretive qualitative methodology, recognizing that collaborative governance and AI-enabled poverty interventions constitute sociotechnical phenomena requiring in-depth understanding of actor perspectives, institutional dynamics, and contextual factors shaping implementation outcomes. This approach aligns with established methodological traditions in collaborative governance research (Ansell & Gash, 2008; Emerson et al., 2012) while incorporating analytical frameworks appropriate for examining technology-mediated governance processes.

3.2 Data collection methods

Data collection employs multiple methods to ensure comprehensive coverage of collaborative governance dimensions:

1. Semi-structured Interviews: Conducted with key stakeholders across the pentahelix model including: (1) government officials from Bappeda (Planning Agency), Dinas Sosial (Social Services Department), Dinas Kependudukan dan Pencatatan Sipil (Population and Civil Registration Department), and Dinas Pemberdayaan, Perlindungan Anak dan Pengendalian Penduduk (Empowerment, Child Protection and Population Control Department); (2) private sector representatives involved in AI technology provision and corporate social

responsibility programs; (3) academic experts in governance, poverty studies, and information technology; (4) civil society organizations engaged in poverty advocacy and community development; and (5) community representatives from targeted beneficiary populations.

2. Focus Group Discussions (FGD): Organized to capture collective perspectives and interaction dynamics among stakeholder groups, particularly regarding collaborative mechanisms, data integration challenges, and ethical considerations in AI deployment.
3. Document Analysis: Examination of policy documents including Governor Regulations, TKPK coordination meeting minutes, poverty alleviation program reports, data management protocols, and system architecture documentation to understand formal institutional arrangements and operational procedures.

3.3 Analytical framework: nvivo-assisted coding

Data analysis employs NVivo qualitative data analysis software, utilizing systematic coding procedures to organize, interpret, and visualize thematic patterns. The analytical process follows established qualitative coding protocols (Miles, Huberman, & Saldaña, 2014) adapted to the specific context of collaborative governance and AI integration.

3.4 First-level coding: SPEAKING model

The initial coding phase employs Hymes' (1967) SPEAKING modela sociolinguistic framework designed to analyze communicative interactions and social objectives embedded within communication practices. This framework facilitates systematic organization of data into thematic categories:

- Setting and Scene: Contextual conditions encompassing temporal, spatial, and physical environments of collaborative interactions
- Participants: Identification of actors, their roles, institutional affiliations, and relational dynamics

- Ends: Objectives, intended outcomes, and motivations underlying collaborative engagement
- Act Sequence: Chronological progression of collaborative activities, decision-making processes, and topic discussions
- Key: Emotional tone, attitudes, and relational climate characterizing collaborative interactions
- Instrumentalities: Communication channels, linguistic forms, and media utilized in collaboration
- Norms: Social and institutional rules governing interaction protocols and interpretation frameworks
- Genre: Types of communicative events including formal meetings, technical consultations, and community dialogues

This framework enables structured examination of how collaborative governance operates in practice, revealing patterns in stakeholder engagement, power dynamics, and consensus-building processes within AI-enabled poverty governance.

3.5 Second-level coding: thematic and process analysis

The second coding phase identifies substantive themes emerging from first-level coding, particularly within the "Act Sequence" and "Ends" nodes. This phase employs Miles, Huberman, and Saldaña's (2014) coding typology including:

- Descriptive codes: Capturing manifest content and observable phenomena
- In vivo codes: Preserving participants' own terminology and conceptual language
- Process codes: Identifying actions, interactions, and sequential activities
- Evaluation codes: Capturing assessments, judgments, and appraisals
- Emotion codes: Recording affective dimensions of collaborative experiences
- Values codes: Identifying normative orientations and ethical considerations

This multi-layered coding approach enables comprehensive capture of collaborative governance dynamics, including both formal institutional structures and informal interaction patterns.

3.6 Case classification and attribute analysis

NVivo's case classification functionality enables systematic organization of participant attributes including organizational affiliation, professional role, sectoral representation (government, private, academic, civil society, community), and experience level with AI technologies. This classification supports comparative analysis of perspectives across stakeholder categories, revealing potential divergences in priorities, concerns, and expectations regarding AI-enabled collaborative governance.

3.7 Data visualization and pattern identification

Following coding completion, the study employs NVivo's analytical features including:

- Hierarchy Charts: Visualizing thematic structures and relative prominence of coded categories
- Matrix Coding Queries: Examining intersections between themes and participant attributes
- Cluster Analysis: Identifying conceptual similarities and differences across data sources
- Word Frequency Analysis: Detecting salient terminology and conceptual emphases

These visualization tools facilitate pattern recognition, enabling identification of convergent understandings, contested issues, and emergent themes across stakeholder perspectives.

3.8 Validity and reliability considerations

Methodological rigor is ensured through: (1) triangulation across data sources (interviews, FGDs, documents) and stakeholder categories; (2) member checking through validation sessions with key informants; (3) systematic coding protocols with explicit decision rules; (4) reflexive documentation of researcher interpretations and analytical decisions; and (5) peer debriefing with academic experts in governance and qualitative methodology.

This comprehensive analytical approach enables systematic examination of collaborative governance processes, institutional enablers and barriers to AI integration, and stakeholder perspectives on ethical, operational, and strategic dimensions of AI-enabled poverty alleviation in metropolitan Jakarta.

4 RESULT AND DISCUSSION

4.1 AI-enabled collaborative governance in poverty alleviation: network structures and stakeholder dynamics

The implementation of AI-enabled collaborative governance in DKI Jakarta's poverty alleviation efforts reveals a complex ecosystem characterized by multi-actor engagement, technological integration challenges, and evolving institutional arrangements. Analysis of stakeholder narratives through NVivo 12 demonstrates that poverty governance has fundamentally transformed from sectoral interventions toward networked, data-driven coordination mechanisms involving government agencies, private sector entities, academic institutions, civil society organizations, and community-level actors.

4.2 Thematic prominence and discourse patterns

Word frequency analysis of interview transcripts, focus group discussions, and policy documents reveals the conceptual landscape dominating stakeholder perspectives on AI-enabled poverty governance. The most prominent terms"poverty" (kemiskinan), "society/community" (masyarakat), and "government" (pemerintah)constitute the foundational triad of collaborative governance discourse, reflecting the persistent centrality of state-society relations in metropolitan poverty interventions.

Figure 3

Word Cloud NVivo

The substantial presence of technology-related terminology"artificial intelligence," "data-based" (berbasis data), "technology," "digital," and "information"signals a discursive shift toward techno-centric governance paradigms. Notably, these terms frequently co-occur with implementation-oriented language such as "how" (bagaimana), "program," and "intervention," suggesting that stakeholder discussions focus not merely on technological capabilities in abstract terms, but on operational mechanisms through which AI augments poverty targeting and service delivery. This pattern aligns with Lartey and Law's (2025) observation that AI adoption in urban governance necessitates integration of technical innovation with procedural and ethical considerations.

The TreeMap visualization provides further granularity regarding thematic hierarchies within collaborative governance discourse. Analysis reveals six distinct thematic clusters:

1) Dominance of core themes: "Poverty," "Society," and "Government" The largest boxes indicate these three constitute the central focus of stakeholder narratives, reflecting the fundamental triad of state-society relations in poverty governance.

"Poverty" emerges as the paramount concept dominating discussions regarding socio-economic conditions, intervention urgency, and causal complexities. "Society" appears prominently due to their roles as beneficiaries, data sources, and participatory actors. "Government" reflects centrality as coordinator, policymaker, and digital system manager.

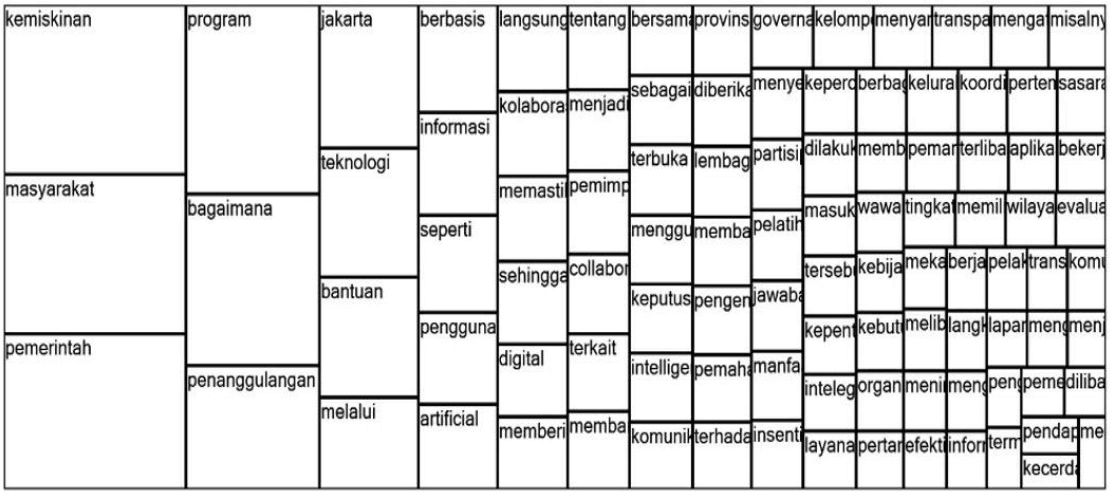
2) Implementation-focused cluster: "Program," "Jakarta," "Alleviation" (Penanggulangan), and "How" This grouping emphasizes stakeholder attention to: program descriptions, operational mechanisms, efficiency concerns, and the geographic context of Jakarta with its population density, social disparities, and data integration challenges. The prominence of "how" (bagaimana) indicates focus on implementation processes rather than abstract principles.
3) Technology transformation cluster: "Technology," "Based" (Berbasis), "Artificial," "Intelligence," "Information," "Digital" Strong presence of this cluster demonstrates that digital transformation is integral to decision-making, poverty mapping, vulnerability assessment, and program evaluation. AI is perceived as instrumental for: enhancing data accuracy, optimizing beneficiary targeting, supporting cross-organizational decisions, and enabling predictive poverty risk mapping.
4) Collaboration mechanisms cluster: "Collaboration," "Together" (Bersama), "Agency" (Lembaga), "Community," "Training," "Participation" Though smaller than poverty and technology themes, these terms' consistent presence indicates acknowledgment of multi-actor coordination, cross-agency communication, community involvement, data transparency, and capacity building through training. This aligns with Ansell & Gash's emphasis on trust-building, shared understanding, and mutual commitment.
5) Service delivery cluster: "Assistance" (Bantuan), "Services" (Layanan), "Application" (Aplikasi), "Through" (Melalui), "User" (Pengguna) Reflects stakeholder discussions on: social assistance distribution effectiveness, digital application usage in registration and validation, technical challenges (digital literacy, internet access), and public perceptions of government service transparency.

6) Overall synthesis The TreeMap structure reveals that AI-enabled poverty alleviation in DKI Jakarta operates through three interdependent pillars: (a) Government as policy leader and digital system manager; (b) Society as participatory actor and data source; and (c) AI technology as catalyst for program precision and collaborative coordination. This visualization confirms that collaborative governance transcends inter-agency coordination, constituting an ecosystem integrating data, technology, and social actors simultaneously."

Significantly, terms associated with collaborative processes" collaboration," "communication," "decision-making," and "stakeholders" appear with moderate but consistent frequency, indicating that coordination mechanisms constitute an acknowledged but not yet dominant dimension of stakeholder consciousness. This suggests potential gaps between the conceptual framework of pentahelix collaboration promoted in formal policy discourse and the operational realities experienced by implementing actors. As Emerson et al. (2012) emphasize, effective collaborative governance requires not only structural arrangements but sustained attention to interaction quality, trust-building, and shared commitmentdimensions that may remain underemphasized when technological capabilities dominate policy narratives.

Figure 4

TreeMap Collaborative Governance

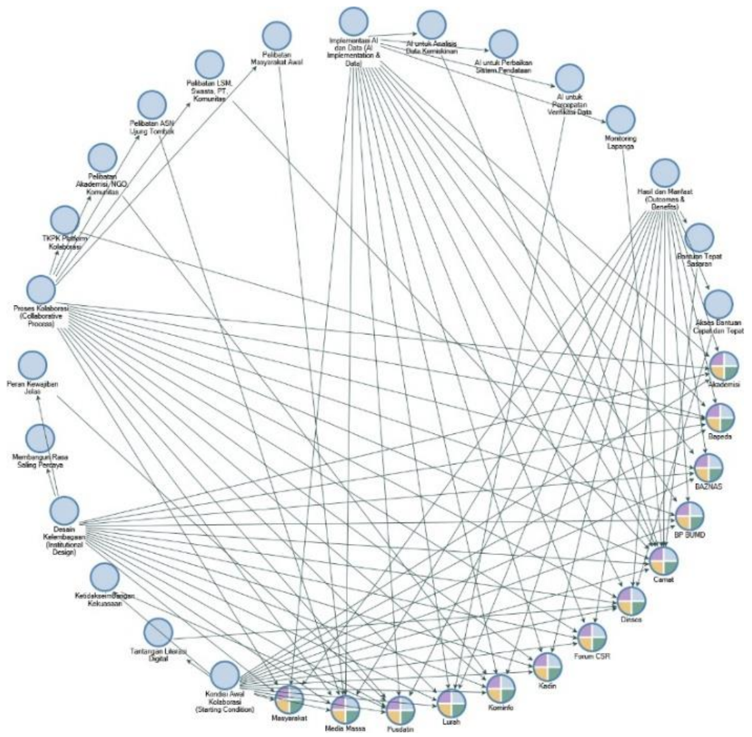


4.3 Pentahelix network architecture and actor centrality

Network visualization of coding relationships reveals the structural configuration of collaborative governance, mapping empirical linkages between pentahelix actorsgovernment agencies (Dinas Sosial, Bappeda, Diskominfotik), academic institutions, private sector representatives (KADIN, CSR Forum), civil society organizations (BAZNAS), and community actors (Lurah/village heads, neighborhood associations)and key governance dimensions including initial conditions, collaborative processes, AI implementation mechanisms, institutional design, and program outcomes.

Figure 5

Network Map Collaborative Governance



The network structure exhibits several theoretically significant characteristics. First, differential actor centrality is evident, with government agenciesparticularly Diskominfotik (Information and Communication Technology Agency) and Pusdatin (Data Centers)occupying hub positions with high betweenness centrality in technology-related subnetworks. These agencies function as critical intermediaries connecting technical AI infrastructure with social welfare objectives, consistent with their mandated roles in data integration and system development.

However, grassroots actorsLurah (subdistrict heads), Camat (district heads), and community cadresdemonstrate stronger connections to nodes representing implementation challenges, particularly "digital literacy barriers" and "power imbalances." This structural pattern reveals a critical implementation gap: while technical agencies focus on system architecture and data analytics capabilities, frontline implementers grapple with sociotechnical challenges stemming from beneficiaries' limited technological access and capacity. This bifurcation aligns with Demirkol's (2025) finding that metropolitan managers frequently lack adequate AI literacy, creating disconnects between policy design and operational realities.

Second, the node "Building Mutual Trust" (Membangun Rasa Saling Percaya) functions as a bridging construct with distributed connections across actor categories, particularly linking government agencies, community representatives, and civil society organizations. This empirical pattern validates Ansell and Gash's (2008) theoretical proposition that trust constitutes a foundational enabler of collaborative effectiveness, particularly in contexts characterized by power asymmetries and divergent institutional logics. The prominence of trust-related discourse across stakeholder groups suggests recognition that AI systems, despite their analytical sophistication, cannot substitute for the relational foundations necessary for sustained multi-actor cooperation.

Third, outcome nodes"Accurate Targeting" (Bantuan Tepat Sasaran), "Measurable Actions," and "Tangible Results"exhibit strong connections to implementation-focused actors including Lurah, BP BUMD (regional enterprises), and service delivery agencies. This pattern indicates that validation of program success and impact assessment occur primarily at the service delivery interface, where beneficiary interactions with governance systems become observable and consequential. Private sector actors, represented through KADIN and CSR Forum, demonstrate concentrated linkages to outcome nodes, reflecting their instrumental orientation toward demonstrable results that generate reputational benefits and stakeholder legitimacy.

4.4 Technological-social segmentation and coordination challenges

Matrix coding analysis comparing actor types against implementation challenges and governance processes reveals systematic narrative fragmentation between technical-policy clusters and implementation-operational clusters. Technical agencies (Kominfo, Pusdatin, Bappeda) and academic actors exhibit high coding density on nodes related to "AI for Poverty Data Analysis," "Data System Improvement," and "Institutional Design," indicating concentrated attention to system architecture, algorithmic capabilities, and data infrastructure. In contrast, these actors demonstrate significantly lower coding intensity on nodes addressing "Digital Literacy Challenges" and "Power Imbalances," suggesting limited engagement with sociotechnical barriers confronting vulnerable populations.

Conversely, civil society actorsparticularly BAZNAS and academic informantsdisplay the highest coding intensity for critical governance issues including digital literacy barriers, power asymmetries, and participatory deficits. This finding reveals that critical voice regarding governance equity and inclusion emerges predominantly from actors positioned outside direct governmental command structures. BAZNAS, functioning as an Islamic philanthropic institution with independent beneficiary databases and community engagement mechanisms, demonstrates particular sensitivity to implementation challenges affecting marginalized populations. This pattern aligns with broader collaborative governance literature emphasizing the essential role of civil society actors in surfacing marginalized perspectives and challenging technocratic assumptions (Saxena et al., 2025).

Implementation actorsLurah, Camat, and Dinas Sosial field staffexhibit moderate coding across both technical and social challenge categories, positioning them as boundary spanners navigating tensions between system requirements and community realities. However, their relatively lower overall coding density compared to technical specialists and critical civil society voices suggests potential voice asymmetries within collaborative forums, wherein actors closest to beneficiary experiences may lack equivalent discursive influence compared to technical experts and policy elites.

This segmentation pattern carries significant implications for AI governance effectiveness. As Sanchez, Brenman, and Ye (2025) caution, algorithmic systems developed without adequate attention to frontline implementation contexts risk perpetuating biases and exclusions embedded in design assumptions disconnected from lived realities of vulnerable populations. The observed network structure suggests vulnerability to top-down technocratic drift, wherein AI development proceeds according to technical optimization criteria without sufficient integration of ground-level knowledge regarding beneficiaries' capabilities, constraints, and contextual circumstances.

4.5 Quantitative validation: ai implementation-outcome correlations

Matrix query analysis examining correlations between AI implementation mechanisms and program outcomes provides empirical evidence regarding technology's operational impacts. The strongest correlations emerge between "AI for Poverty Data Analysis" and "Reduction of Duplicate Records," validating that AI's most immediate and widely acknowledged benefit concerns data quality improvementspecifically, addressing historical challenges of fragmented databases and redundant beneficiary records across agencies.

This finding confirms that current AI applications in DKI Jakarta's poverty governance function primarily at the data infrastructure level, enhancing administrative efficiency through improved record-keeping, deduplication, and cross-referencing capabilities. Such outcomes align with foundational requirements for evidence-based policymaking but represent relatively narrow utilization of AI's potential capabilities. As Ghazinoory et al. (2025) document, AI contributions to poverty alleviation can extend beyond data management to encompass predictive analytics for vulnerability identification, optimization of resource allocation across multiple objectives, and adaptive learning from intervention outcomescapabilities requiring more sophisticated algorithmic architectures and institutional capacities than currently deployed.

Significant correlations also appear between "Beneficiary Eligibility Validation" (incorporating community cadre input) and "Accurate Targeting," demonstrating that targeting precision emerges through sociotechnical integration rather than algorithmic automation alone. This pattern empirically validates participatory AI design principles (Saxena et al., 2025; Nizamani et al., 2025), confirming that local knowledge embedded in community validation processes enhances algorithmic outputs. The finding suggests that optimal AI-enabled governance architectures function not as autonomous decision systems but as hybrid arrangements augmenting human judgment through computational support while preserving human agency in contextual interpretation and final determinations.

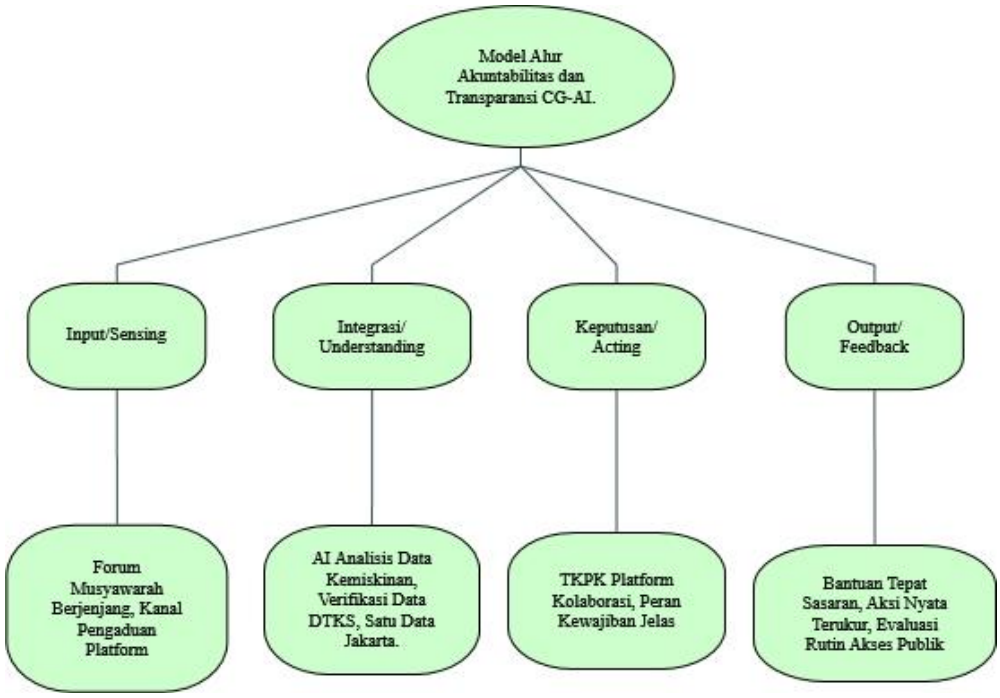
However, correlation strengths between AI implementation and ultimate poverty reduction outcomes"Sustainable Impact" and "Quality of Life Improvement"remain moderate, indicating that causal pathways from technological adoption to substantive welfare improvements involve multiple mediating variables beyond data accuracy alone. This pattern underscores that technology constitutes an enabling instrument rather than sufficient condition for poverty alleviation, requiring complementary investments in service delivery capacity, beneficiary empowerment, and structural economic interventions.

4.6 Accountability and transparency mechanisms: musrenbang integration

Process mapping analysis reveals the institutional architecture through which participatory mechanisms (Musrenbangmulti-stakeholder development planning forums) integrate with digital data systems to establish accountability loops. The "Accountability Flow Model" identified through NVivo's project mapping functionality demonstrates four interconnected operational streams: (1) social input channels (community aspirations, field validation by cadres); (2) technical data integration (consolidation through Jakarta One Data initiative, AI analytics); (3) evidence-based decision-making (policy formulation by planning agencies executive leadership); and (4) output monitoring and feedback (program evaluation, public reporting, iterative refinement).

Figura 6

Project Map Model of Cg-Ai Accountability Flow That Describes the Interconnection Between Citizen Participation Pathways, Data Integration and AI Analysis, Institutional Decision-Making Processes, and Monitoring Mechanisms in Creating a Cycle of Account



This model architecture reflects efforts to operationalize what Robles and Mallinson (2025) term adaptive AI governance frameworksinstitutional arrangements that balance technological capabilities with participatory legitimacy and democratic accountability. The explicit incorporation of bottom-up aspirational input through Musrenbang forums alongside top-down data analytics represents an attempt to mitigate risks of technocratic governance detached from citizen preferences.

However, stakeholder narratives reveal persistent operationalization gaps between formal accountability architecture and practical implementation. Informants frequently reference challenges in "closing the accountability loop"ensuring that analytical outputs genuinely inform decision-making and that citizens receive transparent communication regarding how their input influenced outcomes. As one academic informant observed: "The system architecture exists on paper, but the feedback mechanisms remain weak. Citizens participate in Musrenbang, data gets collected and analyzed, but the connection between community aspirations and final budget allocations remains opaque."

This implementation deficit aligns with broader literature on participatory governance in technologically-mediated contexts. Islam et al. (2026) emphasize that effective accountability requires not merely formal structures but digital citizen hubs functioning as accessible interfaces between AI systems and community stakeholders, facilitating both service uptake and continuous feedback enabling system refinement. The current architecture in Jakarta, while structurally comprehensive, appears to lack sufficient investment in these mediating institutions that translate between technical systems and community engagement.

5 ENABLING FACTORS AND BARRIERS: INSTITUTIONAL READINESS FOR AI-ENHANCED COLLABORATION

5.1 Internal enabling factors: institutional capacities

Analysis of internal factors supporting AI-enabled collaborative governance reveals several critical institutional capabilities. First, formal coordination structures, particularly the Tim Koordinasi Penanggulangan Kemiskinan Daerah (TKPKDRegional Poverty Alleviation Coordination Team), provide essential organizational infrastructure for multi-agency collaboration. TKPKD functions as an institutionalized boundary-spanning mechanism, facilitating information exchange, policy alignment, and resource coordination across departmental silos. This structural arrangement addresses what scholars identify as a fundamental collaborative governance challenge: establishing legitimate authority for cross-boundary coordination in contexts where participating agencies retain independent mandates and resource control (Emerson et al., 2012).

Second, digital infrastructure foundationsthe JAKI (Jakarta Kini) application ecosystem, Citizen Relationship Management (CRM) systems, Jakarta Smart City data platforms, and interconnected agency data centersprovide technical prerequisites for AI implementation. The existing CRM infrastructure offers a transitional pathway toward more sophisticated AI integration, enabling incremental capability development rather than disruptive wholesale system replacement. This gradualist approach aligns with Kopac and Das's (2025) "AI Building Blocks Framework," which emphasizes modular development integrating data infrastructure, analytical intelligence, applications, and governance mechanisms in adaptive, sustainable configurations.

Third, specialized human capitalpolicy analysts, data scientists, information systems techniciansconstitutes essential implementation capacity. Interviews reveal that while aggregate AI literacy among civil servants remains limited, concentrated expertise within technical agencies provides sufficient critical mass for system development and operation. One Diskominfotik official noted: "We don't need every civil servant to be a data scientist. What we need is sufficient specialized expertise to build and maintain systems, combined with broad operational literacy so frontline staff can effectively use AI-generated insights."

However, this reliance on concentrated technical expertise creates single points of failure and limits collaborative governance's inclusive potential if technical specialists monopolize system interpretation and policy translation. Building what Tuan et al. (2025) term "AI literacy ecosystems" across organizational hierarchies and stakeholder categories emerges as essential for democratizing technological capabilities and preventing technocratic capture.

Fourth, data integration initiatives, particularly the Jakarta One Data policy (Provincial Regulation No. 37/2022), establish regulatory frameworks and technical standards for cross-agency data sharing. The Data Terpadu Kesejahteraan Sosial (DTKSIntegrated Social Welfare Database), continuously updated and synchronized across social services, population administration, planning, and subdistrict agencies, provides the empirical foundation enabling AI analytics. As one Bappeda official explained: "AI is only as good as the data feeding it. Our investment in data integration, standardization, and quality assurance directly determines AI's utility for poverty targeting."

5.2 External enabling factors: partnership ecosystems

External factors supporting collaborative governance effectiveness center on multi-sectoral partnership potential. Private sector engagement through the CSR Forum DKI Jakarta provides supplementary financial resources, technical expertise, and implementation capacity extending governmental capabilities. Corporate participants bring operational efficiencies, innovation mindsets, and technological resources augmenting public sector capacities. However, interviews reveal that corporate engagement remains largely transactional and philanthropic rather than deeply collaborative in co-designing interventions or sharing governance authority.

Religious philanthropic institutions, particularly BAZNAS, contribute essential complementary functions. BAZNAS maintains independent beneficiary databases compiled through zakat (Islamic charitable giving) collection and distribution, providing data sources for validating governmental records and identifying coverage gaps. One BAZNAS official noted: "Our community networks and religious legitimacy enable us to reach populations sometimes mistrustful of government data collection. When we share beneficiary information with government while protecting privacy, it enhances targeting accuracy."

Academic institutions provide evaluative capacity and critical perspective, conducting independent assessments of program effectiveness and surfacing equity concerns that may be obscured in administrative reporting. The high coding intensity of academic informants on critical governance issues (power imbalances, digital literacy barriers) empirically demonstrates this function. Universities also contribute through student engagement in community data collection and validation, supplementing limited governmental field staff.

However, partnership ecosystems exhibit asymmetries limiting collaborative depth. Private sector and philanthropic actors operate according to institutional logics prioritizing brand reputation, religious obligation fulfillment, or shareholder value rather than public value maximization, potentially creating misaligned incentives. Academic engagement remains largely consultative rather than deeply embedded in governance operations. Community actors, while rhetorically celebrated in pentahelix frameworks, demonstrate limited structural power in collaborative forums dominated by governmental and corporate elites.

5.3 Internal barriers: organizational and technical constraints

Internal barriers constraining AI-enabled collaborative governance effectiveness cluster around four dimensions. First, data governance deficits persist despite formal integration policies. Informants consistently cite ongoing challenges with data synchronization across agencies, validation dependencies on manual field staff inputs, and data quality assurance insufficient for sophisticated AI applications. One Dinas Sosial official explained: "We have data integration in principle, but in practice, different agencies update at different intervals, use inconsistent categorization schemes, and maintain varying quality standards. Feeding inconsistent data into AI algorithms produces unreliable outputs."

These challenges reflect broader patterns documented in urban governance literature. Bansal and Bhattacharya (2025) note that data integration represents not merely technical interoperability but requires institutional alignment regarding data ownership, privacy protocols, update responsibilities, and quality accountabilitydimensions requiring sustained collaborative negotiation rather than one-time technical solutions.

Second, human capital limitations extend beyond aggregate AI literacy to include uneven skill distribution, high workload burdens on field staff conducting manual verification, and insufficient specialized personnel (data scientists, algorithm developers, system architects) for advancing beyond rudimentary AI applications. Training initiatives remain sporadic rather than systematized, creating dependency on external consultants for complex analytical tasks.

Third, technological infrastructure gaps include AI systems remaining in developmental stages rather than fully operational, hardware capacity constraints (servers, databases) limiting big data processing, and network instability in certain jurisdictions disrupting system access. While DKI Jakarta possesses more advanced infrastructure than most Indonesian jurisdictions, scaling AI applications from pilot projects to comprehensive deployment requires substantial additional investment.

Fourth, coordination inefficiencies persist despite formal collaborative structures. Informants reference communication delays across agencies, divergent operational standards complicating integration, and sectoral mindsets resisting integrative approaches. One TKPKD coordinator observed: "Agencies still operate primarily according to their own mandates and metrics. Collaboration happens through periodic coordination meetings, but daily operations remain largely siloed. AI can't fix organizational culture problems."

5.4 External barriers: digital divides and ecosystem gaps

External barriers center on digital access inequalities among target populations. Despite Jakarta's relatively advanced digital infrastructure, low-income communities face constraints including limited smartphone ownership, unstable internet connectivity, insufficient data plans, and low digital literacy impeding effective engagement with AI-enabled services. These disparities create exclusion risks wherein technologically-mediated governance inadvertently disadvantages populations it aims to assist.

One community cadre explained: "Many poor families have basic phones but not smartphones with data plans needed for JAKI. Even those with smartphones often don't understand how to navigate applications or distrust providing personal information digitally. They prefer face-to-face interaction with neighborhood officials they know."

This barrier aligns with Oyetade and Zuva's (2025) findings regarding digital literacy requirements for equitable AI adoption. Technological solutions alone prove insufficient without complementary investments in digital inclusion infrastructurepublic access points, digital literacy training, trusted intermediaries bridging technological and community interfaces.

Second, partnership activation gaps limit external resource mobilization. While formal collaborative structures exist, private sector engagement often remains superficial, academic involvement stays consultative rather than embedded, and community participation occurs through selective representation rather than broad-based engagement. Building genuine collaborative ecosystems requires sustained relationship investment, aligned incentive structures, and institutional mechanisms for shared authorityelements inadequately developed in current arrangements.

Third, regulatory ambiguities regarding AI utilization in poverty governance create implementation hesitancies. Absence of specific legal frameworks governing algorithmic decision-making, data privacy protections for vulnerable populations, and accountability mechanisms for AI-influenced determinations generates bureaucratic caution. Officials express concerns regarding potential legal liabilities if AI-driven decisions produce erroneous outcomes affecting citizens' welfare entitlements.

The empirical analysis reveals that AI-enabled collaborative governance in DKI Jakarta operates as a hybrid sociotechnical system wherein technological capabilities interact with institutional structures, human capacities, and relational dynamics in complex, often contradictory ways. While technical infrastructure and formal coordination mechanisms provide essential foundations, realization of collaborative governance's transformative potential confronts persistent challenges: fragmented narratives across actor categories, implementation gaps between policy design and operational realities, digital divides excluding vulnerable populations, and coordination inefficiencies limiting genuine integration. These findings underscore that effective AI-enabled governance requires not merely technological sophistication but sustained institutional development addressing capacity asymmetries, power imbalances, and sociotechnical interface challenges.

5.5 A framework for the utilization of artificial intelligence in supporting collaborative governance for poverty alleviation

Building upon the empirical findings presented in Sections 4.1 and 4.2, this subsection synthesizes the observed network dynamics, enabling factors, and institutional constraints into an integrated framework for the utilization of Artificial Intelligence (AI) within pentahelix collaborative governance for poverty alleviation in DKI Jakarta. Rather than introducing a purely normative or abstract model, this framework is grounded in empirical evidence derived from stakeholder narratives, network analysis, and process mapping, reflecting how AI is currently utilized and how it can be systematically strengthened within existing governance arrangements.

The analysis demonstrates that AI-enabled poverty governance in DKI Jakarta operates as a **hybrid sociotechnical system**, in which technological components interact continuously with institutional structures, human capacities, and collaborative processes. Consequently, the proposed framework positions AI not as an autonomous decision-making authority, but as an **enabling mechanism** that enhances coordination, evidence-based deliberation, and adaptive policy implementation across pentahelix actors.

5.6 AI as a sensing system: consolidating shared evidence in collaborative governance

Empirical findings reveal that the most immediate and tangible contribution of AI in DKI Jakarta's poverty governance lies at the sensing level, particularly in the consolidation and harmonization of fragmented data sources. Interviews with government officials and technical agencies confirm that AI-supported data integration has significantly improved the synchronization of social assistance records, population registries, and sectoral databases, thereby reducing duplication of beneficiaries and enhancing targeting accuracy.

As illustrated in the framework figure presented in the document, the sensing function establishes a **shared evidence base** accessible to government agencies, civil society organizations, philanthropic institutions, and community actors. This shared evidence base plays a critical role in mitigating information asymmetries that previously constrained collaborative governance, enabling stakeholders to engage in deliberation based on common factual references rather than sector-specific datasets. However, the findings also indicate that sensing effectiveness remains contingent upon data quality assurance and periodic field validation, underscoring that AI-supported sensing complements rather than replaces human verification mechanisms.

5.7 AI as an understanding system: supporting collective interpretation and deliberation

Beyond data consolidation, AI contributes to collaborative governance by enhancing collective understanding of poverty dynamics through multi-level analytics. The empirical analysis indicates that AI-enabled descriptive and diagnostic analytics are increasingly utilized to map poverty profiles and identify causal factors, while predictive and prescriptive capabilities remain underdeveloped due to institutional and capacity constraints.

Within collaborative forums, AI-generated analytical outputs function as **decision-support instruments** that inform policy discussion rather than dictate outcomes. Stakeholder narratives reveal that these analytics facilitate more structured and evidence-based deliberation, particularly in pentahelix coordination meetings, by reducing subjective bias and enabling cross-sectoral alignment. Importantly, the effectiveness of this understanding function depends on the capacity of actors to interpret AI outputs and integrate them with contextual knowledge derived from community engagement and frontline implementation experience.

This finding reinforces the conclusion that AI enhances collaborative governance not through automation, but through **shared sense-making**, where analytical insights are collectively interpreted and negotiated among actors with diverse institutional mandates and normative priorities.

5.8 AI as an acting system: enabling adaptive and accountable intervention

At the acting level, the framework reflects how AI supports adaptive policy implementation by linking analytical insights to intervention design, monitoring, and adjustment. Empirical evidence shows that AI is primarily used to inform targeting decisions and program prioritization, while final decisions remain embedded within institutional and deliberative processes involving government authorities and collaborative partners.

As mapped in the AI-based collaborative business process, AI-assisted acting is characterized by a continuous feedback loop connecting data updates, analytical refinement, and field-level verification. Community cadres and local officials play a pivotal role in validating AI-informed recommendations, thereby reinforcing social accountability and correcting potential algorithmic bias. This arrangement ensures that AI functions as a **human-in-the-loop governance tool**, aligning technological innovation with democratic legitimacy and ethical safeguards.

5.9 Pathway of change: translating ai utilization into collaborative governance outcomes

To address the need for greater analytical clarity regarding how AI utilization translates into tangible governance and poverty alleviation outcomes, this subsection elaborates the **Pathway of Change** underlying the proposed framework. Drawing on empirical findings and operational logic summarized in **Table 1**, the pathway explicates the causal mechanisms through which AI-enabled collaboration progressively generates institutional, relational, and welfare impacts.

Rather than assuming linear or technologically deterministic change, the pathway conceptualizes transformation as an **iterative sociotechnical process**, in which technological capabilities, institutional arrangements, and actor interactions co-evolve over time.

Table 1

Pathway of Change of AI Utilization in Collaborative Governance

Stages	Main Components	Mechanism of Change (Theoretical)
INPUT	Regulation (governance), human resources, facilities, financing, information systems, cooperation and partnerships	Referring to ***starting conditions and institutional design*** (Ansell & Gash, 2008), the mechanism of change at the input stage occurs through the creation of **an institutional environment conducive** to collaboration. Clarity of rules, availability of resources, and legitimacy of actors create the initial prerequisites for reducing power imbalances and increasing actor readiness in the collaborative process.
PROCESS	AI development and implementation, training, FGD, community deliberation, socialization, participatory monitoring	This stage represents ***a collaborative process*** characterized by face-to-face dialogue, trust-building, and shared learning. **AI serves as a *shared information platform*** that facilitates knowledge exchange and collective decision-making. **The deliberative process** strengthens commitment **to the process** and builds shared **understanding** .
OUTPUT	AI integration in decision making, collaboration between SKPD, real-time data, socio-economic visualization	Outputs are the direct results of collaborative processes, including **institutional and technical artifacts** . Change mechanisms emerge when collaborative outcomes (data, systems, and standard operating procedures) become shared tools that **strengthen coordination and transparency among actors** . This strengthens ***intermediate outcomes*** , such as **collaborative capacity and evidence-based governance**.
OUTCOME (Intermediate)	Public trust, distribution efficiency, transparency, public participation	In line with the concepts of ***trust building and mutual accountability***, the change mechanism at this stage is characterized by **increased trust between actors and the community**. Data transparency and participation in monitoring strengthen policy legitimacy and **reduce conflict and resistance to** poverty alleviation programs.
OUTCOME (Long-Term)	Fair access to assistance, responsive data-driven policies	Long-term change mechanisms occur when **collaborative practices and data use are institutionalized within government systems**. Governments and partners are able to adapt **policies** based on feedback and empirical evidence, in line with the principles of **adaptive governance in collaborative governance.**

Stages	Main Components	Mechanism of Change (Theoretical)
IMPACT	Improving the accuracy of aid targets and the quality of life of the people of DKI Jakarta	Impact is **the cumulative success of a** sustained collaborative process. The mechanisms of change operate through structural improvements in poverty governance, where collaboration, trust, and ***data-driven decision-making*** result in **systemic improvements in well-being**.

5.10 Input stage: establishing enabling conditions for ai-enabled collaboration

The pathway begins at the **input stage**, where enabling conditions are established through regulatory frameworks, organizational mandates, human resources, digital infrastructure, financing mechanisms, and inter-organizational partnerships. Empirical evidence from stakeholder interviews confirms that AI utilization in DKI Jakarta is contingent upon the existence of formal coordination structures, particularly Poverty Alleviation Coordination Team (TKPK), and regulatory instruments governing data integration and cross-agency collaboration.

At this stage, the **mechanism of change** operates through the reduction of structural barriers to collaboration. Clear institutional roles, legitimacy of coordinating bodies, and availability of minimum technological infrastructure lower transaction costs among actors and create the preconditions for collective engagement. Importantly, this stage does not yet produce substantive poverty outcomes, but it determines whether collaborative processes can be initiated and sustained.

5.11 Process stage I: data integration and shared evidence construction

The second stage corresponds to the early **process phase**, where AI is primarily utilized as a sensing system. Empirical findings indicate that this stage produces immediate governance gains through data consolidation, deduplication of beneficiaries, and synchronization of poverty-related datasets.

The causal mechanism at this stage lies in the construction of a **shared evidence base**, which transforms fragmented sectoral knowledge into collectively accessible information. This shared evidence reduces epistemic asymmetries among actors, enabling them to engage in deliberation based on common factual references rather than competing datasets. As observed in network analysis, this mechanism strengthens coordination particularly among technical agencies while gradually enabling broader pentahelix participation.

5.12 Process stage II: collective interpretation and deliberative sense-making

Following data integration, the pathway advances to a second process stage centered on **collective interpretation**. Here, AI-enabled analytics (descriptive and diagnostic) support deliberative sense-making among pentahelix actors. Empirical narratives indicate that AI outputs are most effective when discussed within coordination forums, where technical insights are contextualized through experiential knowledge contributed by frontline implementers, civil society, and community representatives.

The mechanism of change at this stage is **epistemic alignment**. Through repeated deliberation, actors develop shared interpretations of poverty dynamics, intervention priorities, and targeting criteria. This alignment mitigates sectoral bias, reduces conflict arising from divergent problem framings, and strengthens commitment to collaborative processes. Trust-building emerges as a relational outcome of this stage, rather than as a precondition.

5.13 Output stage: institutional and technical artifacts of collaboration

The output stage represents the first set of tangible products generated by AI-enabled collaboration. These outputs include integrated databases, analytical dashboards, standardized operating procedures, and coordinated inter-agency action plans. Empirical evidence indicates that such artifacts enhance operational clarity and facilitate coordination across institutional boundaries.

The mechanism of change at this stage involves **institutionalization of shared practices**. Once outputs are embedded within routine workflows, collaboration shifts from ad hoc coordination to structured, repeatable interaction. This institutional embedding marks a transition from experimental collaboration toward more stable governance arrangements.

5.14 Outcome stage (intermediate): trust, transparency, and targeting precision

Intermediate outcomes emerge when institutional artifacts begin to influence actor behavior and public interaction. Findings demonstrate that improved transparency of data and decision processes enhances trust among stakeholders and reduces public skepticism toward poverty programs. Simultaneously, AI-supported targeting improves efficiency and accuracy, particularly when combined with community-based verification mechanisms.

The causal mechanism here is **behavioral reinforcement**. As actors experience tangible benefits from collaboration—reduced duplication, clearer roles, improved service delivery—the perceived value of collaboration increases, reinforcing continued participation and compliance with shared governance arrangements.

5.15 Outcome stage (long-term): institutionalization of adaptive governance

Long-term outcomes materialize when AI-enabled collaborative practices become routinized within governance systems. At this stage, AI supports adaptive policy learning by enabling continuous feedback loops between data updates, analytical refinement, and implementation adjustments.

The mechanism of change shifts toward **organizational learning and adaptability**. Institutions move beyond static planning toward iterative policy adjustment, responding more effectively to dynamic poverty conditions. Importantly, empirical findings suggest that this stage remains aspirational but attainable, contingent upon sustained capacity building and regulatory clarity.

5.16 Impact stage: systemic improvement in poverty governance and welfare outcomes

The final impact stage reflects cumulative systemic improvements in poverty governance, manifested through sustained targeting accuracy, equitable access to assistance, and improvements in the quality of life of urban poor populations. Rather than attributing impact solely to AI, the pathway emphasizes that welfare gains emerge from the **interaction between technology, collaboration, and institutional learning**.

At this stage, AI functions as a governance infrastructure embedded within collaborative systems, supporting long-term resilience and inclusivity rather than short-term efficiency gains alone.

5.17 Synthesis of the pathway of change

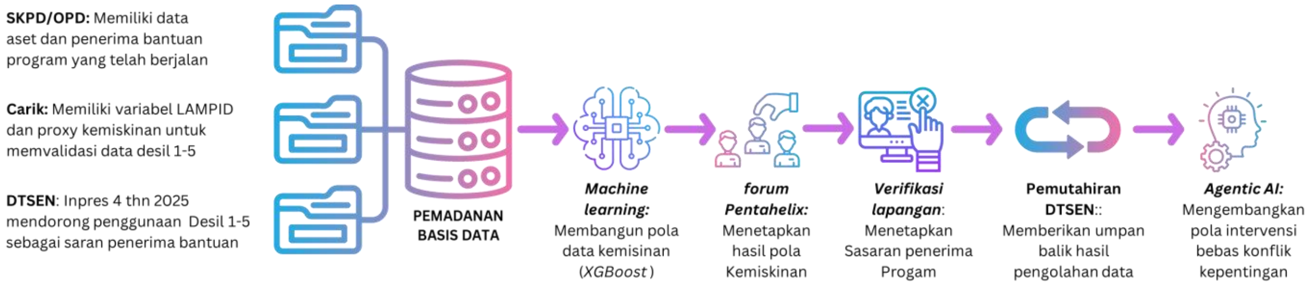
Overall, the Pathway of Change demonstrates that AI-enabled pentahelix collaborative governance operates through **progressive sociotechnical mechanisms**, rather than linear technological causality. Change unfolds through sequential stages of enabling conditions, shared evidence construction, collective interpretation, institutional embedding, behavioral reinforcement, and adaptive learning. This pathway clarifies how AI utilization contributes to poverty alleviation not by replacing governance processes, but by enhancing their coherence, inclusivity, and responsiveness.

5.18 Implementation plan of ai-enabled pentahelix collaborative governance

While the preceding subsections conceptualize and empirically ground the AI-enabled collaborative governance framework, effective poverty alleviation requires a clearly articulated **implementation plan** that translates analytical insights into actionable institutional practices. Based on empirical findings and the operational logic illustrated in **Figure 7**, this study proposes a phased implementation plan that aligns AI utilization with existing governance structures, actor capacities, and collaborative mechanisms in DKI Jakarta.

Figure 7

Business Process of AI-Based Collaborative Governance among SKPD/OPD



Rather than advocating a disruptive or fully automated transformation, the proposed implementation plan adopts an **incremental and adaptive approach**, ensuring institutional feasibility, stakeholder ownership, and sustained legitimacy.

5.19 Data consolidation and institutional alignment

The initial implementation phase focuses on consolidating and harmonizing poverty-related data across Carik Jakarta, SKPD/OPD data, and collaborative partners data. Empirical findings indicate that data fragmentation constitutes the primary bottleneck in AI utilization; therefore, this phase prioritizes agreement on data standards, interoperability protocols, and update responsibilities.

In this phase, AI is applied primarily as a **data-matching and validation tool**, supporting the integration of social assistance records, population data, and socio-economic indicators into a unified shared evidence base. Institutional coordination is facilitated through TKPKD mechanisms, ensuring that data governance arrangements are aligned with existing regulatory frameworks and collaborative mandates.

This phase corresponds to the *input* stage of the Pathway of Change (Table 1), establishing the foundational conditions required for subsequent analytical and operational utilization of AI.

5.20 Analytical deployment and capacity building

Following data consolidation, the second phase emphasizes the deployment of AI analytics to support collective understanding of poverty dynamics. At this stage, descriptive and diagnostic analytics are prioritized to generate shared situational awareness among pentahelix actors. Predictive and prescriptive analytics are introduced selectively, contingent upon data quality and institutional readiness.

Simultaneously, targeted **capacity-building initiatives** are implemented to enhance AI literacy among policymakers, technical staff, and frontline implementers. Empirical evidence highlights that uneven interpretive capacity limits the effective use of AI outputs; therefore, training and facilitated deliberation sessions are essential to ensure that analytical insights inform collaborative decision-making rather than remain confined to technical units.

This phase operationalizes the *understanding* function of AI, reinforcing shared interpretation and reducing epistemic asymmetries across actors.

5.21 Deliberative integration through pentahelix forums

The third phase embeds AI outputs within formal and informal deliberative spaces, particularly pentahelix coordination forums. As illustrated in **Figure 4.9**, AI-generated insights are not treated as final decisions, but as inputs for collective interpretation, negotiation, and prioritization.

During this phase, analytical results are discussed alongside contextual knowledge contributed by community representatives, civil society organizations, and frontline officials. This deliberative integration ensures that intervention priorities reflect both empirical evidence and lived realities, thereby mitigating algorithmic bias and reinforcing trust among stakeholders.

This phase corresponds to the *process* dimension of collaborative governance, where AI functions as a shared information platform that strengthens commitment to collaboration and collective accountability.

5.22 Field verification and adaptive implementation

Subsequent to deliberative agreement, implementation proceeds through **field-level verification and adaptive intervention delivery**. Community cadres and local administrative actors validate AI-informed targeting recommendations, ensuring alignment with actual household conditions. Feedback from this verification process is systematically reintegrated into the data system, creating a continuous learning loop.

AI at this stage supports monitoring and adjustment rather than control, enabling timely identification of targeting errors, implementation gaps, and emerging vulnerabilities. This reinforces the principle of *human-in-the-loop governance*, where technology augments but does not replace institutional responsibility.

This phase operationalizes the *acting* function of AI while safeguarding social accountability and ethical governance standards.

5.23 Institutionalization and adaptive learning

The final implementation phase focuses on institutionalizing AI-enabled collaborative practices within routine governance processes. Lessons derived from implementation cycles inform refinement of analytical models, data governance protocols, and collaborative arrangements. Over time, this adaptive learning process enables gradual expansion toward more advanced AI capabilities, including agentic decision-support systems, while maintaining deliberative oversight.

This phase aligns with the *long-term outcome* and *impact* stages of the Pathway of Change, where AI-enabled collaboration becomes embedded within governance culture, contributing to sustainable improvements in poverty targeting accuracy and quality of life outcomes.

5.24 Synthesis of implementation strategy

Overall, the proposed implementation plan demonstrates that effective utilization of AI in pentahelix collaborative governance requires a **sequenced, participatory, and institutionally grounded approach**. By aligning AI deployment with existing governance mechanisms, capacity constraints, and collaborative dynamics, this plan ensures that technological innovation enhances rather than disrupts poverty governance processes.

6 CONCLUSION

This study examined the integration of Artificial Intelligence (AI) within collaborative governance frameworks for poverty alleviation in DKI Jakarta. The findings indicate that AI-enabled poverty governance operates as a complex sociotechnical system in which technological capabilities interact with institutional structures, human capacities, and multi-actor collaboration. While collaborative governance has evolved toward a pentahelix model involving government, private sector, academia, civil society, and communities, its implementation remains fragmented, particularly between technical-policy actors and frontline implementers.

Empirically, AI has contributed primarily at the level of data infrastructure, improving data integration, record deduplication, and targeting accuracy. However, the study finds that effective targeting does not result from algorithmic automation alone but from sociotechnical integration that combines AI analytics with community-based validation and human judgment. Persistent barriers—such as data governance weaknesses, limited AI literacy, infrastructure constraints, digital inequality, and unclear regulatory frameworks—continue to limit the full potential of AI in poverty governance.

Overall, the study concludes that AI should be positioned as an augmentative tool within collaborative governance rather than a substitute for human decision-making. Effective AI-enabled poverty alleviation requires sustained institutional investment in capacity building, participatory mechanisms, and accountability structures. The proposed AI-Enhanced Pentahelix Collaborative Governance Model provides a conceptual foundation for aligning technological innovation with inclusive, equitable, and context-sensitive poverty governance in metropolitan settings.

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All authors contributed equally to the development of this article.

Data availability

All datasets relevant to this study's findings are fully available within the article.

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