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An AI-Driven Policy Intelligence Framework for Transforming National Data into Evidence-Based Public Policy

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Abstract

The increasing complexity of national development requires public policies that are adaptive, data-driven, and evidence-based. However, many governments, particularly in developing countries, still face significant challenges in utilizing national data effectively due to data fragmentation, limited analytical capabilities of information systems, and the underutilization of Artificial Intelligence (AI). These limitations hinder the formulation of accurate and proactive public policies. This study aims to propose a conceptual framework that integrates national data, Information Systems, and AI to support intelligent policymaking. This research adopts a Design Science Research (DSR) approach to develop an artifact in the form of the National AI-Driven Policy Intelligence Framework (NAPIF). The framework is designed using a layered architecture consisting of data, processing, and output layers, supported by AI capabilities such as pattern recognition, predictive analytics, and policy recommendation generation. The proposed model transforms fragmented data into actionable insights through an integrated system that supports decision-making processes. The results indicate that the proposed framework enhances data integration, improves analytical capabilities, and enables predictive and adaptive policymaking. Compared to conventional systems, the framework provides more comprehensive decision support and supports continuous policy improvement through a feedback-driven mechanism. The study contributes theoretically by integrating the domains of Information Systems, AI, and public policy into a unified framework, and practically by offering a strategic approach for governments to implement data-driven governance aligned with long-term development goals. This study is limited by its conceptual nature; therefore, future research is recommended to validate the framework through empirical implementation and real-world case studies.

Keywords: artificial intelligence, public policy, decision support system, data-driven governance, policy intelligence.

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Introduction

Digital transformation has become a fundamental pillar in the reform of governance systems across countries, particularly in enhancing the quality of public policies that are adaptive, responsive, and data-driven. In the global context, the adoption of digital technologies, especially Artificial Intelligence

(AI), has shifted the paradigm from intuition-based policymaking toward *evidence-based policy* supported by large-scale and complex data analytics. Recent studies indicate that integrating AI into governmental systems can improve the accuracy of policy predictions, enhance public service efficiency, and increase transparency in decision-making processes [1]. Therefore, developing systems capable of managing and analyzing data intelligently has become a strategic necessity for modern governance.

In the Indonesian context, the urgency of digital transformation is increasingly emphasized through the national long-term vision of Indonesia Emas 2045. This vision highlights the importance of sustainable, inclusive, and innovation-driven development [2]. Furthermore, the national development agenda known as Asta Cita underscores the need for effective, transparent, and data-driven governance. However, several structural challenges continue to hinder the optimal utilization of national data in public policy formulation. One of the primary issues is the fragmentation of cross-sectoral data, where data is distributed across multiple institutions without adequate integration [3]. This condition makes it difficult to obtain a comprehensive understanding of national socio-economic conditions, resulting in policies that are often partial and less targeted.

In addition, the use of Information Systems within government institutions remains largely administrative, focusing on data recording and reporting, rather than evolving into analytical systems that support strategic decision-making. In the era of *big data*, Information Systems should function as decision support systems capable of transforming raw data into high-value information for policymaking [4]. This limitation is further exacerbated by the suboptimal adoption of Artificial Intelligence in governmental systems, both in terms of infrastructure, regulatory frameworks, and human resource readiness. Consequently, public policies tend to be reactive rather than predictive and are not yet fully grounded in evidence [5].

Several studies have explored the role of Artificial Intelligence in decision-making across various sectors, including healthcare, industry, and education [6]. However, within the domain of public policy, particularly in developing countries, there remains a significant research gap in developing a comprehensive conceptual framework that integrates national data, Information Systems, and Artificial Intelligence [7]. Most existing studies focus on partial implementations of AI, such as prediction or classification, without systematically linking these capabilities to the broader process of public policy formulation. Moreover, limited research has specifically examined how AI-integrated Information Systems can transform national data into intelligent and adaptive policy recommendations within the context of long-term national development [8].

Based on the above discussion, a significant research gap can be identified, namely the lack of a comprehensive conceptual framework that integrates national data management, Information Systems, and Artificial Intelligence into a unified model for supporting public policymaking [9]. The absence of such a framework has resulted in the suboptimal utilization of national data in enabling *evidence-based policy*, particularly in addressing the complexities of development in the digital era.

Therefore, this study aims to develop a conceptual model of an AI-based Information System designed to transform national data into intelligent, adaptive, and evidence-based public policy recommendations [10]. The proposed model positions Artificial Intelligence as an analytical enabler within the Information System, functioning to perform pattern analysis, predictive modeling, and policy recommendation generation without replacing the role of human decision-makers [11]. Through this approach, public policies are expected to be informed not only by historical data but also by future projections and evolving socio-economic dynamics.

The main contributions of this study are threefold. First, it proposes a conceptual framework that integrates national data, Information Systems, and Artificial Intelligence into a unified model for public policy decision support. Second, it extends the body of knowledge on the application of AI in governance, particularly within the context of developing countries such as Indonesia. Third, it provides strategic implications for advancing data-driven governance to support the achievement of Indonesia Emas 2045 and the implementation of the Asta Cita agenda [12]. Accordingly, this study is expected to contribute both academically and practically to the development of more effective, transparent, and sustainable public policies.

Literature Review

a. Artificial Intelligence in Public Policy

The rapid advancement of Artificial Intelligence (AI) has significantly transformed various sectors, including governance and public policymaking. AI enables large-scale data analysis through techniques such as machine learning, deep learning, and data mining, which can identify patterns, perform predictive analytics, and generate data-driven recommendations [13]. In the context of public policy, the adoption of AI has facilitated the emergence of *data-driven governance*, emphasizing decision-making based on empirical evidence (*evidence-based policy*).

Several studies have demonstrated that AI can enhance the quality of public policy through more accurate and efficient analytical capabilities. For instance, Abdelfattah et al [14] developed a machine learning-based model to predict medical staff work patterns, highlighting the potential of AI in supporting operational decision-making. Similarly, Li et al [15] showed that deep learning-based models improve analytical accuracy in industrial contexts, which can be adapted for public policy analysis.

However, most existing studies focus on sector-specific applications of AI, such as healthcare, manufacturing, or education, without integrating AI comprehensively into public policymaking systems. Moreover, the application of AI in governance still faces challenges related to algorithmic transparency, accountability, and ethical considerations in automated decision-making [16]. Therefore, a more holistic approach is required one that not only emphasizes the technical capabilities of AI but also its integration into a comprehensive policy-support system.

b. Information Systems and Decision Support Systems in Government

Information Systems (IS) play a crucial role in supporting both operational processes and decision-making within organizations, including government institutions. Over time, IS have evolved from administrative tools into *Decision Support Systems* (DSS), which assist decision-makers by providing relevant information and data-driven analysis [17].

In the context of e-government, the implementation of IS has contributed to improved public service efficiency, enhanced transparency, and increased citizen participation. Bibri et al [18] emphasize that the success of government information systems depends on a broader adoption ecosystem involving multiple stakeholders. However, many government information systems remain siloed across agencies, limiting their ability to provide integrated and comprehensive data.

Furthermore, most DSS used in government settings are still rule-based and have not fully incorporated intelligent technologies such as AI. This limitation restricts their ability to manage complex datasets and respond to rapidly changing socio-economic dynamics. Consequently, there is a growing need to develop integrated information systems enhanced with intelligent analytics to support strategic decision-making in governance.

c. National Data Governance and Evidence-Based Policy

National data represent a strategic asset in supporting effective and targeted public policymaking. The concept of *evidence-based policy* emphasizes that policies should be grounded in valid empirical data to improve decision quality and reduce subjective bias [19].

However, in practice, national data governance in many developing countries still faces significant challenges, including data fragmentation, limited interoperability, and inconsistent data quality. These issues hinder the optimal utilization of available data in decision-making processes. An et al [6] highlight the importance of integrated data infrastructures to support research and data-driven decision-making more effectively.

In Indonesia, these challenges are further compounded by the distribution of data across multiple institutions with differing standards, making cross-sectoral integration difficult. As a result, public policies are often not based on comprehensive data and tend to be reactive rather than proactive [19]. This underscores the necessity of strengthening national data governance as a prerequisite for achieving evidence-based policymaking.

d. Integration of Artificial Intelligence and Information Systems in Government

The integration of Artificial Intelligence with Information Systems represents a strategic approach to overcoming the limitations of conventional systems. AI enhances the capabilities of Information Systems by enabling automated data processing, predictive analytics, and real-time policy recommendations. This integration transforms systems from passive data repositories into proactive and adaptive decision-support tools.

Several studies have begun exploring this integration; however, they remain limited to specific domains and lack a comprehensive framework. Bertacchini et al [20] demonstrated the use of AI-based systems in developing national intelligent systems within the education sector. Nevertheless, their work does not address cross-sectoral integration at a national scale.

Moreover, most existing studies do not explicitly link the integration of AI and Information Systems to the end-to-end public policymaking process, from data collection to policy evaluation [21]. This indicates a gap in the development of system models capable of systematically integrating all stages of policymaking within a unified framework.

e. Synthesis and Research Gap

Based on the literature review, it can be concluded that despite significant advancements in Artificial Intelligence, Information Systems, and data governance, several key limitations remain in existing research.

First, studies on AI in public policy are largely partial and sector-specific, lacking integration within a comprehensive policy framework. Second, Information Systems in government are still predominantly administrative and have not fully evolved into intelligent and integrated decision-support systems. Third, national data governance continues to face challenges related to fragmentation and limited interoperability, hindering the implementation of evidence-based policymaking. Fourth, there is a lack of a comprehensive conceptual framework that integrates national data, Information Systems, and Artificial Intelligence into a unified model for public policy support.

Therefore, the research gap addressed in this study lies in the absence of a systematic conceptual model that integrates these three components within a governance context, particularly in transforming national data into intelligent, adaptive, and evidence-based public policies.

Method

a. Research Approach

This study employs the Design Science Research (DSR) approach, which aims to develop and evaluate an artifact in the form of a conceptual model of an AI-based Information System for supporting public policy. The DSR approach is selected because this research not only focuses on analyzing existing phenomena but also on designing an innovative solution to address real-world challenges in governance [22].

Design Science Research is widely used in Information Systems research to produce artifacts such as models, methods, or systems that provide both practical and theoretical contributions [23]. In this study, the developed artifact is a conceptual framework that integrates national data, Information Systems, and Artificial Intelligence to support *evidence-based policymaking*.

b. Design Science Research Stages

This research adopts five main stages of Design Science Research, namely: *problem identification, objective definition, design and development, demonstration, and evaluation*.

1. Problem Identification

This stage aims to identify key issues in national data management and public policymaking. The identification process is conducted through a literature review of scientific journals, policy reports, and relevant official documents. The findings indicate major issues such as data fragmentation, limited analytical capabilities in existing Information Systems, and the suboptimal use of Artificial Intelligence in public decision-making processes.

2. Objective Definition

Based on the identified problems, this stage focuses on defining the objectives of the proposed solution. The primary objective of this study is to develop an AI-based Information System model capable of transforming national data into intelligent, adaptive, and evidence-based public policy recommendations. This includes enabling predictive analytics and data-driven decision support for policymakers.

3. Design and Development

At this stage, a conceptual model of the AI-based Information System is designed and developed. The design process integrates key concepts derived from the literature, including:

- national data governance
- integrated Information Systems
- Artificial Intelligence as an analytical enabler

The proposed model is structured using a layered architecture consisting of a data layer, a processing layer, and an output layer. Each layer is designed to be interconnected to support the transformation of raw data into intelligent policy recommendations.

4. Demonstration

The demonstration stage illustrates how the proposed model can be applied in a real-world context. This is conducted conceptually through *use case scenarios* that describe the process flow from national data integration to the generation of policy recommendations. This stage aims to demonstrate the feasibility and applicability of the proposed model in supporting public decision-making.

5. Evaluation

The evaluation is conducted qualitatively by comparing the proposed model with existing approaches in the literature. The evaluation focuses on the model's ability to:

- integrate cross-sectoral data
- enhance analytical capabilities using AI
- support data-driven decision-making

Additionally, the evaluation considers the relevance, consistency, and contribution of the model to the development of public policy decision support systems. This approach ensures the conceptual validity and practical applicability of the proposed framework.

c. Data Sources and Data Collection Techniques

This study utilizes secondary data obtained from:

1. Literature Review, including reputable journal articles, conference proceedings, and reference books related to Artificial Intelligence, Information Systems, and public policy.
2. Documentation, including policy reports, government documents, and official publications relevant to national data management and digital transformation in governance.

The selection of data sources is conducted carefully based on relevance, credibility, and contribution to the research topic.

d. Data Analysis Techniques

The collected data are analyzed using a qualitative descriptive approach, consisting of the following steps:

1. Data Classification, grouping literature based on key themes (AI, Information Systems, and public policy).

2. Conceptual Synthesis, integrating various concepts and research findings to build a comprehensive framework.
3. Model Design, constructing the conceptual model based on the synthesized literature.
4. Interpretation, explaining the relationships between model components and their implications for public policymaking.

e. Research Validity and Contribution

To ensure research validity, the proposed model is developed based on a synthesis of relevant and up-to-date literature, while also considering real-world governance contexts. The use of the Design Science Research approach provides a strong methodological foundation for artifact development.

The methodological contribution of this study lies in the application of Design Science Research to develop an AI-based Information System model for public policy, which remains relatively underexplored, particularly in developing countries. Therefore, this methodology not only supports the development of the conceptual framework but also contributes to advancing research approaches in the fields of Information Systems and governance.

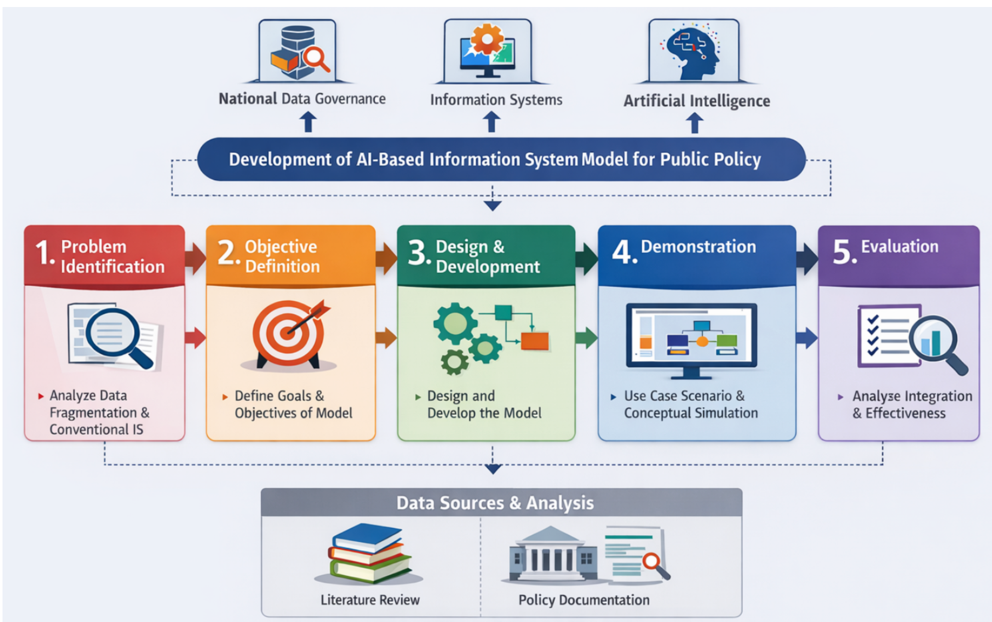

Figure 1. Design Science Research (DSR) Methodology for Developing the AI-based Information System Model for Public Policy

Result and Discussion

a. Analysis of Current Challenges in National Data and Public Policy Systems

The transformation toward data-driven governance has become a fundamental requirement in achieving effective and adaptive public policymaking. However, despite the increasing availability of national data, many countries particularly developing ones still face structural and technological challenges in utilizing such data optimally. In the Indonesian context, these challenges are closely related to issues of data fragmentation, limited analytical capabilities of information systems, and the underutilization of Artificial

Intelligence (AI) in supporting policymaking processes [24], [25].

One of the most critical challenges lies in the fragmented nature of national data. Data generated by various government agencies are often stored in isolated systems with differing standards, formats, and governance policies. This lack of interoperability prevents the integration of cross-sectoral data, thereby limiting the ability of policymakers to obtain a comprehensive and holistic understanding of national conditions [26]. As a result, policies are frequently formulated based on partial insights rather than complete and integrated datasets, which may lead to suboptimal or misaligned policy outcomes.

In addition to fragmentation, the current utilization of Information Systems in government institutions remains largely administrative. Most systems are designed for data recording, reporting, and basic processing, rather than for advanced analytics or strategic decision support. This indicates that the potential of Information Systems as a *Decision Support System (DSS)* has not been fully realized. In the era of big data, such limitations significantly hinder the transformation of raw data into actionable insights for policymaking [27].

The challenges described above are further compounded by the limited adoption of Artificial Intelligence within government systems. While AI has demonstrated its capability in predictive analytics, pattern recognition, and decision automation across various sectors [23], [28], its application in public governance remains minimal and fragmented. Consequently, policymaking processes tend to remain reactive rather than proactive, lacking predictive capabilities that could anticipate future socio-economic dynamics.

To provide a structured overview of these issues, the key challenges in national data management and public policy systems are summarized in Table 1.

Table 1. Challenges in National Data Management and Public Policy Systems

Analyzed Aspect	Current Condition	Impact on Public Policy
National Data Integration	Data is fragmented across multiple institutions and not fully integrated	Policies are not based on comprehensive cross-sectoral data
Information System Utilization	Primarily administrative and reporting-oriented	Limited strategic and analytical capabilities
Artificial Intelligence Adoption	Limited and not standardized	Policies remain reactive rather than predictive
Evidence-Based Policy	Not consistently implemented	Decisions often lack strong empirical foundation
Readiness for Indonesia Emas 2045	Facing governance and technological challenges	Development targets risk being suboptimal

Table 1 highlights several critical gaps between the current condition of national data management and the requirements for effective public policymaking. The fragmentation of data emerges as a fundamental issue that affects all subsequent processes, including analysis and decision-making [29]. Without integrated data, policymakers are unable to capture interdependencies across sectors such as health, education, economy, and social welfare. This limitation significantly reduces the effectiveness of policies, as decisions are often made in isolation rather than through a systemic perspective.

Furthermore, the table demonstrates that Information Systems are still predominantly used for operational purposes rather than strategic analysis. This reflects a maturity gap in digital governance, where systems have not yet evolved into intelligent platforms capable of supporting complex decision-making. The limited adoption of AI further exacerbates this issue, as advanced analytical capabilities such as predictive modeling and scenario simulation remain underutilized.

Another important insight from Table 1 is the inconsistency in implementing evidence-based policy. Although the importance of data-driven decision-making is widely recognized, its practical implementation remains uneven. This inconsistency results in policies that are reactive, addressing problems only after they emerge, rather than anticipating and preventing them [30].

In addition to identifying current challenges, it is also important to analyze the gap between national development targets and existing conditions. This gap provides a clearer understanding of the urgency for systemic transformation in data governance and policymaking.

Table 2. Gap Between National Development Targets and Current Conditions

National Target	Key Requirement	Current Condition
Indonesia Emas 2045	Data-driven and technology-based policy	Data utilization is not yet optimal
Asta Cita	Effective and transparent governance	Systems are not fully intelligent and integrated
Inclusive Development	Accurate and targeted decision-making	Limited analytical capabilities

Table 2 illustrates the disparity between the strategic goals of national development and the current state of data utilization and governance systems. The vision of Indonesia Emas 2045 emphasizes the importance of data-driven and technology-enabled policymaking [31]. However, the current condition indicates that data is not yet utilized optimally, which undermines the ability to achieve this vision. This gap highlights the need for a more integrated and intelligent approach to data management and policy formulation.

Similarly, the implementation of Asta Cita requires effective and transparent governance supported by advanced information systems. Nevertheless, existing systems lack the intelligence and integration needed to support such governance. This limitation suggests that current technological infrastructures are not sufficient to meet the demands of modern policymaking [32].

Moreover, achieving inclusive development requires accurate and targeted decision-making, which depends heavily on robust analytical capabilities. The limited use of advanced analytics, particularly AI, restricts the ability to identify vulnerable populations, predict socio-economic trends, and design targeted interventions [33].

Overall, the analysis of Tables 1 and 2 reveals a significant gap between the current state of national data management and the requirements for intelligent, adaptive, and evidence-based policymaking. These findings underscore the urgency of developing an integrated system that combines national data, Information Systems, and Artificial Intelligence. Such a system is essential not only for improving the quality of public policies but also for ensuring the successful implementation of long-term national development agendas.

b. Proposed AI-Based Policy Intelligence Framework

To address the challenges identified in the previous section, this study proposes a conceptual framework referred to as the National AI-Driven Policy Intelligence Framework (NAPIF). This framework is designed to transform fragmented national data into intelligent, adaptive, and evidence-based public policy recommendations through the integration of national data, Information Systems, and Artificial Intelligence (AI).

The proposed framework is built upon a systematic integration of key components that collectively enable the transformation of raw data into policy intelligence. These components are presented in Table 3.

Table 3. Components of the Proposed AI-Based Policy Intelligence Framework

Solution Component	Main Role	Contribution to Public Policy	Implementation Indicator
National Data Integration	Aggregates cross-sectoral data	Provides comprehensive data foundation	Level of data interoperability across institutions
Integrated Information System	Manages and structures data	Enables strategic analysis	System integration maturity and real-time processing capability
Artificial Intelligence	Performs pattern recognition and prediction	Generates data-driven recommendations	Accuracy of predictions and model performance
Decision Support System	Presents policy alternatives	Assists policymakers	Usability and decision adoption rate
Policy Intelligence Output	Produces intelligent policies	Ensures accuracy and adaptability	Policy effectiveness and responsiveness
Indonesia Emas 2045 & Asta Cita	Final development goals	Supports sustainable development	Alignment with national development indicators

Table 3 illustrates the core components of the proposed framework and their interrelated roles in supporting public policymaking. The integration of national data serves as the foundational layer, addressing the issue of fragmented data across institutions. By consolidating data from multiple sectors into a unified platform, this component enables a comprehensive understanding of national conditions, which is essential for formulating effective policies.

The integrated information system acts as the structural backbone that organizes and processes the aggregated data. Unlike conventional systems that are primarily administrative, this system is designed to support analytical functions, enabling real-time data processing and visualization. This enhances the ability of policymakers to interpret complex datasets and derive meaningful insights .

Artificial Intelligence plays a critical role as the analytical engine of the framework. Its capabilities in pattern recognition, predictive modeling, and recommendation generation significantly enhance the analytical capacity of the system. This aligns with previous studies Ratih et al [34] and Deng et al [35], which highlight the effectiveness of AI in handling large-scale and complex data. The decision support system further bridges the gap between analysis and action by presenting policy alternatives in an accessible format.

Finally, the output of the framework is policy intelligence, which represents policies that are data-driven, adaptive, and aligned with national development goals such as Indonesia Emas 2045 and Asta Cita. Overall, Table 3 demonstrates that the proposed framework is not merely a technological system but a comprehensive policy support ecosystem. To further elaborate on the structural design of the framework, the proposed system adopts a layered architecture consisting of three main layers, as presented in Table 4.

Table 4. Layered Architecture of the AI-Based Information System

System Layer	Main Components	Function	Technological Requirement
Data Layer	Population, economic, education, health, social data	Provides input data	Data warehouse, data lake, interoperability standards (API)
Processing Layer	Integrated Information System and AI	Performs analysis and prediction	Machine learning models, big data analytics, cloud computing
Output Layer	Policy dashboard and analytics reports	Supports decision-making	Visualization tools, dashboards, reporting systems

Table 4 presents the layered architecture of the proposed framework, which is designed to ensure a structured and efficient flow of information. The data layer serves as the entry point of the system, where various types of national data are collected and stored. This layer emphasizes the importance of data diversity and completeness, as it incorporates data from multiple sectors that are essential for comprehensive policy analysis.

The processing layer represents the core of the system, where the integrated information system and Artificial Intelligence work together to analyze the data. This layer is responsible for transforming raw data into actionable insights through advanced analytical techniques [36]. The integration of AI within this layer enables predictive analysis, allowing policymakers to anticipate future trends and potential challenges.

The output layer delivers the results of the analysis in the form of dashboards and analytical reports. These outputs are designed to be user-friendly and accessible, ensuring that policymakers can easily interpret the information and make informed decisions. The layered architecture not only enhances system efficiency but also ensures scalability and flexibility, making the framework adaptable to various policy contexts [37]. In addition to the architectural design, the specific role of Artificial Intelligence within the system is further detailed in Table 5.

Table 5. Role of Artificial Intelligence in the Proposed Framework

AI Function	Role in System	Policy Benefit	Analytical Technique
Pattern Analysis	Identifies trends and anomalies	Improves policy accuracy	Clustering, anomaly detection
Prediction	Forecasts future conditions	Enables proactive policies	Machine learning, time-series forecasting
Recommendatio n	Suggests policy alternatives	Supports strategic decisions	Recommender systems, optimization models
Evaluation	Assesses policy impact	Enables continuous improvement	Simulation, impact analysis models

Table 5 highlights the strategic role of Artificial Intelligence in enhancing the analytical capabilities of the proposed framework. AI enables the system to move beyond descriptive analysis toward predictive and prescriptive analytics. Through pattern analysis, the system can identify trends and anomalies that may not be visible through traditional methods [38].

Predictive capabilities allow the system to forecast future conditions, enabling policymakers to design proactive rather than reactive policies. This is particularly important in addressing complex and dynamic socio-economic challenges. The recommendation function further enhances decision-making by providing alternative policy options based on data-driven insights.

Finally, the evaluation function enables continuous assessment of policy outcomes, creating a feedback loop that supports ongoing improvement. This aligns with the concept of adaptive governance, where policies are continuously refined based on new data and insights [39]. To provide a comprehensive understanding of how these components interact, the overall model of the proposed framework is illustrated in Figure 2.

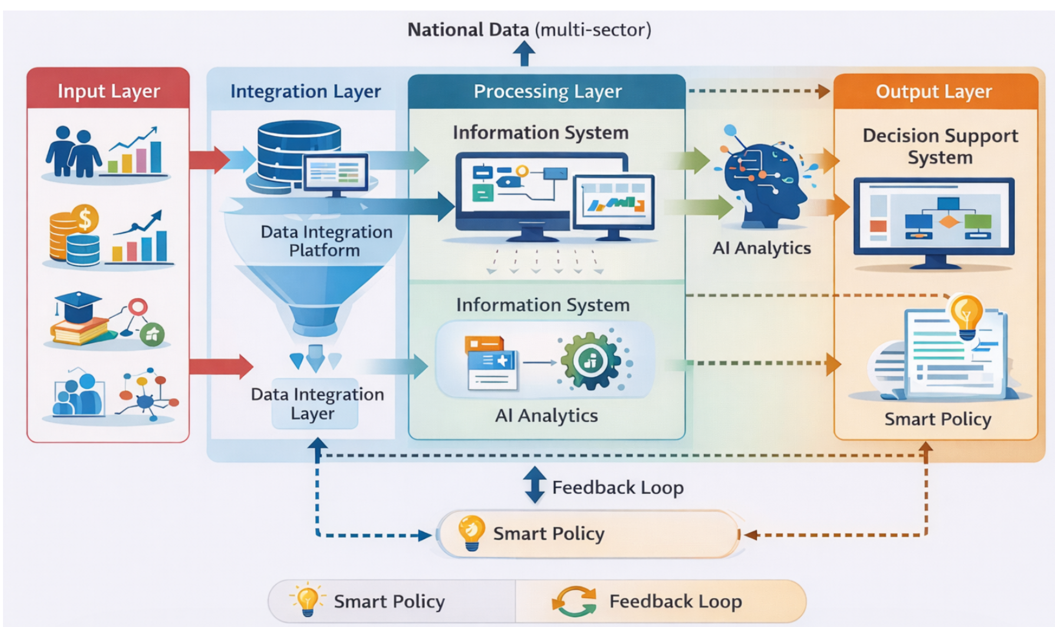

Figure 2. Conceptual Model of the AI-Based Policy Intelligence Framework (NAPIF)

Figure 2 illustrates the end-to-end process of transforming national data into policy intelligence. The model demonstrates how data from multiple sectors is integrated and processed through the information system and AI, resulting in policy recommendations that support decision-making [40]. The inclusion of a feedback loop ensures that the system remains adaptive and continuously improves over time.

In summary, the proposed NAPIF framework provides a comprehensive and systematic approach to addressing the limitations of current public policymaking systems. By integrating data, systems, and AI within a unified architecture, the framework enables the development of intelligent, adaptive, and evidence-based policies that align with national development goals.

c. Implications and Evaluation of the Proposed Framework

The proposed National AI-Driven Policy Intelligence Framework (NAPIF) provides significant contributions both theoretically and practically in advancing data-driven governance. In addition to proposing a conceptual model, this study evaluates the framework by comparing it with conventional systems and existing approaches, as well as illustrating its operational and performance advantages.

From a theoretical perspective, the framework extends the concept of *Decision Support Systems (DSS)* by integrating Artificial Intelligence into a unified architecture that enables predictive and adaptive policymaking. While previous studies have explored AI applications in specific domains Munshi et al [41] and e-government systems separately (Sihotang et al., 2025), the proposed framework contributes by combining these domains into a comprehensive policy intelligence system. This integration supports the realization of *evidence-based policy*, which has been widely recognized as essential for improving policy quality [42], [43].

From a practical perspective, the framework offers a structured approach for governments to transition from reactive to proactive policymaking. By leveraging integrated data and AI-driven analytics, policymakers can anticipate future conditions and design more effective interventions [44]. This is particularly relevant for achieving long-term national development goals such as Indonesia Emas 2045.

To systematically evaluate the proposed framework, a comparative analysis is presented in Table 6.

Table 6. Comparative Evaluation of Conventional Systems, Existing Approaches, and NAPIF

Evaluation Aspect	Conventional System	Existing Approaches	Proposed Framework (NAPIF)
Data Integration	Fragmented	Partially integrated	Fully integrated across sectors
Analytical Capability	Descriptive	Semi-analytical	Predictive and prescriptive (AI-based)
Decision Support	Limited	Moderate	Advanced and adaptive
Policy Response	Reactive	Semi-proactive	Proactive and predictive
Scalability	Low	Medium	High
Adaptability	Low	Moderate	High (feedback-driven)

Table 6 clearly demonstrates the advantages of the proposed NAPIF framework compared to conventional systems and existing approaches. One of the most prominent improvements lies in data integration. While conventional systems operate in silos, limiting cross-sectoral insights, the proposed framework enables full integration of national data, allowing policymakers to analyze interdependencies across sectors more effectively.

In terms of analytical capability, the shift from descriptive to predictive and prescriptive analytics represents a major advancement. Conventional systems rely heavily on historical data, which restricts their ability to anticipate future conditions. Existing approaches incorporate some level of analytics but often lack comprehensive AI integration. In contrast, NAPIF leverages AI to generate forward-looking insights and actionable recommendations, enabling proactive policymaking [45].

Furthermore, the framework significantly enhances decision support by providing adaptive and data-driven policy alternatives. The inclusion of a feedback mechanism also improves scalability and adaptability, ensuring that the system evolves continuously in response to new data and changing conditions. Overall, Table 6 confirms that the proposed framework offers a substantial improvement in supporting intelligent and evidence-based policymaking. To further illustrate how the framework operates in practice, the evaluation mechanism is presented in Figure 3.

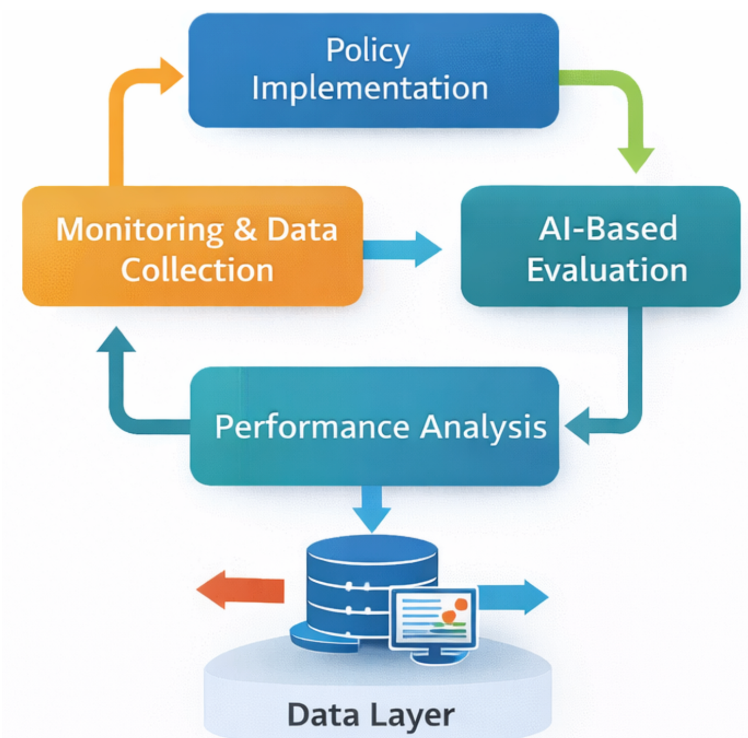

Figure 3. Conceptual Evaluation Diagram of the NAPIF Framework

Figure 3 illustrates the evaluation process embedded within the NAPIF framework, highlighting its adaptive and iterative nature. The process begins with policy implementation, followed by continuous monitoring and data collection. The collected data is then analyzed using AI techniques to assess policy effectiveness and identify areas for improvement.

Unlike traditional evaluation methods that rely on periodic and manual assessments, the proposed framework enables continuous and real-time evaluation. This allows policymakers to respond more quickly to emerging issues and adjust policies accordingly [46]. The feedback loop ensures that evaluation results are reintegrated into the system, creating a continuous cycle of learning and improvement.

This adaptive mechanism is particularly important in dynamic environments where socio-economic conditions change rapidly. By incorporating real-time evaluation and feedback, the framework supports the development of policies that remain relevant and effective over time. Thus, Figure 3 reinforces the framework's capability to support adaptive governance. In addition to qualitative evaluation, a conceptual performance comparison is illustrated in Figure 4.

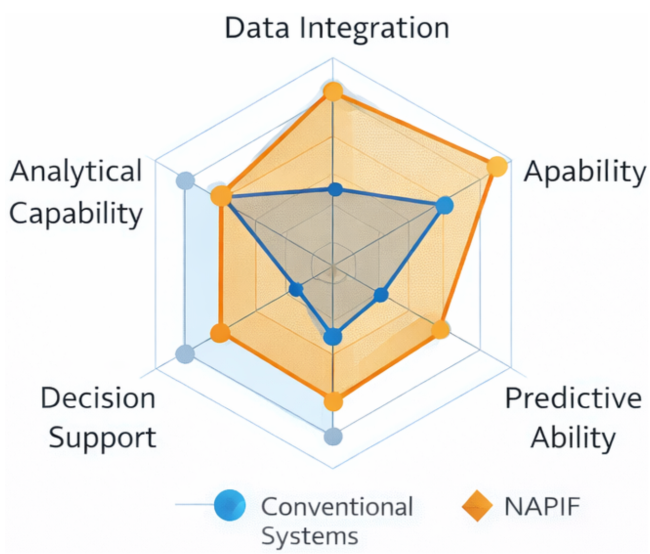

Figure 4. Conceptual Performance Comparison between Conventional Systems and NAPIF

Figure 4 provides a visual representation of the comparative performance between conventional systems and the proposed NAPIF framework. The graph highlights significant improvements across key dimensions, including data integration, analytical capability, decision support, adaptability, and predictive ability.

The most notable improvement is observed in predictive capability, where the integration of AI enables the system to forecast future trends and support proactive policymaking [47]. Similarly, the framework demonstrates higher adaptability due to its feedback-driven mechanism, which allows continuous refinement of policies.

Although the graph is conceptual, it effectively illustrates the relative advantages of the proposed framework in addressing the limitations of existing systems. This visualization helps to reinforce the argument that integrating AI into information systems can significantly enhance the effectiveness of public policymaking.

In summary, the implications and evaluation of the proposed NAPIF framework confirm its potential to transform public policymaking into a more intelligent, adaptive, and data-driven process [48]. By combining strong theoretical contributions with practical applicability, the framework provides a robust foundation for advancing governance systems in the digital era.

Conclusion

This study addresses the critical challenges in national data management and public policymaking, particularly the issues of data fragmentation, limited analytical capabilities of information systems, and the underutilization of Artificial Intelligence (AI). These challenges hinder the effective implementation of *evidence-based policy* and reduce the ability of governments to respond adaptively to dynamic socio-economic conditions.

To overcome these limitations, this study proposes the National AI-Driven Policy Intelligence Framework (NAPIF) as a conceptual model that integrates national data, Information Systems, and Artificial Intelligence into a unified architecture. The proposed framework is designed to transform fragmented and underutilized data into intelligent, adaptive, and data-driven policy recommendations. By adopting a layered architecture consisting of data, processing, and output layers, the framework ensures a structured flow of information from data collection to decision-making.

The findings of this study highlight that the integration of Artificial Intelligence significantly enhances the analytical capabilities of Information Systems, enabling predictive and prescriptive policymaking. In contrast to conventional systems that are predominantly descriptive and reactive, the proposed framework supports proactive and adaptive governance through real-time analysis and continuous feedback mechanisms. The inclusion of a feedback loop further strengthens the framework by enabling ongoing evaluation and refinement of policies.

From a theoretical perspective, this study contributes to the literature by providing a comprehensive conceptual framework that bridges the domains of Information Systems, Artificial Intelligence, and public policy. It extends the traditional concept of Decision Support Systems into a more advanced policy intelligence system capable of handling complex and large-scale data environments. From a practical perspective, the framework offers a strategic approach for governments to enhance policy effectiveness, improve data integration, and support long-term development goals such as Indonesia Emas 2045.

Despite its contributions, this study is limited by its conceptual nature and the absence of empirical validation. Therefore, future research is recommended to implement and test the proposed framework through case studies, simulations, or prototype development to evaluate its effectiveness in real-world contexts. Additionally, further studies may explore issues related to data governance, ethical considerations, and system scalability to ensure the sustainable implementation of AI-based policy intelligence systems.

In conclusion, the proposed NAPIF framework provides a robust foundation for advancing data-driven governance and supports the development of intelligent, adaptive, and evidence-based public policies in the digital era.

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