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UTILIZING BIG DATA AND ARTIFICIAL INTELLIGENCE TO MONITOR SDG ACHIEVEMENTS

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Article Info

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Abstract: This study aims to formulate a Big Data and Artificial Intelligence (AI)-based model for monitoring the SDGs within a data-driven governance framework. Using a descriptive qualitative approach and a conceptual study, the study focuses on four aspects: current monitoring mechanisms, potential Big Data-based data sources, opportunities for AI utilization, and data governance and inter-agency interoperability. Data were obtained from literature reviews, policy documents, and news sources on the implementation of the SDGs, Big Data, AI, and data governance. The results show that the weakness of SDGs monitoring lies not in the availability of indicators or data, but rather in the monitoring and governance architecture, which remains administrative, periodic, and sectoral, resulting in slow information flow and minimal analytics. Abundant data sources actually meet the characteristics of Big Data, and AI can transform indicator readings into real-time, analytical, and predictive insights. However, their utilization has not been optimal due to interoperability constraints and procedural data governance. Monitoring transformation requires the integration of Big Data, the use of AI, and a shift in governance towards interoperability across agencies. Further research suggestions include the empirical testing of the model through case studies in local governments/agencies, the development of a Big Data and AI-based monitoring dashboard prototype, and the measurement of its impact on the quality of policy-making.

Kata Kunci:
Big Data;
Kecerdasan Buatan (AI);
Pemantauan SDGs;
Tata Kelola Data;
Interoperabilitas.

Abstrak: *Studi ini bertujuan untuk merumuskan model berbasis Big Data dan Kecerdasan Buatan (AI) untuk memantau SDGs dalam kerangka tata kelola berbasis data. Dengan menggunakan pendekatan kualitatif deskriptif dan studi konseptual, studi ini berfokus pada empat aspek: mekanisme pemantauan saat ini, potensi sumber data berbasis Big Data, peluang pemanfaatan AI, dan tata kelola data serta interoperabilitas antar lembaga. Data diperoleh dari tinjauan literatur, dokumen kebijakan, dan sumber berita tentang implementasi SDGs, Big Data, AI, dan tata kelola data. Hasil menunjukkan bahwa kelemahan pemantauan SDGs terletak bukan pada ketersediaan indikator atau data, melainkan pada arsitektur pemantauan dan tata kelola, yang masih bersifat administratif, periodik, dan sektoral, sehingga mengakibatkan aliran informasi yang lambat dan analitik yang minimal. Sumber data yang melimpah sebenarnya memenuhi karakteristik Big Data, dan AI dapat mengubah pembacaan indikator menjadi wawasan analitis dan prediktif secara real-time. Namun, pemanfaatannya belum optimal karena kendala interoperabilitas dan tata kelola data prosedural. Transformasi pemantauan membutuhkan integrasi Big Data, penggunaan AI, dan pergeseran tata kelola menuju interoperabilitas antar lembaga. Saran penelitian lebih lanjut mencakup pengujian empiris model melalui studi kasus di pemerintahan/lembaga* *lokal, pengembangan prototipe dasbor pemantauan berbasis Big Data dan AI, serta pengukuran dampaknya terhadap kualitas pembuatan kebijakan.*

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INTRODUCTION

The Sustainable Development Goals (SDGs) agenda established by the United Nations through the United Nations Development Programme requires every country, including Indonesia, to monitor development achievements in a measurable, sustainable, and data-driven manner (Samuel et al., 2022). The complexity of the 17 goals, 169 targets, and hundreds of SDG indicators presents significant challenges in terms of data availability, reporting accuracy, cross-sector integration, and timeliness of information (Ardani, 2022). In practice, SDG monitoring at the national and regional levels is still dominated by conventional approaches based on periodic reporting, surveys, and sectoral data compilation, which are often fragmented, slow, and unable to capture real-time dynamics on the ground (Efthymiou et al., 2022).

In the era of digital transformation, the emergence of Big Data and Artificial Intelligence (AI) offers a new, more precise, predictive, and adaptive approach to supporting development monitoring systems(Yu & He, 2021). Big Data enables the utilization of vast, diverse, and rapidly flowing data volumes from various sources, such as government administrative data, IoT sensors, satellite imagery, social media, and even digital community transactions (W. Wang et al., 2023). Meanwhile, AI can perform intelligent analysis through machine learning, data mining, and pattern recognition to identify patterns, trends, anomalies, and projected SDG indicator achievements more sharply and quickly (Zhu, 2020).

The use of these two technologies is relevant in the context of SDG monitoring, which is no longer merely descriptive but also diagnostic and predictive (Yuen et al., 2021). This means that the system not only reports indicator achievements but also detects potential problems early, provides data-driven policy recommendations, and assists decision-makers in formulating more targeted interventions (Aji, 2020). The integration of Big Data and AI also opens the way for the development of a real-time, interoperable, and cross-sectoral monitoring system, in line with the spirit of data-driven governance and the One Data principle (Pribadi, 2021).

In the Indonesian context, the challenges of SDG monitoring are increasingly complex due to the country's vast geography, diverse local government capacities, and heterogeneous data sources (Anser & Adebayo, 2026). Limited data integration between agencies, differing data standards, and the suboptimal use of analytical technology are major obstacles to producing accurate and comprehensive information on SDG achievements (Sürme et al., 2026). Therefore, a Big Data and AI-based approach is seen as an innovative strategy capable of bridging these gaps and strengthening evidence-based policymaking (Gravili et al., 2023).

This study aims to analyze how the use of Big Data and AI can improve the accuracy of the SDGs monitoring system, both in terms of data accuracy, analysis speed, information integration, and its relevance to policymaking needs (Krúpová & Koman, 2026). Therefore, this research is expected to provide conceptual and practical contributions to the development of an SDGs monitoring model that is adaptable to advances in digital technology and the needs of modern governance (Ma et al., 2026). Within this framework, the indicators to be reviewed cover four main aspects: current SDG monitoring mechanisms, potential Big Data sources, opportunities for AI in indicator analysis, and data governance and inter-agency interoperability (Wu et al., 2026). These four study indicators serve as the basis for the analysis in formulating a Big Data and AI-based SDG monitoring model that is more precise, responsive, and supports evidence-based policymaking.

RESEARCH METHOD

This study uses a descriptive qualitative approach with a conceptual study design that aims to formulate a monitoring model for SDGs achievements based on the use of Big Data and Artificial Intelligence (AI) within a data-driven governance framework (Sugiyono, 2017). This approach was chosen because the study does not focus on quantitative measurement of indicators, but rather on an in-depth analysis of the concepts, practices, challenges, and opportunities for integrating intelligent analytical technology into a sustainable development monitoring system. The analysis is directed at building a framework that can bridge the needs of SDGs monitoring with the development of digital technology and public data governance. This study aims to analyze how the use of Big Data and AI can improve the sharpness of the SDGs achievement monitoring system, both in terms of data accuracy, analysis speed, information integration, and its relevance to policy-making needs. The indicators studied cover four main aspects: current SDG monitoring mechanisms, Potential data sources based on Big Data, Opportunities for utilizing AI in indicator analysis, and Data governance and interoperability between agencies.

The data sources in this study are secondary data, obtained through literature reviews, policy document analysis, and news searches relevant to the implementation of SDGs, Big Data, AI, and data governance in the public sector. The literature review includes scientific journal articles, academic books, and international research reports discussing the use of Big Data and AI in development monitoring. Document analysis focused on regulations, guidelines, official government reports, and policy implementation documents such as the national SDGs policy and the One Data Indonesia framework. Meanwhile, news data was used to capture actual practices, government innovations, and the latest dynamics related to the use of data and technology in development monitoring in various regions.

Data collection techniques were carried out through a systematic documentation study, involving the search, identification, and classification of documents and literature based on the main research themes: SDG monitoring, Big Data, AI, and data governance. All collected data were then organized based on the relevance of the substance and the context of implementation in Indonesia. Data analysis techniques were carried out through the stages of content analysis and thematic analysis. Content analysis was used to extract concepts, findings, and recommendations from the literature and documents, while thematic analysis was used to identify patterns of relationships between concepts related to the integration of Big Data, AI, and SDGs monitoring.

RESULT AND DICUSSION

A. THE CURRENT SDGS MONITORING MECHANISM

The Sustainable Development Goals (SDGs) agenda, initiated by the United Nations, places a monitoring system as a crucial component in ensuring the achievement of measurable development targets (Burton, 2023). Through the United Nations Development Programme, countries are encouraged to develop reliable, standardized, and sustainable indicator reporting mechanisms (Samuel et al., 2022). Official government reports and reports on implementation practices on the ground show that the SDGs monitoring mechanism in Indonesia—coordinated by Bappenas with statistical support from the Central Statistics Agency—still exhibits an administrative, periodic, and sectoral work pattern (W. Wang et al., 2023).

Research findings indicate that the primary problem lies not in the availability of SDG indicators, but rather in a monitoring architecture that has not been designed to interpret data dynamics in real time and with analytical support (Zhang et al., 2022). The existing system still positions monitoring as a routine reporting activity, rather than as a policy control instrument that adapts to changing conditions on the ground (Gravili et al., 2023). The retrospective (lagging) nature of monitoring is a significant finding. Most indicator data comes from periodic surveys and routine reports from regional government agencies, so the resulting information reflects past conditions (Krúpová & Koman, 2026).

Consequently, the monitoring system has not functioned as an early warning system to detect potential declines in indicator performance (Xia et al., 2026). This information lag directly impacts policy responses, particularly for highly dynamic indicators such as poverty, health, the environment, and urban issues (Ma et al., 2026). A further finding is the fragmentation of sectoral data (data silos), which hinders indicator integration (Che et al., 2026).

Each agency manages data using different standards, formats, and systems. Although the One Data Indonesia policy has emphasized the principle of interoperability, data integration for SDG monitoring is still carried out through manual or semi-manual compilation (Sampaio & Gomes, 2021). This situation poses the risk of inconsistency, duplication, and delays in the presentation of integrated data (Acharya et al., 2023). Monitoring quality also depends heavily on regional reporting capacity. Variations in technical capabilities, digital infrastructure, and data governance across regions result in inconsistent indicator data quality (Damhuis et al., 2023).

The impact is evident in the accuracy of national-level data aggregation and the limitations of spatial analysis at the micro-level, such as villages or sub-districts (Skog et al., 2022). In other words, regional capacity imbalances also affect the accuracy of national information on SDG achievements. Furthermore, current monitoring focuses more on descriptive reporting than indicator analysis (Sonkamble et al., 2021).). SDG achievement dashboards and reports generally present only numerical data without analytical capabilities to identify patterns, trends, anomalies, or projected achievements (Abdalrahman et al., 2022).

This indicates that monitoring has not yet reached the diagnostic stage, let alone the predictive analytics essential to evidence-based policymaking. Slow data cycles and a lack of adaptability to field dynamics further exacerbate the limitations of the existing system (Power et al., 2024). The lengthy process of data collection, reporting, and recapitulation often results in the information being irrelevant to actual conditions (Maulidya et al., 2022). For rapidly changing indicators, this lag leads to inaccuracies and delays in policy interventions (Menpan.go.id, 2022).

Overall, the current SDGs monitoring architecture has not been designed as an integrated data ecosystem capable of leveraging various data sources, such as administrative, spatial, sensor, and digital-trace data (Muhammad Firdaus, 2022). Monitoring is still understood as a cross-agency reporting obligation rather than as an intelligent, adaptive, data-driven monitoring system (Kaltimprov.go.id, 2021). A synthesis of these findings confirms that the current SDGs monitoring mechanism can be characterized as periodic, sectoral, fragmented, slow, and lacking in analytics (Kemnaker.go.id, 2022). These limitations underscore the urgency of transforming toward a real-time, integrated, and predictive monitoring model using Big Data and AI (Kominfo.go.id, 2021).

B. POTENTIAL DATA SOURCES BASED ON BIG DATA

Based on a review of policy documents, scientific literature, and reports on implementation practices, this research shows that the main problem with SDG monitoring in Indonesia lies not in a lack of data, but rather in the failure to position this abundant data as an integrated Big Data ecosystem for analytical purposes. Various data sources—from government administrative systems, environmental sensors, remote sensing imagery, to citizens' digital footprints—are readily available and continually updated. However, their utilization remains partial, sectoral, and operational, and is not yet directed toward interpreting SDG indicators in real-time, comprehensively, and predictively.

Government administrative data essentially meets the characteristics of Big Data, including large volume and continuous updating (Ida Fauziah, 2020). Databases on population, social assistance, health, education, local taxes, and public services store dynamic information that is highly relevant to various SDG indicators (Setda Kab.Bandung, 2022). However, this data remains confined within institutional silos and is used solely for the administrative needs of individual agencies, rather than as a source for cross-indicator analysis that can comprehensively depict development achievements (Bappenas, 2022).

On the other hand, satellite imagery and spatial data provide objective time-series information that enables real-time monitoring of environmental and regional conditions without relying on field reports (Bappeda.Kaltimprov, 2021). Land cover changes, slum development, deforestation, and disaster risk can be precisely monitored using this technology (Ady Thea, 2022). Although highly relevant for environmental and urban SDG indicators, this spatial data has not yet been integrated into national or regional SDG monitoring systems (Fabiola Febrinastri, 2022).

Environmental IoT sensors also generate a continuous stream of data that is invaluable for health, climate, and disaster indicators (Rizky Maulidya, 2022). Data on air quality, rainfall, river water levels, and weather conditions provide a strong foundation for data-driven early warning systems (Dinnakerind, 2021). However, in practice, this data is managed independently by technical agencies and has not been processed as a strategic analytical resource to support dynamic reading of SDG achievements (Jambi.Prov.go.id, 2022).

Furthermore, citizens' digital footprints—such as public service complaints, social media conversations, and government digital service usage logs—hold important information about public perception, service quality, and social dynamics (Park & Park, 2019). By leveraging artificial intelligence, particularly natural language processing techniques, this data can be transformed into real-time institutional performance indicators (Stöckl et al., 2021). However, this potential has not been systematically utilized within the SDGs monitoring framework.

Furthermore, digital economic transaction data reflects the dynamics of community welfare quickly and realistically (Arnoldus Kristianus, 2021). Non-cash transaction activity, daily food price movements, and digital economic activity can be effective proxies for assessing regional economic vulnerability and food security, far more responsive than periodic survey approaches (Wibowati, 2021). Unfortunately, these data sources have not yet been incorporated into the SDGs monitoring ecosystem.

Synthetically, this study confirms that a Big Data-based data ecosystem relevant for SDG monitoring is already available within government systems and public life (Eman Sulaiman et al., 2021). However, administrative, spatial, sensor, digital footprint, and economic transaction data are still managed sectorally without analytical integration (Kementerian PPN/Bappenas, 2022). The main challenge is not data availability, but rather the governance capacity to integrate, process, and analyze it (Zaitseva et al., 2023). These findings reinforce the argument that the use of Big Data and artificial intelligence is a crucial prerequisite for transforming SDG monitoring from mere periodic reporting to a real-time, precise, and predictive monitoring system (Forney & Epiney, 2022).

C. OPPORTUNITIES FOR UTILIZING AI IN INDICATOR ANALYSIS

The development of Big Data and Artificial Intelligence (AI) presents a new paradigm in development monitoring. Big Data is characterized by the volume, velocity, variety, and veracity of data originating from various sources such as administrative data, satellite imagery, environmental sensors, digital transactions, and social media (Burton, 2023). This research finding shows that the use of Artificial Intelligence (AI) in the analysis of development indicators—including the SDGs—has reached an operational and applicable level, in line with the massive, diverse, and continuously updated nature of government data (Samuel et al., 2022).). AI shifts the meaning of indicators from mere periodic reporting output to dynamic signals that reflect real-world conditions quickly, precisely, and predictively (Zhang et al., 2022). In this context, indicators are no longer produced through slow administrative processes but are read directly from the data streams that underpin government and community activities (Che et al., 2026).

Empirically, AI enables real-time indicator readings by processing millions of rows of administrative data such as population, social assistance, health, education, and public services (Leńko-Szymańska, 2026). Machine learning techniques can identify patterns of poverty, access to healthcare, and educational participation from daily activities without waiting for survey cycles (Wu et al., 2026). In the spatial and environmental dimensions, the use of computer vision-based AI on time-series satellite imagery can automate the detection of land cover changes, slum areas, deforestation, urban sprawl, and disaster risks consistently and objectively, allowing environmental and urban indicators to be monitored without relying on manual regional reports (Anser & Adebayo, 2026).

Furthermore, AI, through natural language processing (NLP), enables the extraction of social indicators from people's digital footprints (Sürme et al., 2026). Unstructured public service complaints, social media conversations, and feedback on government applications can be analyzed to produce real-time measures of service performance and public perception based on sentiment and dominant issues (Balci & Dogan, 2026). At the same time, streaming data from environmental IoT sensors—such as air quality, rainfall, and water levels—can be analyzed by AI to generate prediction-based early warning systems, shifting environmental health and regional resilience indicators from incident reports to risk projections (Hamadou et al., 2026). Even in the economic realm, AI modeling of non-cash transaction data, daily food price movements, and community mobility allows for the identification of local economic vulnerabilities and potential crises much more quickly than official survey instruments (Tian et al., 2026).

The synthesis of these findings confirms that AI has the real capacity to transform indicator monitoring from a descriptive and retrospective approach to an analytical, real-time, and predictive one (Xu, 2026). The main obstacle lies not in data availability but rather in the ability to integrate diverse data sources into an AI-based analytical architecture that can interpret indicator dynamics across sectors, sustainably, and relevantly for policymaking (Pronello, 2026). Several international studies, facilitated by the World Bank and the Organization for Economic Co-operation and Development, have shown that the use of Big Data and AI can improve the accuracy of monitoring indicators for poverty, environmental quality, population mobility, and even food security (Alghalbie et al., 2026). For example, satellite imagery processed with AI can estimate land cover changes for environmental indicators, while digital transaction data can map community economic dynamics more quickly than periodic surveys (Çakir & Çetinkaya, 2026).

D. DATA GOVERNANCE AND INTEROPERABILITY BETWEEN AGENCIES

Studies of data governance in the public sector emphasize the importance of data standards, system interoperability, metadata, and institutional coordination (C. Wang et al., 2026). Data fragmentation across agencies often results in SDG indicators being compiled from unintegrated sectoral data compilations (Fu et al., 2026). In the Indonesian context, the One Data Indonesia policy addresses this issue through the principles of data standards, metadata, interoperability, and reference (KAVAK & Gültekin, 2026). However, various studies have found that implementation in the field still faces obstacles such as differences in data formats, sectoral egos, and infrastructure limitations (Sáez-Hernández et al., 2025).

This research finding indicates that the main problem with data governance for monitoring SDG indicators in Indonesia lies not in the absence of regulations, but rather in the gap between the normative framework and interoperability practices between agencies (Sandoval-Almazan et al., 2024). Although the One Data Indonesia principle has established metadata standards, data references, and interoperability, its implementation in the field remains administrative-procedural in nature, lacking systemic integration that enables automatic, real-time, and cross-sectoral data exchange and utilization (Sandoval-Almazan et al., 2024). As a result, data remains managed within sectoral ecosystems (data silos), requiring manual or semi-manual compilation for SDG analytics needs, which is slow, prone to inconsistencies, and inefficient (Sandoval-Almazan et al., 2024).

Institutionally, this study found that each agency views data as an organizational asset, rather than as an asset within the government ecosystem (Mukhlis et al., 2024). This perspective results in a tendency toward data protection, differing technical standards, and a lack of structured data sharing mechanisms. Interoperability is more request-based than automatic data exchange based on an Application Programming Interface (API) (Yulfitri, 2020). This situation results in discontinuous data flow between agencies, thus not supporting the need for indicator monitoring, which requires rapid and integrated data reading (Kominfo.go.id, 2020).

From a technical perspective, differences in data formats, information system architectures, and cybersecurity standards between agencies present significant obstacles to integration (Bappeda Kaltim, 2022). Many information systems are built for internal needs without considering interoperability by design from the outset (Kemnaker.go.id, 2021). Consequently, data integration requires time-consuming, iterative cleaning, format adjustments, and validation (Jelita, 2020). This explains why the SDGs monitoring dashboard is unable to automatically pull data directly from agency primary sources, but instead relies on periodic reporting (Leski Rizkinaswara, 2020).

This research also highlights that data governance has not fully accommodated the needs of intelligent analytics (Jpnn.com, 2021). Data governance is still oriented toward reporting compliance, rather than data readiness for analysis by Big Data and AI technologies (Jpnn.com, 2021). Data quality, data lineage, and semantic standardization have not been consistently managed, even though these aspects are key prerequisites for the utilization of cross-sector predictive analytics (Anam, 2021).

The synthesis of these findings confirms that the interoperability challenge is not simply a technical issue of system integration, but a paradigm shift in data governance. As long as data is viewed as sectoral and interoperability is positioned as an administrative obligation, monitoring of SDG indicators will remain fragmented and slow (Kominfo.go.id, 2020). The transformation to Big Data and AI-based monitoring requires a shift in governance toward an integrated data ecosystem, where data exchange is automated, technical standards are mutually agreed upon, and system architecture is designed from the outset to support real-time cross-agency analytics (Bappeda Kaltim, 2022).

CONCLUSION

The results of this study confirm that the weakness of SDG monitoring in Indonesia lies not in the availability of indicators or a lack of data, but rather in the monitoring architecture and data governance, which are unable to interpret development dynamics in real time, in an integrated and analytical manner. The administrative, periodic, and sectoral mechanisms produce retrospective, slow information, and lack analysis of patterns, trends, and projections.

Data fragmentation between agencies, reliance on regional reporting capacity, and an orientation toward numerical reporting prevent monitoring from functioning optimally as an evidence-based policy control instrument. On the other hand, relevant data sources are actually abundant—including administrative data, satellite and spatial time-series imagery, environmental IoT sensors, people's digital footprints, and digital economic transactions—which already meet the characteristics of Big Data. The main problems lie in gaps in the implementation of One Data Indonesia, request-based data exchange (rather than APIs), differences in technical standards, and sectoral paradigms that hinder integration. In synthesis, the transformation of SDGs monitoring into a real-time, integrated, and predictive system requires: the integration of Big Data sources, the use of AI as an analytical engine, and a shift in governance toward interoperability across agencies.

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