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Artificial intelligence-driven green economy and sustainability transformation in South Africa: Insights from a systematic literature review

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Abstract

This study conducts a systematic literature review to explore the development of an AI-driven Green Economy and Sustainability Transformation (AIGE-ST) model tailored for South Africa. In response to the country's pressing environmental, economic, and social challenges, this research investigates the intersection of artificial intelligence (AI), green economy principles, and sustainable development strategies. Through a comprehensive analysis of global-based peer-reviewed literature, policy documents, and book chapters, the study identifies key trends, gaps, and opportunities in applying AI technologies to support climate resilience, sustainable resource management, and inclusive economic growth that are adapted to South Africa context. The findings reveal a fragmented knowledge base, with limited integration between AI, sustainability frameworks, and national policy agendas. The review emphasises the need for a transdisciplinary approach that bridges technological innovation with ethical, regulatory, and socio-economic dimensions. Based on the synthesis of existing works, the study proposes a contextual AIGE-ST model highlighting critical enablers such as integrated data ecosystems, artificial intelligence technologies, digital infrastructure, human capital development, and multi-stakeholder collaboration. This research provides a foundational framework to guide policymakers, researchers, and practitioners in leveraging AI for South Africa's green and sustainable development transformation.

Keywords: Artificial Intelligence Technologies; Green Economy; South Africa; Sustainable Development; Transformation Model

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1. Introduction

The global transition towards a green digital economy has gained significant momentum as nations seek to reconcile economic growth with environmental sustainability. According to the United Nations Environment Programme (UNEP, 2011), a green economy is one that improves human well-being and fosters social equity while significantly reducing environmental risks and ecological scarcities. In recent years, the concept of a green digital economy, where digital technologies drive environmentally sustainable economic activities has gained increasing prominence in both global and national development agendas, as it seeks to balance economic growth with environmental sustainability and social equity.

In the face of escalating environmental challenges and the imperative for inclusive economic growth, the integration of digital innovation with sustainable development has emerged as a critical pathway for nations worldwide. Artificial Intelligence (AI) has become a transformative force in this transition, offering innovative solutions to optimise resource efficiency, reduce carbon emissions, and enhance sustainable development (Pan and Nishant, 2023). Artificial Intelligence, with its capacity for complex data analysis, predictive modelling, and automation, is uniquely positioned to accelerate sustainable development across various sectors, including energy, agriculture, water management, waste reduction, and urban planning.

In South Africa, a country grappling with energy crises, environmental degradation, and deep-rooted socio-economic inequalities, the integration of AI into sustainability initiatives presents a critical opportunity to drive climate resilience, accelerate renewable energy adoption, and promote circular economy practices (Kuzmina et al., 2024). AI-driven solutions can support data-informed decision-making, optimise resource use, and reduce environmental footprints, while simultaneously creating new pathways for economic inclusion and innovation (Pimenow et al., 2025). According to Amini and Baradaran Rohani (2024), AI can accelerate digital economy transition by enabling smart grid management, predictive maintenance in renewable energy infrastructure, and precision agriculture to mitigate climate risks. Furthermore, AI-driven data analytics and automation can enhance waste management, water conservation, and sustainable urban planning, aligning with the United Nations Sustainable Development Goals (SDGs) (Vinuesa et al., 2020; Alshawi, 2022).

Despite these opportunities, challenges such as digital inequality, skills gap, data privacy concerns, and high implementation costs hinder AI adoption in South Africa's green economy (Raihan, 2024). The ethical implications of AI deployment, including algorithmic bias, data accessibility and job displacement are also considered as impediments to inclusive and equitable sustainability transitions (Kumar et al., 2024). The potential exacerbation of social inequalities arising from the deployment of digital technologies remains a significant concern. The concentration of AI-driven systems in well-resourced regions risks reinforcing existing social and digital disparities in low-resourced and disadvantaged areas of the country. Mienye et al. (2024) advise that policymakers, industry leaders, and researchers must collaborate to develop AI governance frameworks that prioritise environmental justice and socio-economic inclusivity to ensure that AI-driven sustainability does not exacerbate existing inequalities.

Additionally, limited technical expertise and skills in sustainable technologies and AI are also regarded as a major challenge (Atiku and Lawal, 2022; Wang et al., 2023). This assertion is further validated by the findings of Li and Imran (2025), asserting that many developing countries face gaps in education, training, and capacity building aligned with green transitions. Without skilled labour and innovation-driven mindsets, green and sustainable initiatives will struggle to scale or sustain expected impact. It is also noted that financing and investment for green economy and sustainability initiatives remain limited due to high perceived risks and long return timelines (Goncharenko and Shapoval, 2021; Zhironkin and Cehlár, 2022). As a result, many Global South countries face constraints in attracting private capital and lack access to climate finance mechanisms.

This study therefore investigates the intersection of artificial intelligence (AI), sustainability, and digital economic transformation within the South African context. Its primary objective is to design a contextual AI-

driven model for a green economy and sustainability transformation that aligns technological innovation with environmental stewardship and socio-economic equity. The study introduces a novel conceptual contribution by synthesising the multi-level perspective (MLP) of the socio-technical transitions theory, ecological modernisation theory, and the frameworks of data-driven governance and digital transformation to formulate a data-driven, ecosystem-based AIGE-ST Model designed to advance green-economy and sustainability strategies in South Africa.

The research further addresses a significant gap in the literature by grounding the development of the proposed model in context-specific insights related to South Africa's socio-economic dynamics, infrastructural constraints, and environmental vulnerabilities, thereby enhancing its relevance, applicability, and potential impact within the national sustainability landscape. The proposed model explores the interconnection of digital infrastructure, data ecosystems, policy environment, and inclusive multi-stakeholder collaboration. It is specifically tailored to South Africa's unique developmental needs, infrastructure realities, and cultural dynamics, targeting key sectors such as renewable energy, climate adaptation, sustainable agriculture, smart urban development, and green finance.

2. Literature review

The green economy is a development paradigm that seeks to harmonize economic growth with environmental sustainability and social inclusion. It offers a practical framework for sustainable development in the 21st century through its promotion of low carbon, resource efficiency, and social inclusiveness. D'Amato et al. (2017) expand this definition to emphasise a systemic reconfiguration of economic sectors, such as energy, transport, agriculture, and manufacturing towards more circular, regenerative, and resilient systems. Likewise, sustainability transformation refers to the fundamental and systemic changes in societal structures, values, institutions, and technologies to achieve long-term ecological integrity, economic viability, and social well-being (Abson et al., 2017; Salomaa and Juhola, 2020). This implies a profound and conscious reorganisation of economic systems and cultural worldviews that support unsustainable practices (Scoones et al., 2020; Sancak, 2023).

In the context of South Africa, the country's development challenges, such as carbon-intensive energy systems, high socio-technological inequality, and resource extraction dependency have stressed the need for green economy and sustainability transformation through green industrialisation, nature-based solutions, and social protection mechanisms (Udeagha and Ngepah, 2024). Jayaweera et al. (2023) note that sustainability transformation in South Africa involves addressing post-colonial development legacies, social injustice, and resource extraction economies, while fashioning pathways that are both ecologically responsible and socially equitable.

Artificial Intelligence (AI) has emerged as a transformative driver of sustainable development, offering capabilities in advanced data processing, predictive analytics, and real-time decision-making that enable optimisation, resource efficiency, and system modelling in both economic and environmental domains (Vinuesa et al., 2020; Mienye et al., 2024). In the Global South, particularly South Africa, AI provides opportunities to bypass industrial constraints while aligning with sustainability frameworks such as the UN Sustainable Development Goals and the Paris Agreement (United Nations, 2015; Delbeke et al., 2019; Tinonetsana et al., 2024).

The applications of AI for digital economy and sustainability span renewable energy forecasting and smart grid management (Safari et al., 2024; Krishnamurthy et al., 2024), circular economy resource tracking and recycling optimisation (Bressanelli et al., 2022), precision agriculture for climate-resilient food production (Suresh and Shaw, 2024; Bhattacharya et al., 2025), sustainable urban planning and development (Musa et al.,

2025), and productivity gains in sectors like fintech and logistics (Damioli et al., 2021). AI also strengthens environmental monitoring through climate modelling, biodiversity protection, disaster risk reduction, and pollution management using drones, sensors, and image recognition (Reichstein et al., 2019; Rolnick et al., 2022; Duong et al., 2020; Shah, 2025).

Rieder et al. (2022) argue that, by integrating these capabilities, AI can advance South Africa's green economy through data-driven governance, circular economy practices, and climate-resilient infrastructure. However, Netshakhuma (2021) and Sikhakhane et al. (2023) highlight uneven digital and data infrastructures, data inequality, skills shortage, ethical risks, weak policies, lack of robust data ecosystems and inclusive innovation strategies as challenges of integrating AI into green economy in South Africa. Similarly, Song and Deng (2025) maintain that the magnitude and direction of AI's effect on green outcomes depend on governance, regulatory regimes and institutional capacity, factors that determine whether AI drives inclusion or reinforces existing inequalities.

According to Chen et al. (2023) and Mmbando (2025), AI-driven precision agriculture and environmental monitoring systems in South Africa are helping farmers adapt to climate variability while reducing resource waste. Moreover, Gryshova et al. (2024) and Safari et al. (2024) posit that through smart grid technologies and AI-enabled forecasting, the country can better manage its renewable energy transitions. Furthermore, AI can strengthen South Africa's green economy by promoting data-driven policy-making, enhancing governance transparency, and enabling circular economy practices. As highlighted by Rieder et al., (2022), AI-powered decision support systems are being explored in urban planning and climate-resilient infrastructure development to ensure resource efficiency and social inclusion.

However, for AI to effectively advance sustainability and green economy objectives, issues such as data inequality, ethical AI deployment, and capacity building must be addressed to avoid exacerbating existing socio-economic divides (Sikhakhane et al., 2023). Although, the literature provides conceptual scaffolding and sectoral case examples but lacks integrated, country-specific modelling that unites AI technical interventions, multi-level governance levers, and socio-economic transition pathways equity. There is a clear research demand to develop an AI-driven Green Economy and Sustainability Transformation Model tailored to South Africa that combines systems modelling and stakeholder-informed constraints, like infrastructure, data governance, and skills.

3. Methodology

3.1. Research design

This study employs a Systematic Literature Review (SLR) methodology to develop a contextual model for an AI-driven green economy and sustainability transformation tailored to the South African context. The goal is to uncover prevailing opportunities and critical challenges associated with AI integration into green economy and sustainability transformation, with a particular focus on its environmental, economic, and social implications in the South Africa context. The review is guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework to ensure methodological transparency and reproducibility in identifying, selecting, and synthesising relevant academic and grey literature (Page et al., 2021), while ensuring their relevance in both international, regional and South Africa contexts.

3.2. Identification and selection

Relevant peer-reviewed literature was identified using a stepwise search strategy conducted across Google Scholar and Scopus. Google Scholar was selected for this study due to its extensive multidisciplinary scope,

which encompasses a wide range of academic, policy, and grey literature relevant to artificial intelligence, green economy, sustainability, and South Africa's developmental context. Similarly, Scopus was included for its rigorous indexing standards, provision of high-quality peer-reviewed publications, and robust bibliometric features that support a systematic and replicable review process. Collectively, the two databases offer complementary breadth and depth, enabling comprehensive evidence coverage and enhancing the overall validity of the SLR findings.

The search process was iteratively refined to ensure both thematic relevance and comprehensive coverage, with a specific focus on peer-reviewed journal articles. The search also includes grey literatures, such as conference proceedings, book chapters, and organisation reports derived from the Google Scholar and other international organisations associated with AI-driven green economy and sustainability to capture wider. Search keywords were derived from the core concepts of the research topic, while Boolean operators (AND, OR) and wildcards were used to maximize relevant returns. The search strings used are ("Artificial Intelligence" OR "AI" OR "AI Technologies") AND ("Green Economy" OR "Green Digital Economy" OR "Sustainable Development" OR "Sustainability") AND ("South Africa" OR "Africa") AND ("Digital Transformation" OR "Smart Technologies").

The sample of the search strings used in the database is: ABS-KEY ("Artificial Intelligence "AND (Green Economy" OR "Green Digital Economy" OR "Sustainable Development" OR "Sustainability) Developed Economies AND South Africa) AND (LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "re")) AND (LIMIT-TO (LANGUAGE, "English"))

Records were eligible if they (i) discussed an empirical evidence, policy, frameworks or conceptual application of AI in environmental or green economy contexts; (ii) addressed at least one pillar of sustainability (environmental, social, economic); (iii) focused on AI applications for sustainability, green economy, or digital transformation; (iv) studies applicable to emerging economies or directly focused on South Africa; (v) were peer-reviewed journal articles, conference proceedings, white papers, and book chapters published in English between 2015 and 2025 to capture modern AI and green economy developments. Purely technical AI algorithm development without sustainability context, opinion pieces or editorials lacking empirical or theoretical rigour, articles before 2015 (unless highly cited and foundational), and non-English publications were excluded. The inclusion of grey literature was to allow for the capture of recent governmental and industrial advancements, while focusing on South Africa is to ensure contextual relevance of the study. At this stage, 11,090 peer-reviewed articles and 80 grey literature were identified for the study.

The initial screening was performed using the title and abstract review to eliminate clearly irrelevant works. 9,068 and peer-reviewed articles and 80 grey literature were screened, and thereafter the full articles were assessed against the inclusion/exclusion criteria. Following the exclusion of duplicate, irrelevant, and out of focus studies, 178 articles and 26 grey literature consisting of conferences proceedings, books chapters and policy reports were assessed for eligibility. The de-duplication features of the specialized screening tool, Systematic Review Accelerator, were used to identify duplicate records, which were then further examined through a side-by-side comparison to confirm their validity as true duplicates.

A final set of 108 peer-reviewed articles, 21 book chapters, 3 conference proceedings and 2 organisation reports were eligible and selected for thematic analysis. Among the studies included in the review, 44 examined AI-driven green economy and sustainability initiatives in developed economies, 28 concentrated on countries within the Global South, and 62 specifically addressed the South African context. These publications formed the analytical foundation for the findings presented in section 4.

3.3. Data extraction and synthesis

The data extraction was conducted using standardised data collection template, the variables for the data extraction include author(s), year, title; country/region of focus; type of AI technology in use; sector (such as, energy, agriculture, biodiversity); key findings; relevance to South Africa; and identified challenges, barriers and opportunities. The themes Artificial Intelligence in Environmental and Economic Systems; Governance, Ethics, and Policy Considerations; Infrastructure and Capacity Enablers; and Current AI-for-Sustainability Landscape in South Africa were selected to capture the multifaceted challenges and opportunities in integrating AI, data ecosystems, and policy instruments to develop an AI-driven green economy and sustainability transformation model for South Africa.

PRISMA flow diagram was constructed to illustrate the document selection process, ensuring transparency and methodological rigour (Figure 1). The diagram outlines the number of records identified through databases searches and other sources, screened for relevance, and included in the final synthesis.

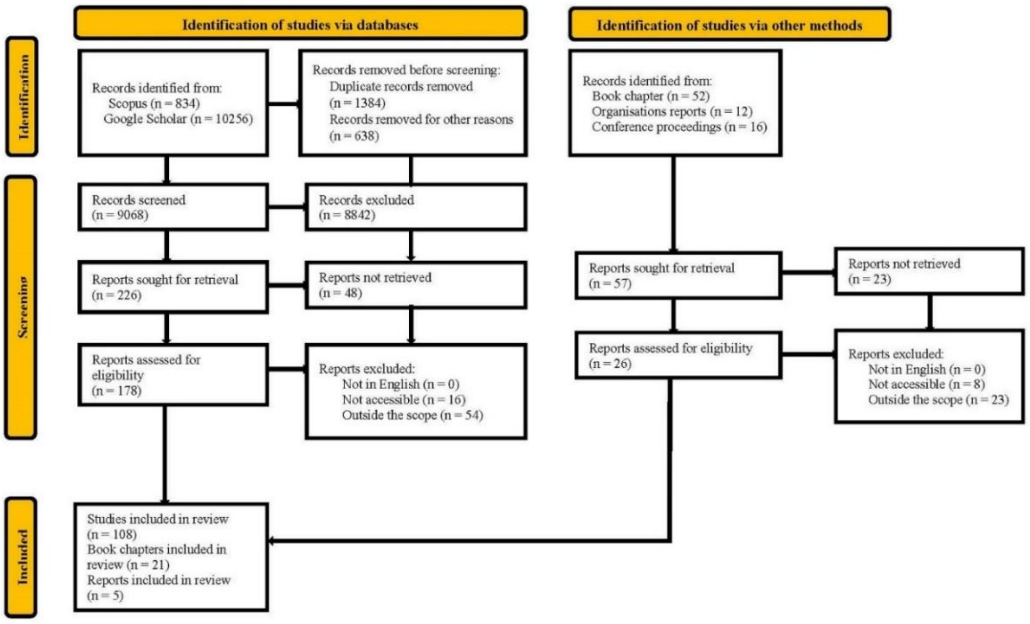


Figure 1. Prisma Flow Diagram for the Study (Source: Authors)

The progression from extracted data to thematic categories and, ultimately, to the formulation of model components followed a rigorous and iterative analytical process. First, relevant data were systematically extracted from the selected studies using a predefined coding framework that captured conceptual, empirical, and contextual insights related to artificial intelligence, green economy practices, and sustainability transformation. These coded data segments were then subjected to thematic analysis, during which patterns, convergences, and conceptual linkages were identified and synthesised into higher-order themes that reflected the dominant narratives and recurring constructs across the literature. Through axial coding, the relationships among these themes were examined to uncover structural connections, dependencies, and potential causal pathways underpinning AI-driven sustainability transitions. The emergent themes were subsequently distilled into core model components, ensuring that each component was grounded in evidence from the literature while also representing a coherent building block for the proposed framework.

The quality appraisal process was conducted in accordance with the PRISMA framework, which prioritises methodological transparency, rigorous evaluation of evidence, and the minimisation of bias throughout the

review process. All eligible literature and reports were evaluated using the Critical Appraisal Skills Programme (CASP) Qualitative Checklist, a structured tool designed to systematically assess the methodological robustness and credibility of qualitative research. The two authors independently applied the appraisal criteria to enhance consistency and minimise subjectivity, with any discrepancies resolved through discussion. The results of the appraisal informed decisions regarding the inclusion, exclusion, and weighting of studies in the findings, thereby reinforcing the reliability, credibility, and overall methodological integrity of the systematic review.

4. Findings

The systematic literature review highlights a growing convergence between artificial intelligence (AI) technologies and sustainability-oriented economic transformation across both developed nations and the Global South, including South Africa. The findings are synthesised into five thematic areas: technological applications of AI for the green economy and sustainability, governance and ethical policy considerations, infrastructure and capacity enablers, current AI-for-sustainability landscape in South Africa, and the research gaps.

4.1. AI technologies for green economy and sustainability

The identified key AI technologies with promising applications in advancing the green economy and sustainability, particularly within the developing economies, include machine learning (ML), natural language processing (NLP), computer vision, and the Internet of Things (IoT).

4.1.1. Machine Learning (ML)

Machine learning is extensively used across different sectors for predictive analytics, climate modelling, agricultural forecasting, and energy optimisation within the literature. In South Africa, ML models can be used to predict crop yields, monitor soil health, and detect pest or disease outbreaks, thereby promoting sustainable farming (Dotse et al., 2024). Similarly, the models have the potential for forecasting droughts and optimising water usage in water-scarce provinces like the Western Cape (Sibiya et al., 2024). The ML predictive maintenance and demand forecasting ability can also be beneficial to optimise renewable energy grids and forecast solar/wind energy availability (Gupta et al., 2024).

4.1.2. Natural language processing

Natural Language Processing (NLP) has proven highly valuable in extracting public sentiment, analysing environmental policies, and enhancing stakeholder engagement, particularly through the inclusion of local languages. It facilitates the processing of environmental reports, sustainability-related policies, and public feedback, thereby supporting data-driven decision-making and ensuring regulatory compliance (Kang and Kim, 2022). Additionally, NLP plays a critical role in green finance by enabling assessments and detecting fraud within sustainability funds (Boulieris et al., 2024). In the South African context, NLP can be effectively applied to analyse national policies in sectors such as energy, mining, and climate change, ensuring alignment with sustainability objectives. Moreover, by enabling local language processing, NLP can significantly enhance climate change awareness and environmental education through community-based engagement initiatives (Mabokela et al., 2025).

4.1.3. Computer vision

Findings from the literature also indicate that computer vision plays a significant role in environmental monitoring, wildlife conservation, and waste management (Samaei et al., 2024). Its applications include deforestation tracking, water quality assessment, and biodiversity conservation through image recognition and satellite imagery (Garcia-del-Real and Alcaráz, 2024). In the South African context, computer vision technology incorporated with autonomous systems can be applied in smart waste management systems to detect and sort recyclable materials in urban waste facilities, monitor endangered species within national parks, and support land use monitoring to identify illegal mining activities and land degradation.

4.1.4. Internet of things (IoT) with AI integration

The integration of Artificial Intelligence (AI) with Internet of Things (IoT) devices has also proven effective in collecting real-time environmental data which are further process and interpret to support sustainability interventions (Alotaibi and Nassif, 2024; Miller et al., 2025). The technology can also be used as smart sensors to collect data on air quality, water usage, and waste levels, providing actionable insights to enhance urban sustainability and resource efficiency (Krishnan et al., 2022). For South Africa green economy and sustainability, AI based IoT devices can be used in Precision Agriculture to monitor soil moisture to control irrigation (AlZubi and Galyna, 2023), and in water management to track municipal leaks and optimise supply.

4.1.5. Digital twin and simulation models

The use of AI-driven digital twins to simulate real-time operations and assess environmental impacts across cities, factories, mines, and utilities gained increasing attention as a means to enhance operational efficiency and promote sustainability (Hassani et al., 2022; Samuel et al., 2023; Cordes et al., 2024; Long et al., 2025). These digital twin models can be effectively applied in the mining sector in South Africa to simulate water consumption and tailings management for more environmentally sustainable practices. Similarly, in major urban areas, they can support the optimisation of traffic flow, energy consumption, and emergency response systems (Yitmen et al., 2025).

4.1.6. Reinforcement learning

Reinforcement learning (RL) is widely recognised in recent literature for its capacity to enable adaptive and optimised decision-making within dynamic systems. Its applications span several critical domains, including smart infrastructure management (Serrano, 2019; Xinfa and Wang, 2025), renewable energy systems (Slama and Mahmoud, 2023; Li et al., 2024), sustainable adaptive education systems (Fu, 2022; Tariq and Habib, 2024; Du et al., 2025; Stasolla et al., 2025), autonomous transportation (Dinneweth et al., 2022; Feng et al., 2023), and adaptive irrigation systems (Campoverde and Palmieri, 2022; Chen et al., 2023; Ding and Du, 2024) where it facilitates real-time optimisation of energy and resource utilisation.

Furthermore, RL has proven effective in managing energy consumption in smart homes and urban energy networks (Hossain et al., 2025). Within the South African context, RL models hold significant potential for supporting renewable energy integration by dynamically balancing variable solar and wind inputs into Eskom's national grid and enhancing real-time decision-making to minimise energy losses and mitigate load shedding.

The Findings highlight that the applications of AI in the green economy span across agriculture, energy, urban development, mining, and conservation sectors. Given the South Africa's developmental challenges and sustainability priorities, such as water scarcity, high carbon emissions, biodiversity loss, and socio-economic inequality, AI technologies present innovative tools for building a green, inclusive, and data-driven economy that align to environmental sustainability. The identified AI technologies and tools for green economy and sustainability are shown in Table 1.

Table 1. AI technologies and tools for green economy and sustainability

Economic Sector	AI Technologies	Applications in Sustainability	Sustainability Impact Areas	References
Agriculture	- Computer Vision - Machine Learning - AI-Enabled IoT	-Precision agriculture - Water-efficient irrigation - Early pest/disease detection - Crop yield optimisation	Food security	Dotse et al. (2024); Sibiya et al. (2024)
Energy	- Machine Learning - Deep Learning - Reinforcement Learning - Natural Language Processing	- Demand forecasting - Grid load balancing - Renewable energy optimisation - Energy theft detection	Climate change mitigation, Clean energy	Safari et al. (2024); Gupta et al. (2024)
Mining	- AI-Enabled IoT - Predictive Analytics (ML) - Digital Twins - Natural Language Processing	- Emission monitoring - Energy use optimisation - Worker safety and hazard detection	Emission and Air pollution reduction	Reichstein et al. (2019); Hanto et al. (2022)
Water and Sanitation	- AI-Enabled IoT - Reinforcement Learning - Digital Twins	- Leak detection - Demand prediction - Smart waste management	Water resource efficiency, Waste reduction	Vinuesa et al. (2020); Rolnick et al. (2022)
Transport and Mobility	- Machine Learning - Computer Vision - Reinforcement Learning	- Reduction in carbon footprint - Smart logistics - Fuel efficiency	Emission reduction, sustainable transport	Feng et al. (2023); Yitmen et al. (2025)
Finance and Investment	- Machine Learning - NLP - Reinforcement Learning	- Green finance assessments - Climate risk modelling - Fraud detection in sustainability funds	Green finance, Governance, awareness, and transparency	Yunus and Zouya, (2024); Boulieris et al. (2024)
Urban Development	- ML for Urban Planning - AI-Enabled IoT - Digital Twin and Simulation Models - Reinforcement Learning	- Eco-friendly urban design - Energy-efficient infrastructure	Urban sustainability, land resource planning,	Krishnan et al. (2022); Ahmed, (2024); Lakhouit, (2025)
Forestry and Biodiversity	- Computer Vision - Digital Twin and Simulation Models - Reinforcement Learning	- Forest fire prediction - Biodiversity mapping - Poaching detection	Biodiversity conservation, ecosystem monitoring	Samaei et al. (2024); Garcia-del-Real and Alcaráz, (2024).

Economic Sector	AI Technologies	Applications in Sustainability	Sustainability Impact Areas	References
Manufacturing (Industry 4.0)	- Machine Learning - AI-Enabled IoT - Digital Twins - Reinforcement Learning	- Low-carbon production processes - Waste minimisation - Sustainable supply chain tracking	Energy optimisation, Circular production and consumption	Bressanelli et al. (2022); Yunus and Zouya, (2024).
Education and Skills	- Machine Learning - NLP - Reinforcement Learning	- Green skills development - Sustainable curriculum personalisation	Ethical governance, inclusion, accountability	Du et al. (2025); Stasolla et al. (2025).

The most substantive evidence of AI contributing to green economy and sustainability in South Africa is concentrated in sectors with relatively advanced digital infrastructure and data maturity, notably energy, environmental monitoring, and commercial agriculture. In the energy sector, the increasing use of AI-driven predictive maintenance and load forecasting (Azodo et al., 2025), alongside machine learning applications in climate modelling and air-quality monitoring (Upadhyay et al., 2024), illustrates tangible operational gains. Similarly, commercial agriculture has seen growing adoption of AI-enabled IoT technologies, including drone-based crop analytics, automated irrigation systems, and satellite-derived soil assessments which have produced measurable improvements in water efficiency and crop resilience (Guebsi et al., 2024).

However, substantial gaps remain in smallholder farming, waste management, biodiversity conservation, and municipal services, where limited connectivity, fragmented data ecosystems, and insufficient human capital continue to impede meaningful AI uptake (Naidoo, 2024). Moreover, the expectation of rapid transitions to advanced robotics, fully autonomous farms, or city-scale smart infrastructure often overlooks foundational deficits in data quality, digital infrastructure, skills capacity, and institutional coordination. This underscores a persistent disconnect between isolated pilot successes and the systemic conditions necessary for scalable, inclusive AI-driven sustainability transformation in South Africa.

4.2. Governance, ethics, and policy considerations

The need for robust governance mechanisms in green economy and sustainability development is well emphasised across the literature to ensure transparency, accountability, and inclusivity (Söderholm, 2020; Batrancea et al., 2021; Wang et al., 2024). Robust governance structures are needed to oversee the ethical deployment of required technologies across sectors such as energy, agriculture, water, and urban infrastructure. Dignum (2019) argue that good technologies (such as, AI, IoT, Robotics) governance should balance innovation with social protection by embedding mechanisms for risk assessment, bias mitigation, and human oversight. In the context of South Africa and similar developing economies, this principle requires multi-level governance frameworks that integrate national priorities with global sustainability goals (Mashiane, 2024).

Furthermore, ethical considerations have been considered as a major factor in the sustainability transformations strategy, particularly in the deployment of fourth industrial revolution technologies, such as artificial intelligence (Jaiswal et al., 2025). Issues like algorithmic bias, data privacy, and the socio-economic impacts of automation must be carefully managed to avoid exacerbating existing inequalities. Mittelstadt et al. (2016) emphasise the importance of fairness, accountability, and transparency (FAT) principles in AI systems, especially when these systems influence environmental policy or public resource management. Policy frameworks are also identified as critical elements in aligning technologies innovation with green economy objectives (Udeagha and Muchapondwa, 2023; Mensah et al., 2024).

Therefore, looking at these submissions, it is evident that an effective AI-driven green economy and sustainability model requires interdisciplinary coordination across governance, ethics, and policy domains which must be guided by contextually relevant principles that promote equity, ecological integrity, and democratic participation in technology development and deployment.

4.3. Infrastructure and capacity enablers

The sustainability of green economy and that of the environment has been hinged on the critical infrastructure and capacity enablers which include digital infrastructure, human capital development, institutional frameworks, and cross-sectoral collaboration, all of which serve as foundational elements for supporting the integration of artificial intelligence in sustainability initiatives.

Aldoseri et al. (2024) identify digital infrastructure is a prerequisite for any AI-enabled transformation. This infrastructure includes reliable internet connectivity, cloud computing resources, data centres, and access to IoT devices and smart sensors. Reliable internet access is essential for cloud-based AI systems, IoT-enabled green solutions, and remote monitoring in agriculture, water, and conservation. However, many developing countries, like South Africa face significant gaps in digital infrastructure, which hinders real-time data acquisition and algorithmic decision-making (Sasmal, 2023). Gu et al. (2024) and Wang et al. (2025) argue that, to bridge this digital infrastructure gap, investments must be focused on expanding broadband access, establishing national data platforms, and leveraging open-source AI tools.

In like manner, capacity building and human capital development are identified as equally critical enablers (Mukhuty et al., 2022). Danquah et al. (2023) contend that the effective implementation of AI requires a skilled workforce with expertise in AI, data science, sustainability science, and sector-specific knowledge such as energy systems, water management, and environmental planning. Unfortunately, many developing nations, including South Africa face a shortage of technical expertise and academic programmes that integrate AI with green economy, environmental or sustainability studies (Singh et al., 2025). Institutional and policy frameworks also act as enablers by creating a conducive environment for AI integration (Wahid et al., 2024). Ndoka et al. (2025) posit that clear guidelines on data privacy, transparency, and environmental AI ethics are crucial for mitigating risks associated with technological deployment which increase public trust and sustainability. Kumar (2022) highlights the role of green public procurement policies and fiscal incentives in enabling sustainable AI systems.

Additionally, cross-sectoral collaboration and knowledge sharing between academia, industry, government, and civil society can accelerate the co-development of context-specific AI solutions that are instrumental to green economy and sustainability. Mutambara (2025) argue that platforms for regional collaboration and South-South knowledge exchanges can enable countries to share lessons learned, pool resources, and localise AI tools effectively. These collaborations are vital for aligning AI development with broader sustainability and green economy transformation goals in resource-constrained settings, like South Africa.

4.4. Current AI-for-sustainability landscape in South Africa

The South Africa's AI-for-sustainability ecosystem is nascent but active, technical advances and pilot studies demonstrate potential to support decarbonisation, environmental monitoring and climate-resilient in energy, mining, and agriculture.

The energy sector provides some of the clearest, empirically documented examples of AI being applied to sustainability challenges. Utilities firms and researchers have employed machine learning approaches for load forecasting, anomaly classification and predictive maintenance to improve grid reliability and integrate variable renewables work (Hlalele, 2025). For instance, the country's leading energy provider (Eskom)

operational reports show active use of data-driven forecasting and asset-health analytics using an ensemble of deep learning techniques aimed at reducing unplanned capacity losses and diesel-dependent back-up generation (Motepe et al., 2022).

In commercial agriculture the strongest evidence is clustered around remote sensing, drone analytics and farm-level decision support. Multispectral drone imagery and satellite data coupled with machine learning models are being used for crop stress detection, irrigation scheduling and yield estimation (Kapari et al., 2025). Systematic reviews and case studies from the sector document growing adoption of drone-as-a-service and precision irrigation platforms using IoT technology for smart agriculture among the commercial farms and agri-service providers, although uptake among the smallholders remains limited due to connectivity, cost and data access constraints (Guebsi et al., 2024).

Similarly, the water and urban services sectors demonstrate promising pilot deployments of AI for leak and anomaly detection in smart metering networks, predictive demand modelling, and optimisation of treatment processes using machine learning algorithms (Kanyama et al., 2025). However, the deployment remains unevenly distributed across municipalities and universities rather than widespread integration in municipal water utilities. Kanyama et al. (2024) highlights robust prototype results for anomaly detection and resource optimisation but emphasises persistent barriers, like fragmented data architectures, limited sensor coverage, and capacity gaps that prevent large-scale, citywide roll-out.

Furthermore, AI applications are visible in predictive maintenance, fleet optimisation and environmental monitoring in the mining and sanitation sectors, with studies proposing predictive maintenance frameworks and automation that can reduce energy use and material waste (Patil et al., 2025). Nonetheless, the evidence base is chiefly clustered in pilot studies and industry research, rather than independent, longitudinal evaluations of sustainability outcomes. Therefore, across sectors the common pattern is credible, high-value AI pilots and research, particularly in energy, commercial agriculture, mining, and smart water, accompanied by notable systemic gaps, such as data governance, rural connectivity, workforce skills, and financing that limit equitable, large-scale sustainability impact (Chambi et al., 2025).

4.5. The research gaps

The analysis of the literature highlights critical gaps that necessitate urgent attention, particularly regarding the integration of artificial intelligence (AI) into green economy and sustainability initiatives within the Global South. Existing studies are often siloed, as much of the current AI literature emphasises technical optimisation without embedding these innovations within broader sustainability frameworks (Dedeurwaerdere, 2024). This underscores the need for transdisciplinary research that bridges AI, environmental science, public policy, and economics to co-create comprehensive transformational models.

Moreover, most empirical studies and AI applications originate from high-income countries with advanced digital infrastructure and governance systems, making them less transferable to low-resource, rural, and low-connectivity settings. Aderibigbe et al. (2023) affirm that Global South contexts, particularly in Africa, are significantly underrepresented in AI and sustainability research. In response to this assertion, Jamba and Marambi (2024) advocate for the development of localised AI frameworks that are tailored to the specific socio-economic, infrastructural, and cultural conditions of the Global South, such as South Africa.

Additionally, there is a noticeable absence of unified models that effectively integrate governance, technological infrastructure, social equity, and environmental sustainability. Researchers, such as Floridi (2023), Hariram et al. (2023), and Saranya and Chandrasekar (2025) emphasise this gap, while Almulhim and Yigitcanlar (2025) call for co-designed, systemic transformation models that link AI with sustainability transition pathways. Perhaps most concerning is the lack of open, high-quality, real-time, and localised data,

which significantly hampers AI training and deployment in many developing countries. This challenge, often described as "data poverty" is identified as a major bottleneck by Mutambara (2025) and Ekpemuaka et al. (2025). To address this, investment in open data platforms, interoperable data ecosystems, and public–private data collaborations is essential to enhance AI readiness and support its integration into green economy and sustainability initiatives.

These gaps limit the strategic deployment of AI in addressing challenges such as climate vulnerability, resource inefficiency, and economic exclusion. Without a clear, evidence-based framework, policy-makers and stakeholders may struggle to unlock AI's transformative potential in ways that are ethical, inclusive, and environmentally sound.

5. Green economy and sustainability transformation model for South Africa

5.1. Adapted theoretical theories

This study employs socio-technical transitions theory, ecological modernisation theory, and the frameworks of data-driven governance and digital transformation to inform the development of our AIGE-ST Model. This theoretical foundation supports inclusive, equity-oriented transformation aligned with South Africa's developmental goals. Collectively, these theories provide a context-sensitive approach for integrating AI into sustainable development strategies.

5.1.1. Socio-technical transitions theory

The Socio-Technical Transitions Theory, particularly the Multi-Level Perspective (MLP) provides a robust analytical lens for examining systemic transformations across economic sectors such as energy, mobility, food systems, and environmental governance. The theory was originally developed by Geels (2002). It conceptualises transitions as dynamic and multi-dimensional processes shaped by interactions across three interrelated analytical levels (Geels, 2019). At the micro-level, niches represent protected spaces where radical innovations, such as AI-driven technologies emerge and nurture. The meso-level comprises socio-technical regimes, which consist of the dominant technologies, infrastructures, institutions, policies, norms, and user practices that sustain existing systems. At the macro-level, the socio-technical landscape focuses on the broader contextual developments, including climate change, global digitalisation, and socio-political shifts, that influence regimes and niches (Wu et al., 2021).

This layered model is especially valuable for analysing how emerging AI innovations related to sustainability, such as machine learning for smart grids, precision agriculture, or real-time environmental monitoring can challenge and potentially transform entrenched, carbon-intensive systems. In the context of South Africa, where such technologies are still largely incubated within niche environments, the MLP can illuminate pathways for AI to catalyse wide-scale structural change in support of a green economy and sustainable development.

5.1.2. Ecological Modernisation Theory (EMT)

Ecological Modernisation Theory (EMT) originated in the 1980s as a response to the perceived conflict between environmental protection and economic growth. Contrary to traditional assumptions that environmental degradation is an unavoidable consequence of industrial capitalism, EMT argues that economic

development can be harmonised with ecological sustainability through technological innovation, institutional reform, and proactive policy interventions (McLaughlin, 2012). At its foundation, EMT supports the greening of capitalism, asserting that under appropriate conditions, economic progress and environmental stewardship can be mutually reinforcing.

The theory emphasises the transformative potential of modern science, advanced technologies such as artificial intelligence (AI), and effective governance in shifting production and consumption systems toward sustainability (Bugden, 2022). In the context of South Africa, EMT provides a valuable conceptual framework for applying AI to decouple economic development from environmental degradation. This is particularly relevant given the country's complex challenges, including entrenched socio-economic inequality, significant ecological pressures, and a continued reliance on coal-based energy (Nel et al., 2023).

5.1.3. Data-driven governance and digital transformation theories

Data-Driven Governance and Digital Transformation Theories explore how organisations, institutions, and societies adapt and reconfigure their structures, processes, and cultures through the strategic adoption of digital technologies (Vial, 2019). The theories emphasise the role of data ecosystems, real-time analytics, and algorithmic decision-making in enhancing governance, service delivery, and public participation (Mikhaylov et al., 2018).

In the sustainability domain, these theories facilitate the integration of AI, big data, IoT, and cloud computing into economic, environmental, and social systems to achieve sustainability outcomes more efficiently and inclusively. At the core of the theories is the recognition that technology adoption is not merely a technical exercise, but a deeply socio-technical process involving organisational change, human capacity, and stakeholder collaboration (Govers and Van Amelsvoort, 2023). These theories thus provide a foundational insight in understanding how digital governance can enhance the effectiveness of AI in driving green transformation, particularly within South Africa contexts, where digital infrastructure remains uneven.

5.1.4. Application of the theoretical theories to our study

The socio-technical transitions theory, alongside the ecological modernisation theory (EMT) provide a robust conceptual foundation for analysing and shaping the development of our AIGE-ST model for South Africa. These theories support the integration of niche technological innovations, the restructuring of incumbent regimes, and the harnessing of South Africa landscape pressures.

Crucially, the adaptation of MLP and EMT is enriched by critical, inclusive, and justice-oriented perspectives to ensure that transitions are equitable, democratic, and culturally grounded within the South Africa context. This approach acknowledges South Africa's unique context, including the enduring impacts of apartheid-era spatial planning, the resulting digital and environmental inequalities, the significance of informal innovations, and the importance of community-led green practices.

The data-driven governance and digital transformation theories provide insights into how economic and institutional systems can be reconfigured through technology, enabling sectoral integration, cross-agency coordination, and the transition from legacy systems to AI-enabled green infrastructures. The three theories emphasise the need for contextualised strategies that reflect South Africa's socio-political landscape, infrastructural realities, and historical inequities. They guide how AI and data can be mobilised responsibly and inclusively. Table 2 shows how each theory informs specific aspects of the model.

Table 2. The influence of each theory on specific aspect of the proposed model.

Theory	Core Theoretical Insight	Model Components Influenced
Socio-Technical Transitions Theory (MLP)	Sustainability transitions occur through interactions across the landscape (macro forces), regime (existing systems), and niches (innovations). The MLP is adopted for niche-regime-landscape interactions in the model.	✓ Multi-Stakeholder Collaboration ✓ Ethical & Regulatory Frameworks ✓ Digital Infrastructure ✓ M&E Systems (tracking transitions)
Ecological Modernisation Theory (EMT)	Environmental protection and economic growth can be jointly achieved through technological innovation, institutional reform, and eco-efficient industrial practices. The EMT is adopted for decoupling and green competitiveness.	✓ Financing & Investment Models ✓ AI Technologies & Algorithms ✓ Human Capital Development
Data-Driven Governance Theory	Governance systems improve when decisions rely on high-quality, interoperable data, predictive analytics. The DDGT is incorporated to design the integrated data ecosystems to support environmental monitoring, emissions tracking, water management, and sustainability metrics.	✓ Integrated Data Ecosystems ✓ Monitoring & Evaluation (M&E) ✓ Ethical & Regulatory Frameworks ✓ Digital Infrastructure
Digital Transformation Theory	Societal and organisational transformation is driven by ICT, automation, AI adoption, and reconfiguration of processes, skills, and institutions. The digital transformation theory adopted for the data governance design.	✓ Human Capital Development ✓ Digital Infrastructure ✓ AI Deployment Strategies ✓ Institutional Capacity Building

5.2. Key components of the AIGE-ST model

The development of our AI-driven green economy and sustainability transformation (AIGE-ST) model integrates diverse, interrelated components tailored to the country's socio-economic, environmental, and technological landscape. These components serve as foundational pillars to support the shift toward a low-carbon, resource-efficient, and socially inclusive economy. The model's key components include data infrastructure and governance, AI technologies and innovation ecosystems, policy and regulatory frameworks, human capacity development and financing, and stakeholder engagement and inclusivity. These components are highlighted here and further summarised in table 2 with the description and implication of each component to the green economy and sustainability initiatives of South Africa.

5.2.1. Robust data infrastructure and governance

At the core of the transformation model lies a comprehensive, interoperable data ecosystem, underpinned by an Open Green Data Architecture (OGDA) which integrates diverse data sources from satellites, sensors, citizen

reports, and employs federated learning, edge AI, and privacy-preserving analytics. Therefore, South Africa must invest in national green data infrastructure, such as environmental monitoring networks, IoT sensor arrays, and distributed data platforms that collect and harmonise data from energy, water, waste, transportation, and land use systems. Equally important is the establishment of data governance frameworks to ensure data quality, accessibility, privacy, and ethical use. Public and open data, especially from government, research institutions, and utilities must be made available for AI applications focused on environmental monitoring, sustainable resource management, and climate resilience.

Potential measurable indicators for the Digital Infrastructure component of the framework include the number of operational IoT sensor networks deployed for environmental and energy monitoring, broadband penetration rates in both rural and urban areas align with AI utilisation, the percentage uptime of critical digital infrastructure such as data centres and cloud storage facilities, and the number of edge-computing installations supporting real-time sustainability analytics. Similarly, the Integrated Data Ecosystem component can be assessed using several measurable indicators, including the volume of real-time environmental and industrial data collected per month, the number of interoperable databases integrated across sectors such as energy, water, transport, and waste, the number of data-sharing agreements established among public, private, and research entities, and the adoption rate of geospatial and sensor-based platforms for sustainability monitoring.

A data ecosystem for the AIGE-ST model is presented in figure 2 showing the components, technologies samples and their connectivity.

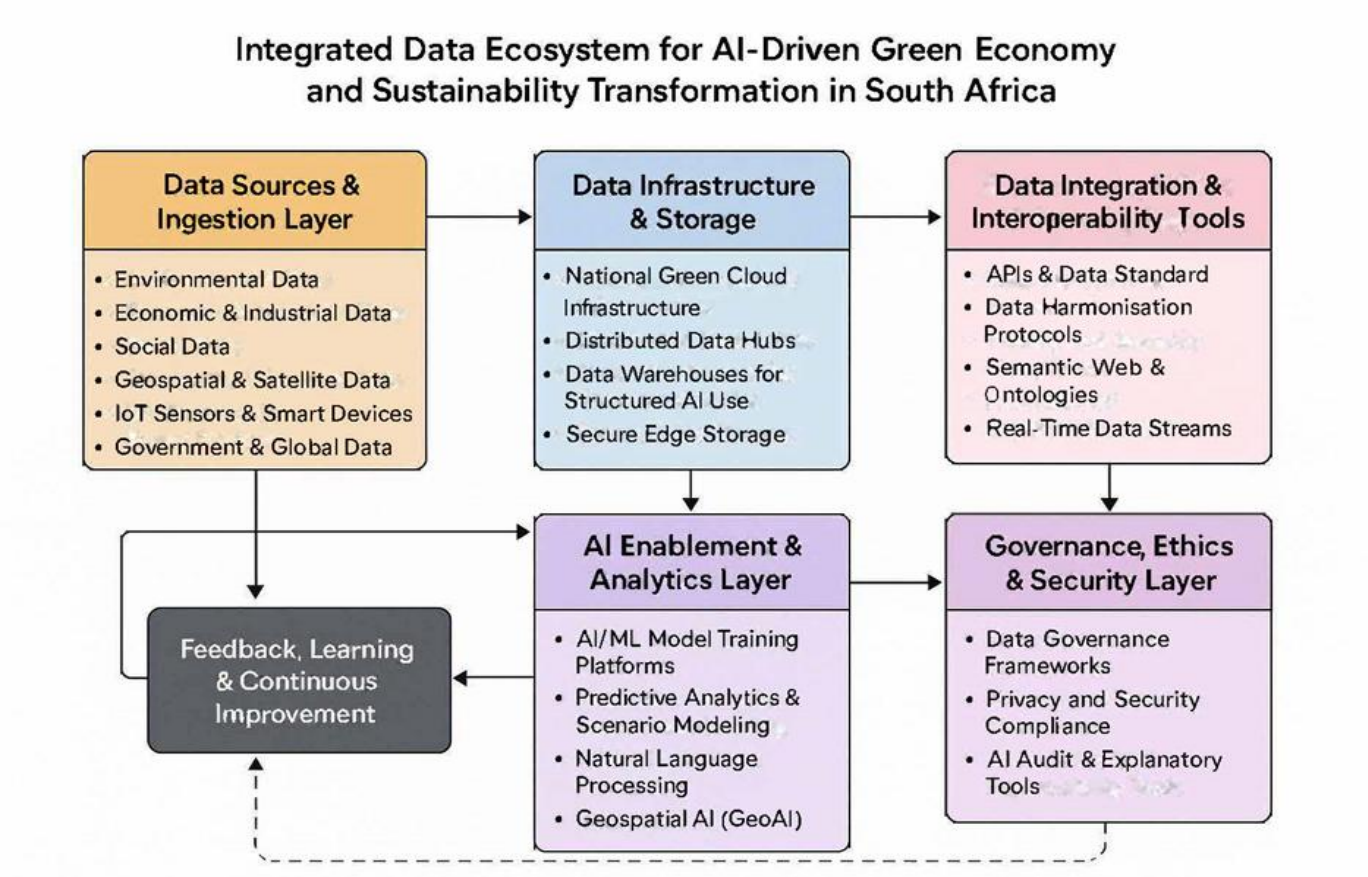


Figure 2. AIGE-ST model data ecosystem diagram

5.2.2. AI technologies and green innovation

The application of AI technologies, including machine learning, reinforcement learning, natural language processing, and computer vision, can optimise energy usage, predict environmental trends, and enhance smart infrastructure systems. For example, AI-driven predictive analytics can improve renewable energy integration into the grid or support water resource allocation during droughts. Developing a green innovation ecosystem that includes incubators, research centres, and partnerships between universities, startups, and industries is essential. This ecosystem will facilitate co-creation of AI tools that are context-specific, equitable, and aligned with local environmental priorities such as biodiversity protection, decarbonisation, and just transition.

The potential measurable indicators for the AI Technologies and Algorithms component of the proposed model encompass the number of AI models developed for green economy applications, such as energy optimisation, waste sorting, and climate forecasting, the proportion of deployed algorithms that meet predetermined accuracy or precision thresholds for sustainability-related tasks, the quantifiable reduction in carbon emissions (CO_2e) attributable to AI-enabled optimisation solutions, and performance metrics related to processing speed and system scalability of deployed AI systems.

5.2.3. Enabling policies and regulatory frameworks

A strong, adaptive policy and regulatory environment is critical to support AI integration in the green economy. South Africa must develop AI ethics guidelines, sustainability standards, and data-sharing policies aligned with the country's environmental goals and the global sustainable development agenda. Such policies will promote AI for public good, encourage green entrepreneurship, and provide incentives for industries to adopt low-carbon and circular economy models powered by AI. Additionally, national AI and green economy strategies must be harmonised to address issues of algorithmic bias, environmental justice, and digital inclusion.

The ethical and regulatory frameworks measurable indicators include the number of AI systems audited for compliance with national AI ethics guidelines; the volume of regulatory policies enacted to govern the application of AI for environmental sustainability; the frequency of reported AI-related ethical breaches or environmental governance violations; and the stakeholder satisfaction scores related to transparency and accountability in AI governance.

5.2.4. Human capacity, skills development, and financing models

Human capital is vital for sustaining AI-driven sustainability efforts. South Africa must prioritise education and skills development in areas such as AI engineering, data science, sustainability science, and systems thinking. This involves upskilling the current workforce, training youth in emerging green digital skills, and embedding sustainability and ethics into science, technology, engineering and mathematics (STEM) curricula. Empowering local innovators and researchers, especially from marginalised communities, to contribute to AI solutions that ensures cultural relevance and long-term sustainability of transformation efforts.

The human capital development component of the model can be assessed through several indicators, including the number of professionals trained in green AI, data science, and sustainability analytics; the proportion of STEM graduates specialising in AI-for-environment applications; and the annual frequency of capacity-building workshops delivered to government and industry stakeholders. Additional measures can also include employment growth in AI-enabled green sectors, such as renewable energy, smart agriculture, and recycling.

Furthermore, mobilising adequate financial resources is essential to support research, innovation, infrastructure development, and the deployment of advanced AI technologies across sectors such as energy,

agriculture, water management, urban planning and transport. In the South African context, where economic disparities and fiscal constraints persist, a blended financing approach that combine public funding, private sector investment, development finance, and green bonds is necessary to stimulate innovation and scale green AI solutions. Such robust financial mechanisms are not only enablers of AI integration in green economy-sustainability transitions but are also vital to ensuring long-term resilience, economic competitiveness, and environmental justice in South Africa.

The financing and investment dimension of the proposed model can be evaluated through several indicators, including the total funding committed to AI-driven green economy initiatives; the proportion of the national innovation budget allocated to sustainable AI solutions; the return on investment (ROI) generated from the deployment of AI-based green technologies; and the number of start-ups supported within the green AI innovation ecosystem.

Additionally, monitoring and evaluation (M&E) is vital for tracking the effectiveness of green economy initiatives to ensure that goals related to environmental sustainability, social equity, and economic growth are met (Sarkodie et al., 2024). It provides data-driven insights for policy adjustments and resource optimisation. Monitoring and evaluation fosters transparency, accountability, and continuous improvement in sustainability transformation efforts (Islam, 2025). This component can be evaluated through several indicators, including the number of baseline assessments and periodic evaluation reports produced; the percentage attainment of predefined sustainability key performance indicators (KPIs), such as emissions reduction and energy efficiency; and the extent to which impact metrics demonstrate the contribution of AI initiatives to national SDG targets.

5.2.5. Multi-stakeholder collaboration and inclusivity

Finally, an inclusive stakeholder engagement is central to a just and democratic AI-driven transition. Therefore, our model recognises the contribution of government agencies, academic institutions, private sector actors, civil society, and local communities in co-designing and implementing solutions. The Communities, labour unions, and environmental justice groups will enhance the model by contributing locally grounded knowledge, ensuring that system design reflects diverse socio-economic and ecological realities, while their participation will help align AI-enabled sustainability interventions with community priorities, just transition principles, and environmental justice outcomes. By allowing participation of the historically disadvantaged groups in South Africa in the transition model, the model addresses social equity, environmental justice, and economic empowerment. Participatory AI governance structures, such as citizen assemblies or community data trusts can foster trust, accountability, and responsiveness in the deployment of AI for green transformation.

The potential measurable indicators for the multi-stakeholder collaboration and inclusivity component include the number of public–private partnerships (PPPs) established to support AI-driven sustainability initiatives; the volume of joint research projects undertaken across academia, government, and industry; the number of community-level co-design projects employing AI to address local sustainability challenges; the extent of civil society organisations' participation in AI governance processes; and the number of international collaborations or donor-funded AI initiatives focused on sustainability.

Incorporating these key enabling components to form the model makes it technologically robust, ethically grounded, socially inclusive, and environmentally sustainable by not only addresses the current ecological and economic challenges in the country, but also supports a resilient and equitable future. These components are extensively presented in Table 3 with their description and implications to the South Africa's green economy and sustainability.

Table 3. Core components of the AIGE-ST Model

Component	Description	Implications for South Africa	References
Digital Infrastructure	Cloud computing, IoT, high-performance computing, broadband connectivity, and data centres that support AI deployment.	Critical for implementing smart grids, remote monitoring, and scalable AI platforms in rural and urban areas.	Sasmal (2023); Gu et al. (2024); Wang et al. (2025)
Integrated Data Ecosystem	Real-time collection, sharing, and analysis of multi-sectoral data from agriculture, energy, water, transport, government, and climate systems.	Facilitates evidence-based policy, targeted interventions, and predictive modelling for resource efficiency.	Danquah et al. (2023); Singh et al. (2025)
AI Technologies and Algorithms	Deployment of machine learning, reinforcement learning, AI-Enabled IoT, NLP, and digital twin models for pattern recognition, prediction, and optimisation.	Enables climate modelling, smart agriculture, energy forecasting, urban planning, adaptive education, and infrastructure resilience.	Kang & Kim (2022); Sibiya et al. (2024); Samaei et al. (2024); Long et al. (2025).
Human Capital Development	AI literacy, technical training, STEM education, and capacity building for public servants and communities.	Promotes local innovation, reduces digital divide, and supports sustainable entrepreneurship and workforce transformation.	Atiku and Lawal (2022); Wang et al. (2023); Li and Imran (2025)
Ethical and Regulatory Frameworks	Development of data governance laws, ethical AI standards, privacy protection, and environmental AI regulations.	Ensures responsible AI use, builds trust among stakeholders, and prevents exclusion, surveillance, or algorithmic bias.	Wahid et al. (2024); Wang et al. (2024); Ndoka et al. (2025).
Financing and Investment Models	Green finance platforms, AI-driven environmental, social, and governance (ESG) analytics, public-private partnerships, and impact investment strategies.	Mobilises funding for AI-enabled green infrastructure and supports inclusive financing for SMEs and local innovators.	Goncharenko and Shapoval (2021); Kumar (2022)
Multi-Stakeholder Collaboration	Engagement of government, academia, civil society, technological industry, community leaders, and private sector.	Enhances legitimacy, inclusivity, and alignment with local needs and indigenous knowledge systems.	Mienye et al. (2024); Mutambara (2025)
Monitoring & Evaluation (M&E)	Use of AI-based dashboards and KPIs for real-time sustainability metrics, SDG progress tracking, and adaptive policy.	Ensures accountability, iterative model improvement, and transparent progress reporting for national and international stakeholders.	Aoki-Suzuki (2015); Sarkodie et al. (2024); Islam (2025)

The table 4 presents a summary that explicitly maps each dominant theme identified in the systematic literature review to the corresponding components of the AIGE-ST Model, thereby demonstrating how the derived thematic insights inform and align with the structure of the developed model.

Table 4. Mapping of SLR Themes to AIGE-ST Model Components

S/N	SLR Themes	Mapped AIGE-ST Model Components	Mapping Description
1	AI Technologies for Green Economy and Sustainability	➢ AI Technologies and Algorithms ➢ Integrated Data Ecosystem ➢ Digital Infrastructure ➢ Monitoring & Evaluation (M&E)	The literature emphasises AI applications, data-driven decision-making, and automation as essential to green transitions. These insights directly inform the model components relating to technical AI capabilities, data pipelines, digital systems, and M&E structures that are required for sustainable outcomes.
2	Governance, Ethics, and Policy Considerations	➢ Ethical and Regulatory Frameworks ➢ Multi-Stakeholder Collaboration ➢ Financing and Investment Models	The governance-related findings, including alignment with ethics, policy mechanisms, and institutional coordination. These support the model's components that focused on policy regulation, collaborative governance arrangements, and funding mechanisms that are needed to operationalise AI-driven sustainability.
3	Infrastructure and Capacity Enablers	➢ Digital Infrastructure ➢ Human Capital Development ➢ Integrated Data Ecosystem ➢ Multi-Stakeholder Collaboration	The insights from the SLR highlighting infrastructure readiness, digital capacity, skills development, and organisational capability are directly map to components building institutional capacity, digital systems, workforce competence, and stakeholder partnerships.
4	Current AI-for-Sustainability Landscape in South Africa	➢ Digital Infrastructure ➢ Integrated Data Ecosystem ➢ Human Capital Development ➢ AI Technologies and Algorithms	The literature provides a detailed overview of the current AI-for-sustainability landscape in South Africa across multiple sectors, aligning these insights with the corresponding strengths and weaknesses observed within the model's components.
5	Research Gaps	➢ Digital Infrastructure ➢ Monitoring & Evaluation (M&E) ➢ Human Capital Development ➢ Ethical and Regulatory Frameworks	Identified gaps, such as insufficient digital infrastructure, weak evaluation structures, limited workforce expertise, and inadequate regulatory guidance help refine components that address deficiencies in infrastructure, evaluation systems, skills pipelines, and oversight mechanisms.

Our AIGE-ST model is therefore built upon a triad of intelligent technologies, integrated data ecosystems, and transformative policy instruments. Such an approach not only enhances efficiency and resilience across ecological and economic systems but also enables a more participatory and equitable sustainability transformation. A coordinated strategy that bridges technology, governance, and societal values is essential for realising a just and future-proof green economy. The proposed AIGE-ST model is represented in figure 3.

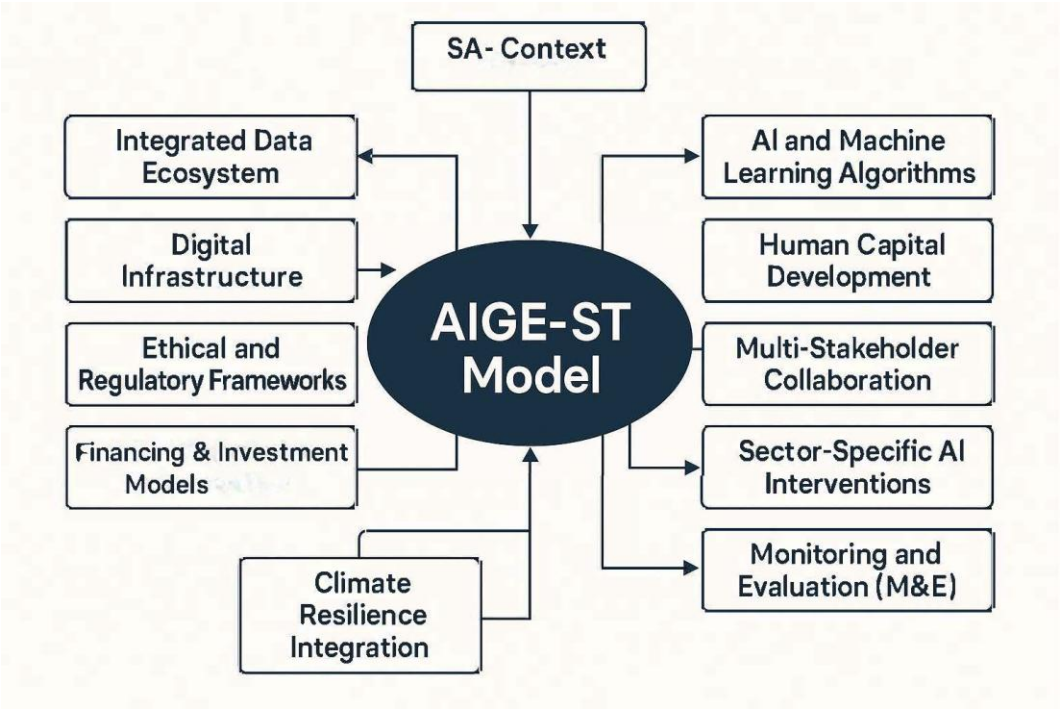


Figure 3. AIGE-ST contextual model

5.3. Stakeholder roles and multi-level collaboration

The implementation and long-term success of the AIGE-ST model requires clearly defined stakeholder roles and multi-level collaboration. The green economy and sustainability agendas intersect with numerous sectors, including energy, agriculture, industry, education, environment, and governance making it imperative to engage a broad spectrum of stakeholders. These include government agencies, private sector actors, research institutions, civil society organisations, local communities, and international development partners. Each of these actors contributes unique knowledge, data, resources, and mandates that can shape a more holistic and impactful transformation model.

The government and policy makers are expected to play regulatory and policy strategic coordination roles by providing the policy frameworks, regulatory environments, and public investment required to support AI and sustainability integration enabling policies, infrastructure, and funding mechanisms. Academic institutions and research organisations will contribute critical capacity through interdisciplinary research, modelling, scenario analysis, and development of AI algorithms tailored to South Africa's socio-environmental realities. More importantly, universities and think tanks will provide capacity building and the development of human capital through a mentorship role, training future AI and sustainability experts to sustain long-term innovation and policy support (Fung and Hosseini, 2023).

The data providers and digital Infrastructure agencies that are responsible for data generation and storage, including satellite data providers, smart city platforms, and IoT systems form the backbone of the AI ecosystem. Their major role includes the maintenance of data quality, accessibility, and interoperability. Therefore, a close coordination is required between these entities and the data users. At the civil society and community level, their engagements will ensure that the sustainability transformation is inclusive and responsive to local needs, especially in historically marginalised and climate-vulnerable areas. The international organisations and development partners will provide technical assistance, funding, and policy guidance that will help South

Africa benchmark and align its green economy strategies with global sustainability goals such as the SDGs and the Paris Agreement (Ziemba et al., 2024).

Finally, multi-level collaboration across local, provincial, national, regional, and international scales is essential to harmonise policies, ensure data interoperability, and facilitate cross-border knowledge transfer. Collaborative platforms that bring together stakeholders at these various levels can help foster a co-innovation ecosystem, avoid duplication of efforts, and promote integrated sustainability outcomes in line with the Sustainable Development Goals (SDGs).

The steps required to operationalise the proposed model across different sectors in South Africa will vary according to the specific AI technologies needed within each domain. For example, in the context of smart agriculture, the initial priorities should centre on establishing a robust data foundation and essential digital infrastructure prior to the deployment of more advanced AI applications. This process should begin with the rollout of sensor networks, mobile-enabled data collection systems, and interoperable agricultural databases capable of capturing soil characteristics, weather patterns, crop health indicators, and market dynamics. In parallel, enhancing farmers' digital literacy through targeted training programmes and strengthened extension services is crucial to ensuring meaningful and sustainable adoption. Once these foundations are in place, AI-powered tools, such as predictive analytics for yield forecasting, early-warning systems for pests and diseases, and optimisation algorithms for irrigation and fertiliser use can be gradually introduced, starting with low-cost, high-impact applications suitable for smallholder and commercial farms.

6. Conclusion

6.1. Policy recommendations

To effectively implement our AIGE-ST model for South Africa, a comprehensive, multi-sectoral policy framework is necessary. One of the most critical recommendations is the development of a national AI and sustainability strategy that clearly aligns artificial intelligence applications with the country's environmental goals, climate action commitments, and socio-economic development plans. Another essential policy action is the establishment of a robust data governance and digital infrastructure framework. This includes investing in secure, interoperable, and inclusive data ecosystems that facilitate real-time environmental monitoring, predictive analytics, and decision-making. Policies should encourage the creation of a National Green Cloud and distributed data hubs that support equitable access to AI technologies, especially in underserved rural and peri-urban areas.

Capacity building and human capital development are equally vital. Policymakers should invest in AI-focused education, training, and reskilling programmes, particularly targeting youth, women, and marginalised communities. Initiatives such as public-private partnerships, AI laboratories in universities, and green innovation hubs can accelerate the growth of local talent and entrepreneurship in AI for sustainability. Finally, a further recommendation is the need to promote inclusive multi-stakeholder collaboration. National and provincial governments must foster stronger coordination between academia, industry, civil society, and indigenous communities to co-create contextually appropriate and culturally sensitive AI solutions. Policy instruments should encourage collaborative platforms, knowledge-sharing mechanisms, and public engagement forums to ensure diverse perspectives shape the AI-green economy agenda.

6.2. Conclusion

This study set out to explore the development of an Artificial Intelligence-Driven Green Economy and Sustainability Transformation (AIGE-ST) model tailored to the South African context. Through an extensive

examination of literature, frameworks, technologies, and contextual drivers, the research has highlighted the potential of AI to serve as a catalyst in accelerating sustainable development goals, particularly in emerging economies such as South Africa. The integration of AI technologies into key sectors, such as energy, agriculture, transport, water management, and waste systems offer a transformative pathway to address climate change, improve resource efficiency, and foster socio-economic resilience. By leveraging data from diverse sources, including environmental sensors, socio-economic databases, satellite imagery, and IoT-enabled infrastructure, AI can provide actionable insights for policy formulation, monitoring, and implementation of green development strategies.

One of the key conclusions drawn is the critical importance of a robust and integrated data ecosystem as the foundation of the AIGE-ST model. The research underscores the need for coordinated efforts in data governance, standardisation, and interoperability to ensure seamless access, integration, and ethical use of data across sectors and institutions. Furthermore, the study emphasises that the successful implementation of the model requires a synergistic approach involving technological innovation, institutional readiness, regulatory frameworks, and multi-stakeholder collaboration. Human capital development through investments in education, digital literacy, and AI research also emerged as a fundamental pillar to build local capacity and foster inclusive innovation.

The research also reveals that while there is growing interest in the application of AI in sustainability, the existing literature and implementation efforts are fragmented and often siloed, particularly in the Global South. This calls for transdisciplinary research approaches that integrate technological, environmental, social, and policy perspectives to ensure the model is both contextually relevant and adaptable. Additionally, the ethical, legal, and policy dimensions of AI deployment in green economy initiatives require urgent attention to avoid exacerbating inequalities and ensure that AI serves as a force for equitable and just transformation.

In conclusion, developing an AI-driven green economy and sustainability transformation model for South Africa presents a unique opportunity to position the country at the forefront of digital-led sustainability transitions. The insights from this study can guide policymakers, researchers, and development practitioners in designing inclusive, scalable, and future-oriented interventions. While challenges remain in terms of infrastructure, skills, and regulatory alignment, the proposed AIGE-ST model provides a comprehensive framework for navigating these complexities and unlocking the potential of AI to support a greener, more resilient, and prosperous South Africa.

6.3. Contribution to knowledge

This research contributes significantly to the growing body of interdisciplinary scholarship at the intersection of artificial intelligence (AI), environmental sustainability, and economic transformation. It uniquely positions itself within the context of the Global South, responding to a pressing need for contextually relevant, innovative, and inclusive approaches to sustainable development. By synthesising insights from environmental science, AI technology, economics, and public policy, the study offers a novel concept that integrates socio-technical transitions theory, ecological modernisation theory, and the frameworks of data-driven governance and digital transformation to develop a data-driven ecosystem based AIGE-ST Model to support green economy and sustainability strategies in South Africa.

Furthermore, the research fills a critical gap by drawing the developed model from the South Africa-specific insights of socio-economic dynamics, infrastructure limitations, and environmental vulnerabilities. By grounding the analysis on South Africa's unique developmental landscape, the study offers practical insights into how AI can be a catalyst for inclusive and resilient green growth. Lastly, the study produces inform evidence-based implications for policymaking as regards the development of a national AI and sustainability

strategy that clearly aligns artificial intelligence applications with the South Africa's environmental goals, climate action commitments, and socio-economic development plans.

6.4. Suggestions for future research

The proposed model will benefit empirically through validation by the local stakeholder on South African case studies, as its lack of prior testing within the South African context represents a key limitation of the study. Also, future research can explore the integration of indigenous knowledge systems and local socio-cultural contexts into AI-driven green economy. Studies can examine how AI tools can be aligned with community-based sustainability practices and traditional ecological knowledge to foster inclusive and culturally relevant solutions.

Another key area for future investigation is the development of ethical, legal, and governance frameworks tailored to South Africa's socio-political realities. Research is needed to address the regulatory gaps and ethical concerns related to data privacy, algorithmic bias, and decision transparency. Additionally, future research can also investigate the capacity-building and human capital development needed to sustain an AI-driven green economy in South Africa. This includes identifying skills gaps, designing relevant educational and training programmes, and evaluating the role of public and private sector partnerships in nurturing AI and sustainability talent. Emphasis on youth and gender inclusion in these initiatives would further promote a just and inclusive green transition.

Finally, future research should explore adaptive learning loops for real-time policy feedback, cost–benefit analysis of AI-enabled interventions, and community-driven data co-creation approaches to ensure that technological innovation remains both inclusive and impactful in achieving South Africa's sustainable development goals.

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