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A Design Science Framework for AI-Driven Waste Recovery and Economic Value Creation in Nigeria

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Abstract
Rapid urbanisation, changing consumption patterns, and linear disposal models in Nigeria have exacerbated environmental degradation and resource depletion. This study proposes an integrated Design Science Research (DSR) framework connecting Artificial Intelligence (AI), digital innovation, circular resource recovery, and economic value creation within the Nigerian waste management ecosystem. The seven-layer architecture spans waste generation, digital data acquisition (IoT, computer vision, GPS/GIS), data management, AI analytics (predictive modelling, deep learning classification, route optimization), smart operations, circular recovery, and economic value evaluation. Based on national empirical data, the model demonstrates that optimizing the recovery of urban recyclable municipal solid waste (7.68 million tonnes in 2023) can unlock revenue expanding from US267.05 million in 2023 to US332.93 million by 2030, alongside substantial operational fuel and disposal cost savings. Furthermore, the framework provides inclusive pathways to formalise and connect informal waste pickers via digital platforms. This study establishes a robust conceptual bridge between Computer Science and Environmental Economics, providing actionable intelligence for sustainable urban waste management.

Keywords*: Artificial Intelligence, Circular Economy, Digital Innovation, Sustainable Waste Management, Economic Value Creation, Nigeria, Machine Learning.*

I. INTRODUCTION

a. Background to the Study

The increasing generation of solid waste, rapid urbanisation, and changing consumption patterns have intensified the need for sustainable approaches to waste management. Conventional waste systems operate primarily on a linear model organized around collection, transportation, and final disposal, with limited attention to material recovery. In Nigeria, these challenges are compounded by infrastructure limitations, fragmented institutional responsibilities, weak enforcement, and inadequate waste data, making the transition toward a circular economy particularly critical (Onungwe et al., 2023; Omokaro et al., 2026).

The circular economy (CE) provides an alternative model that maintains the utility and value of products and materials through reduction, reuse, repair, recycling, and recovery. Concurrently, Artificial Intelligence (AI) and digital technologies—including machine learning, computer vision, Internet of Things (IoT) sensors, and route optimization—offer powerful tools to improve waste forecasting, automated sorting, and logistics (Fang et al., 2023; Dawar et al., 2025; Yevle & Mann, 2025). Integrating AI, digitalisation, and circularity can significantly improve operational efficiency and resource utilization (Seyyedi et al., 2024; Olawade et al., 2026). However, recent reviews emphasize barriers such as operational fragmentation, data scarcity, and lack of system integration (Jano et al., 2026; Abbanura et al., 2026).

b. Statement of the Problem

Nigeria waste management crisis stems not only from escalating waste volumes but also from inefficient collection, manual sorting, inadequate recycling infrastructure, and fragmented data systems (Omokaro et al., 2026). Existing AI and digital waste management solutions remain isolated—focusing on single tasks like route planning or image classification—without connecting digital intelligence to circular material recovery and macroeconomic value creation (Dawar et al., 2025; Olawade et al., 2026). The central problem is the absence of an integrated, context-sensitive AI framework that simultaneously addresses smart waste operations, circularity, economic feasibility, and informal sector inclusion in Nigeria.

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c. Aim study
The main aim of this study is to design an AI-driven digital framework for sustainable waste management and economic value creation within a circular economy context in Nigeria.

d. Objectives of the Study
1. Examine the roles of Artificial Intelligence and digital innovations in circular waste management.
2. Identify technical, environmental, and economic requirements for AI-enabled circular waste systems.
3. Design an integrated AI-driven framework for waste management, resource recovery and circularity in Nigeria
4. Formulate an economic value-creation model evaluating operational savings, market revenues, and informal sector integration.
5. Incorporate economic value-creation mechanisms into the proposed framework.

e. Research Questions
1. What specific roles do AI and digital innovations play in enhancing circular waste management?
2. What technical and economic requirements are necessary for deploying AI-driven waste systems in Nigeria?
3. How can digital data acquisition, AI analytics, smart operations, and circular recovery be integrated into a unified framework?
4. How can circular waste management generate measurable economic value and promote Socio-economic inclusion?

f. Significance and Scope of the Study
The study is significant because it connects **Computer Science, environmental sustainability and Economics** within a single framework. For Computer Science, it demonstrates how AI, IoT, computer vision, data analytics and optimisation can be applied to a complex societal problem. For Economics, it provides a basis for examining waste recovery, cost reduction, secondary-material markets, enterprise development and value creation. For waste-management authorities and policymakers, the framework provides a conceptual basis for integrating digital intelligence into collection, sorting, recycling and resource-recovery decisions. It may also support recycling enterprises and other circular-economy actors in identifying opportunities for improved resource utilisation and economic returns

.g. Scope of the Study
The study focuses on the design of an AI-driven digital framework for sustainable waste management and economic value creation in Nigeria. It covers AI techniques, digital technologies, waste collection and monitoring, waste classification, sorting, recycling, resource recovery and economic value creation within a circular-economy perspective. The study is conceptual and design-oriented; it does not involve primary questionnaire administration or the collection of new field data. Future empirical work may be used to validate and implement the proposed framework.

II. CONCEPTUAL AND LITERATURE REVIEW

a. Concept of Circular Economy
The circular economy (CE) represents a shift from the conventional linear model of take–make–use–dispose towards systems that retain the value and utility of products, components and materials for as long as possible. Its major principles include waste prevention, reuse, repair, refurbishment, remanufacturing, recycling and recovery. In waste management, the circular-economy perspective therefore treats discarded materials as potential inputs for further economic activity rather than merely as materials requiring final disposal.

The relationship between AI and circular economy has received increasing scholarly attention. A 2025 critical analysis of AI applications in the circular economy identified waste management, recycling, reverse logistics, reuse and remanufacturing as important research clusters, indicating that AI can contribute to circularity beyond conventional waste collection (Kumar et al., 2025). Similarly, Seyyedi et al. (2024) demonstrate that digitalisation can support circular waste-management practices through improved information management, process optimisation and decision-making.

For Nigeria, circularity is particularly relevant because materials contained in municipal, industrial, plastic and electronic waste can potentially support secondary-material markets and reduce dependence on virgin resources. However, achieving circularity requires coordinated technological, institutional and economic systems rather than recycling activities alone.

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b. Sustainable Waste Management

Sustainable waste management involves the coordinated control of waste generation, collection, transportation, sorting, treatment, recycling, recovery and final disposal while considering environmental, social and economic consequences. An effective system therefore seeks not only to remove waste from communities but also to minimise waste generation and maximise material and resource recovery.

Recent literature indicates that conventional waste systems can be improved through digital technologies capable of generating real-time information and supporting evidence-based operational decisions. A 2025 systematic review covering 152 studies found applications of AI and ICT across waste forecasting, collection, route optimisation, sensor-based monitoring and automated sorting (Abbanura et al., 2025). Similarly, recent reviews report that AI can support waste prediction, bin monitoring, transportation planning and material recovery (Dawar et al., 2025).

Table 1 should be inserted here: "Major Waste-Management Activities and Potential Digital/AI Interventions."

Waste Stage	Key Digital / AI Technology	Operational & Circular Outcome
Waste Generation & Bin Monitoring	IoT Fill-Level Sensors, Mobile Apps, Smart Bins	Real-time volume tracking, automated collection alerts, spill prevention.
Collection & Logistics	GPS/GIS, Route Optimisation, Predictive Analytics	Reduced fuel consumption, optimized fleet schedules, lower carbon emissions.
Sorting & Classification	Computer Vision, CNNs, Deep Learning, Robotic Arms	High-accuracy material separation, increased purity of secondary resources.
Resource Recovery & Recycling	Process Optimisation, Demand Forecasting, Market Dashboards	Maximised material recovery rates, dynamic pricing for secondary raw materials.

c. Artificial Intelligence in Waste Management

Artificial Intelligence provides computational techniques through which waste-management systems can learn from data, identify patterns, make predictions and support operational decisions. Relevant techniques include machine learning, deep learning, computer vision, artificial neural networks, clustering, optimisation algorithms and predictive analytics.

AI applications extend across different stages of the waste-management lifecycle. Predictive models can estimate future waste volumes; computer vision can identify and classify waste materials; machine-learning algorithms can optimise collection routes; and intelligent systems can support recycling and resource-recovery decisions. Yevle and Mann (2025) particularly identify AI-based image analysis and classification as important areas for automated waste sorting, while recent systematic reviews emphasise machine learning applications across the wider waste lifecycle (Yevle & Mann, 2025; Zhang et al., 2025).

d. Digital Innovation for Circular Waste Management

Digital innovation provides the infrastructure through which AI can interact with physical waste-management processes. Important technologies include **Internet of Things (IoT) sensors, smart bins, GPS/GIS, mobile applications, cloud computing, digital platforms, computer vision and data analytics**.

IoT-enabled bins, for example, can provide information about waste levels and collection points, while GPS and GIS can support dynamic routing. Cloud platforms can integrate information from multiple sources, and AI can subsequently analyse these data to generate operational recommendations. Seyyedi et al. (2024) identify IoT, digitalisation, route optimisation and energy-efficiency applications as important mechanisms through which digital technologies can support circular waste management. A 2025 review similarly reports that AI-IoT integration can improve collection, sorting and recycling processes (Seyyedi et al., 2024; Elmahalawy et al., 2025).

The implication is that digital innovation should not be considered an isolated technological intervention. Rather, it can form a connected information infrastructure linking waste generators, collection operators, recycling facilities, government agencies and markets for recovered materials.

e. AI-Enabled Waste Classification and Resource Recovery

Waste classification is an important component of circular resource recovery because the economic value of waste depends partly on the ability to identify and separate useful materials. Traditional manual sorting can be labour-intensive and inconsistent, particularly when different materials are mixed.

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Computer vision and deep-learning techniques provide opportunities for automated identification of plastics, metals, paper, glass, electronic components and other waste categories. Yevle and Mann (2025) report substantial research activity around AI-based waste classification and image analysis, while Jano et al. (2026) found that deep learning and computer vision are dominant approaches in recent AI research on circular e-waste management. Their review also shows that AI applications extend beyond identification to collection, sorting, disassembly, material recovery and second-life use.

This progression is important to the proposed framework because classification is treated not simply as a technical exercise but as the first stage in determining the potential economic pathway of a recovered material.

f. Circular Economy and Economic Value Creation

The economic rationale for circular waste management lies in converting materials that would otherwise incur disposal costs into resources capable of generating economic returns. Economic value can arise through the sale of recovered materials, reduced collection and disposal costs, reduced demand for virgin materials, improved resource productivity and the development of recycling and recovery enterprises.

AI can contribute indirectly to this value creation by improving the efficiency and accuracy of operational decisions. For example, better waste-volume prediction can reduce unnecessary collection trips; route optimisation can reduce fuel and transportation expenditure; accurate material classification can improve recovery rates; and predictive analytics can assist recycling facilities in planning capacity and material flows. Recent literature identifies operational efficiency, material recovery and cost reduction among the potential benefits of AI-enabled waste-management systems (Dawar et al., 2025; Abbanura et al., 2025).

Thus, the economic component of the proposed framework will consider waste not only as an environmental liability but also as a potential **economic input**. The framework will subsequently incorporate indicators such as operational cost, recovered-material value, avoided disposal cost, revenue potential, investment requirements and return on investment.

g. AI, Digital Innovation and Waste Management in Nigeria

Nigeria presents a particularly important context for AI-enabled circular waste management because the country's waste-management challenges coexist with a growing digital economy and expanding interest in resource recovery. However, the application of advanced technologies must account for practical conditions such as limited infrastructure, fragmented data, financing constraints, technical capacity and institutional coordination.

The Nigerian context also requires attention to the informal waste sector, which plays an important role in collection and material recovery. Rather than designing a framework that excludes existing actors, digital technologies can potentially provide mechanisms for connecting informal collectors, recycling enterprises, municipalities and material markets within a more coordinated value chain.

The broader international literature reinforces the importance of contextualisation. The 2025 review by Dawar et al. identifies infrastructure readiness, data standardisation, scalability and economic barriers as continuing challenges to AI implementation, while Jano et al. (2026) similarly identify data availability, interoperability, regulatory gaps and fragmented logistics as barriers in circular e-waste systems.

h. Review of Related Frameworks and Studies

Existing studies demonstrate significant progress but tend to emphasise particular components of the waste-management problem. AI reviews have concentrated on prediction, classification and operational optimisation; digitalisation studies have examined IoT, sensors and information systems; and circular-economy studies have emphasised resource recovery and material retention.

For example, Seyyedi et al. (2024) connect digitalisation with circular waste management and demonstrate the relevance of simulation and process optimisation. Dawar et al. (2025) provide a broad review of AI applications in municipal waste management, including forecasting; bin monitoring, routing and planning. Yevle and Mann (2025) focus strongly on AI-based classification, while Jano et al. (2026) extend the discussion across the circular e-waste lifecycle. The 2025 review of AI in the circular economy further identifies waste management, recycling, reverse logistics, reuse and remanufacturing as interconnected research areas.

Table 2 should be inserted here: "Comparison of Existing AI/Digital Waste-Management Approaches and the Proposed Framework."

Domain / Approach	Primary Focus	Key Limitations	Proposed Framework Advantage
Conventional Smart Bins	IoT fill-level monitoring	No AI analytics or route optimization	Integrates IoT with dynamic predictive routing.

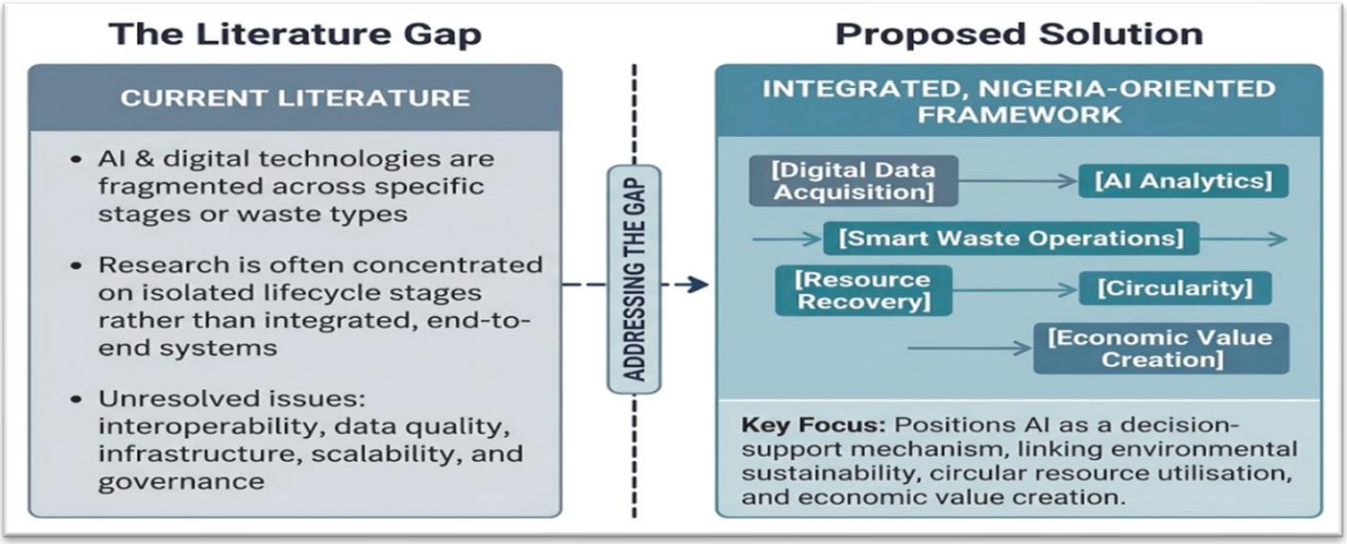
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AI Sorting Models	Image-based Classification	Isolated from logistics and market demand	Links image classification to secondary material markets.
E-Waste AI Reviews	Lifecycle tracking of Electronics	Narrow waste stream focus	Multi-stream coverage (plastics, organics, metals, e-waste).
Proposed Integrated Model	End-to-End AI & Circular Economy	Requires initial digital infrastructure	Connects data acquisition, AI, circular recovery, and economic ROI.

i. Gap in Literature

The literature demonstrates that AI and digital technologies can improve individual waste-management activities, including forecasting, monitoring, classification, route optimisation and recycling. Nevertheless, the evidence also indicates that many applications remain fragmented across particular stages or waste types. Jano et al. (2026), for example, observe that AI research in circular e-waste management has often been concentrated on specific lifecycle stages rather than functioning as an integrated end-to-end system. Similarly, recent reviews identify interoperability, data quality, infrastructure, scalability and governance as unresolved implementation issues.

The gap addressed by this study is therefore the need for an **integrated, Nigeria-oriented framework** that connects: **Digital Data Acquisition → AI Analytics → Smart Waste Operations → Resource Recovery → Circularity → Economic Value Creation**



Source: Author`s elaboration based on literature review and the proposed AI-enabled Circular waste management framework (2026)

Figure 1: The literature Gap and Proposed Integrated Solution

The diagram illustrates how the proposed research bridges existing limitations in current literature to deliver an integrated framework:

1. The Literature Gap: Current studies present fragmented AI applications focused on isolated waste types or specific lifecycle stages, while leaving implementation issues like interoperability, data quality, infrastructure, scalability, and governance unresolved.

2. The Proposed Solution: It introduces an integrated, Nigeria-oriented framework structured as a 6-step sequential pipeline:

3. Core Value: Instead of viewing AI merely as an automated classification or collection tool, the framework positions AI as a strategic decision-support mechanism linking environmental sustainability with circular resource utilization and economic value creation.

The proposed Framework goes beyond viewing AI merely as a tool for automated waste classification or collection optimisation. It positions AI as a **decision-support mechanism linking environmental sustainability with circular resource utilisation and economic value creation**. This integrated perspective provides the foundation for the methodology and framework presented in the subsequent sections.

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III. METHODOLOGY

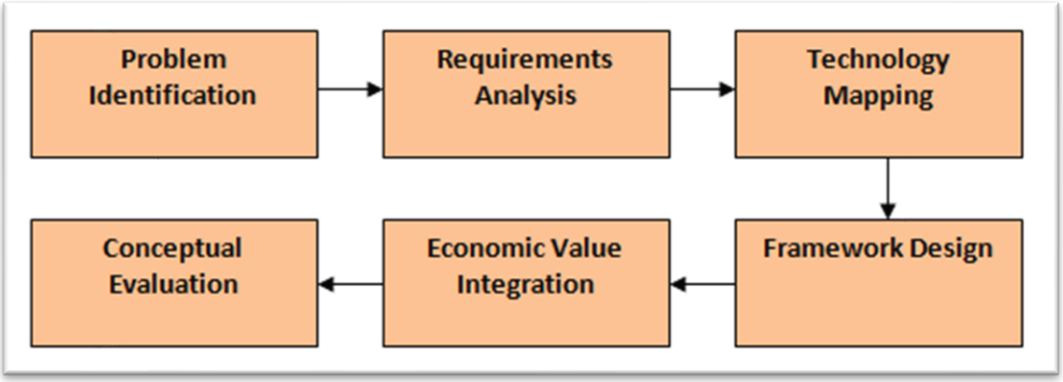
a. Research Design

This study adopts a Design Science Research (DSR) approach because its primary outcome is the design of a technological and conceptual artifact rather than the collection and statistical analysis of primary survey data. DSR provides a systematic approach for identifying a practical problem, defining requirements, designing an artifact and evaluating its relevance to the problem context. The approach is appropriate for this study because the proposed artifact is an AI-driven digital framework for sustainable waste management and economic value creation.

The methodology follows a design-oriented sequence comprising problem identification, requirement analysis, technology selection, framework design, economic-value integration and conceptual evaluation. The approach allows knowledge from Computer Science, environmental management and Economics to be integrated into a single framework.

b. Framework Development Process

The proposed framework will be developed through six sequential stages:



Source: Author`s Conceptualization/design (2026)

Figure 2: Design Science Research Process for Developing the Proposed AI-Driven Circular Waste Management Framework.

The first stage establishes the waste-management and circular-economy problems requiring technological intervention. The second identifies the information, operational, technological and economic requirements of the proposed system. The third maps appropriate AI and digital technologies to specific waste-management activities. The fourth integrates these components into the proposed framework. The fifth introduces mechanisms for assessing economic value, while the sixth evaluates the framework conceptually against technical, environmental, circularity and economic criteria.

c. Data and Information Requirements

Although the study does not involve primary field data collection, the proposed framework is designed to accommodate **secondary and operational datasets** that may be obtained from waste-management agencies, recycling facilities, municipalities, environmental databases and other relevant sources during future implementation.

The anticipated data categories include:

1. Waste Generation and Composition Data;
2. Geographical Locations of Waste-Generation Points;
3. Smart-Bin and Iot Sensor Data;
4. Waste Collection and Transportation Records;
5. Gps/Gis Information;
6. Waste-Classification Images;
7. Recycling and Material-Recovery Records;
8. Market Prices of Recovered Materials;

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9. Fuel and Transportation Costs;

10. Processing and Operational Costs; Andrevenue Associated With Recovered Materials.

These data would provide the foundation for AI-based prediction, classification, optimisation and economic analysis. The approach is consistent with recent research emphasising the importance of integrating heterogeneous data sources when developing intelligent waste-management systems (Abbanura et al., 2025; Dawar et al., 2025).

d. AI and Digital Technology Selection

Technology selection will be based on the function that each technology performs within the waste-management value chain. Machine learning and predictive analytics will support waste-generation forecasting and operational prediction. Computer vision and deep learning will support automated waste identification and classification. IoT sensors and smart devices will provide real-time information about waste levels and collection points. GIS and GPS technologies will support spatial analysis and collection-route optimisation. Cloud or centralised data platforms will facilitate the integration and processing of information from multiple sources.

The selection principle is therefore not to incorporate technology for its own sake, but to match each digital technology with a specific operational or economic requirement. Recent studies support this approach by demonstrating applications of AI, IoT, computer vision and optimisation across different stages of waste management (Fang et al., 2023; Seyyedi et al., 2024; Yevle & Mann, 2025).

e. Economic Evaluation Parameters

The economic component will assess how improved waste-management decisions can contribute to value creation and cost efficiency. The proposed framework will consider:

1. Collection and Transportation Cost;

2. Waste-Processing Cost;

3. Value of Recovered Materials;

4. Avoided Disposal Costs;

5. Recycling Revenue;

6. Operational Savings;

7. Investment Requirements;

8. Return On Investment (Roi); Andemployment And Enterprise Opportunities.

These indicators enable the framework to connect technical decisions with economic consequences. For example, an AI system may recommend a particular collection route based on predicted waste volumes. The economic layer can subsequently estimate the resulting fuel savings and compare them with alternative routes. Similarly, AI-based classification can identify materials with different recovery values and support decisions concerning sorting and processing.

f. Conceptual Evaluation of the Proposed Framework

Because this study is framework-oriented, evaluation at this stage will be **conceptual rather than empirical**. The framework will be assessed according to five criteria:

Evaluation dimension	Key consideration
Technical feasibility	Can the proposed technologies perform the specified functions?
Operational efficiency	Can AI improve collection, sorting and recovery decisions?
Circularity	Does the framework promote reuse, recycling and resource recovery?
Economic value	Can the system reduce costs or increase recoverable-material value?
Nigerian applicability	Can the framework accommodate Nigeria's infrastructure and institutional realities?

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The conceptual evaluation will also consider practical challenges identified in recent literature, including data availability, infrastructure, interoperability, implementation cost, technical skills and regulatory requirements (Dawar et al., 2025; Jano et al., 2026).

g. Methodological Alignment

The methodology maintains a direct relationship between the research problem, objectives and proposed artifact. The identified waste-management problems provide the design requirements; the literature provides the technological and conceptual foundations; the DSR process guides framework construction; and the economic indicators ensure that the resulting framework addresses both **environmental sustainability and economic value creation**.

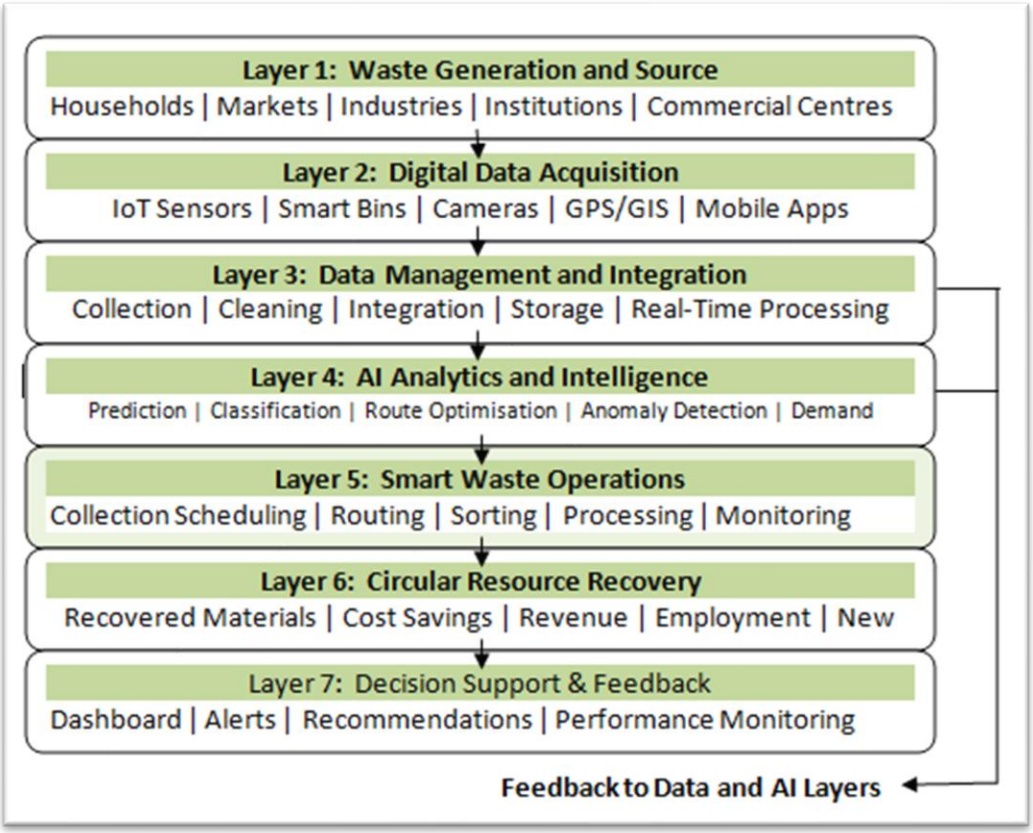
IV. PROPOSED AI-DRIVEN CIRCULAR WASTE MANAGEMENT AND ECONOMIC VALUE-CREATION FRAMEWORK

The proposed framework integrates Artificial Intelligence, digital technologies, circular-economy principles and economic decision-making into unified waste-management architecture. Rather than treating waste collection, recycling and economic activities as separate processes, the framework establishes a continuous information and material flow from **waste generation and data acquisition to AI-supported decision-making, resource recovery and economic value creation**.

Recent research supports the need for such integration. A 2026 systematic review found that AI research in circular waste management is increasingly moving towards optimisation and resource recovery but that system-level integration remains insufficiently consolidated. Similarly, a 2025 smart-waste framework integrates Edge-AI, digital twins, routing and circularity into a multi-layer architecture, demonstrating the feasibility of combining digital intelligence with circular waste operations.

a. Architecture of the Proposed Framework

The framework consists of **seven interconnected layers**:



Source: Author`s Conceptualization/design (2026)

Figure 3: Proposed AI-Driven Circular Waste Management and Economic Value-Creation Architecture

The seven operational layers function as follow:

The provided text details 7-layer of AI-driven circular waste management architecture. It structures waste management into a continuous, end-to-end digital pipeline: it begins at the **Waste Generation & Source Layer**, where heterogeneous materials enter the system, and captures real-time physical data (IoT, images, GPS) via the **Digital Data Acquisition Layer**. This data is cleaned,

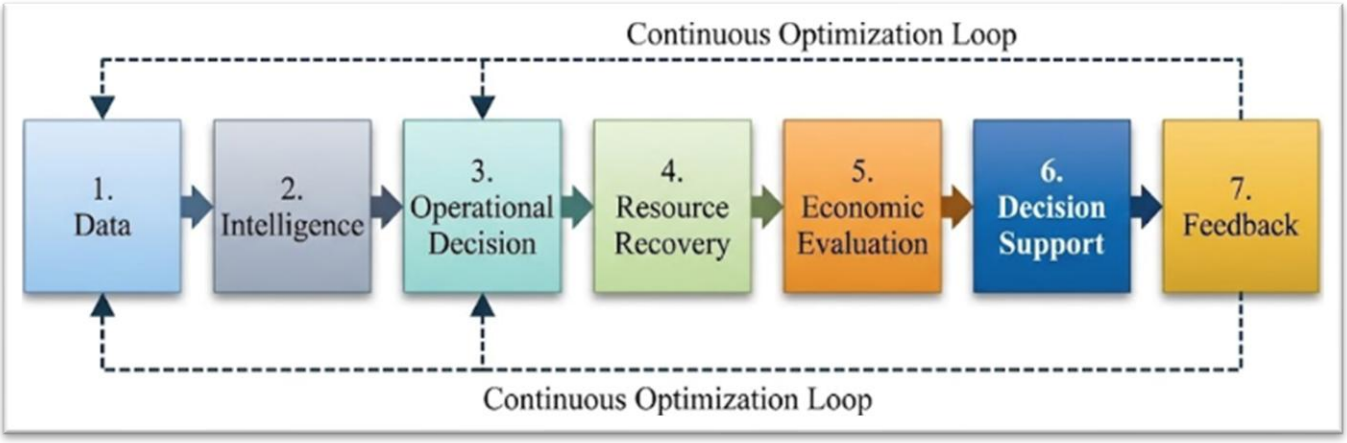
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integrated, and organized in the **Data Management & Integration Layer** before entering the **AI Analytics & Intelligence Layer**, which leverages machine learning, computer vision, and optimization algorithms to generate predictions and routing strategies. These insights translate into dynamic, demand-based collection and automated sorting in the **Smart Waste Operations Layer**, which feeds materials into circular loops (reuse, recycling, recovery via the **Circular Resource Recovery Layer**. Finally, the framework evaluates financial parameters, secondary material values, and market opportunities in the **Economic Value-Creation Layer**, presenting performance indicators and routing operational data back into the system through the **Decision-Support & Feedback Layer** to continuously train and optimize future AI models.

The architecture is deliberately designed as a feedback system rather than a one-way waste-disposal process. This reflects recent evidence that AI can support connected decision-making throughout the waste lifecycle, while circular-economy systems require information about materials and flows to remain available across different stages of recovery and reuse (Jano et al., 2026).

b. Integrated Framework Logic
The proposed framework can therefore be summarised as:

Data → Intelligence → Operational Decision → Resource Recovery → Economic Evaluation → Decision Support → Feedback



Source: Author`s conceptualization (2026)
Figure 4: Integrated Framework Logic in Circular Waste Management

1. Data: Raw information gathered from waste generation sources (e.g., smart bins, sensors, cameras, and mobile apps).
2. Intelligence: Processing and analyzing data using AI algorithms for volume prediction, material classification, and pattern recognition.
3. Operational Decision: Translating AI analytics into actionable schedules, optimized collection routes, and resource allocation.
4. Resource Recovery: Sorting, recovering, and processing reusable materials to divert waste from landfills into circular loops.
5. Economic Evaluation: Assessing financial feasibility, operational cost savings, secondary material values, and market revenue potential.
6. Decision Support: Presenting integrated insights, key performance indicators (KPIs), and recommendations via administrative dashboards.
7. Feedback: Routing operational performance data back into the system to continuously train and optimize future AI models.

This creates a continuous connection between environmental and economic objectives. It also addresses a limitation identified in recent literature: many AI waste applications remain focused on individual technical tasks, whereas an integrated approach is required to connect AI applications with circular-economy outcomes across the wider waste value chain.

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Table 3. Framework Layers, Technologies, Functions and Expected Outcomes

Framework layer	Key technologies	Major function	Expected outcome
Waste source	Smart containers, mobile systems	Identify waste generation	Better source information
Data acquisition	IoT, cameras, GPS/GIS	Capture real-time data	Improved visibility
Data management	Databases, cloud/edge systems	Integrate and process data	Usable datasets
AI intelligence	ML, DL, computer vision	Predict/classify/optimise	Intelligent decisions
Smart operations	Routing, scheduling, automation	Improve operations	Cost and time efficiency
Circular recovery	Sorting, recycling, reuse systems	Recover resources	Reduced disposal
Economic value	Markets, cost models, dashboards	Evaluate value	Revenue and savings
Feedback	Monitoring and analytics	Learn from outcomes	Continuous improvement

V. ECONOMIC VALUE-CREATION MODEL FOR AI-ENABLED CIRCULAR WASTE MANAGEMENT

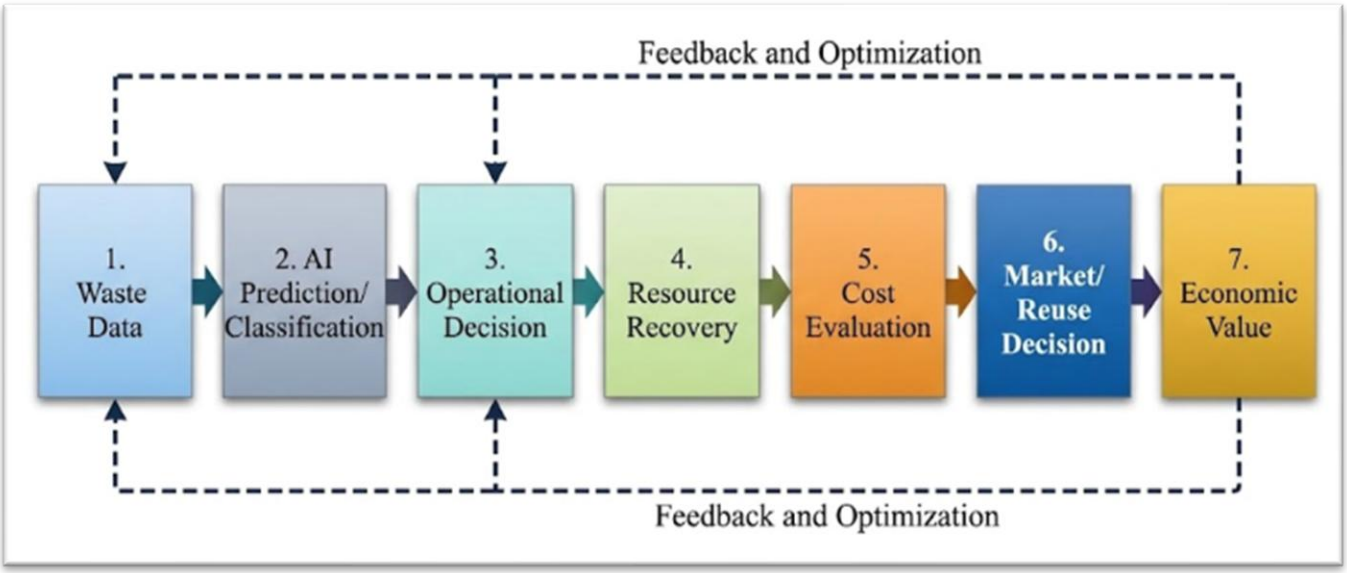
The economic dimension of the proposed framework is based on the principle that effective waste management should not end with the removal and disposal of waste but should seek to recover materials, reduce operational costs and generate economic value. In a circular economy, materials recovered from waste can become inputs into secondary production, recycling, reuse and other value-adding activities. This is particularly relevant to Nigeria, where recent research estimates substantial quantities of recyclable materials within the urban municipal waste stream and identifies significant revenue potential from their recovery and processing (Omokaro et al., 2026).

The proposed model therefore connects **AI-supported operational efficiency** with **resource recovery and economic evaluation**. AI does not itself create economic value; rather, it improves the quality and timeliness of decisions that determine how waste is collected, classified, transported, recovered and directed towards appropriate markets.

a. AI-to-Economic-Value Decision Process

The proposed economic decision process follows the sequence:

Waste Data → AI Prediction/Classification → Operational Decision → Resource Recovery → Cost Evaluation → Market/Reuse Decision → Economic Value



Source: Author`s conceptualization (2026)

Figure 5: AI-to-Economic Value-Decision Process in Circular Waste Management

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1. Waste Data: Gathers raw data from generation sources (smart bins, sensors, cameras, and mobile apps).
2. AI Prediction / Classification: Uses machine learning to categorize waste types and forecast generation volumes across locations.
4. Operational Decision: Optimizes collection schedules, truck routing, and logistics to lower fuel and labor costs.
3. Resource Recovery: Guides physical sorting and processing to recover reusable and high-value materials efficiently.
5. Cost Evaluation: Calculates operational expense against potential revenue to determine financial feasibility.
4. Market / Reuse Decision: Directs recovered materials to the best secondary markets, recyclers, or manufacturing processes.
6. Economic Value: Generates direct revenue, creates job opportunities, and achieves operational cost savings.
5. Feedback & Optimization Loop: Feeds performance and market data back into the system to continually refine future predictions and decisions.

For example, AI may predict the volume of recyclable waste at different collection points. The system can then determine an efficient collection route; estimate transportation costs and identify the materials likely to be recovered. The recovered materials can subsequently be assigned estimated market values. This allows decision-makers to compare the expected economic return with collection, processing and other operational costs.

b. Major Economic Value Channels

Economic value within the proposed framework can arise through five principal channels:

1. **Operational Cost Reduction:**
   AI-based route optimisation and waste-generation forecasting can reduce unnecessary vehicle movement, fuel consumption, labour requirements and collection frequency.

2. **Material Recovery Revenue:**
   Recovered plastics, metals, paper, glass and other materials can be sold as secondary raw materials. Recent Nigeria-focused analysis estimated revenue from urban recyclable materials at approximately US$267.05 million in 2023, based on the quantities collected and processed.

3. **Avoided Disposal Costs:**
   Increasing the proportion of materials diverted from landfills or dumpsites can reduce costs associated with transportation, disposal and landfill management.

4. **Enterprise and Employment Creation:**
   Circular activities can support collection enterprises, sorting centres, recycling facilities, repair businesses, remanufacturing activities and other waste-to-value enterprises. Evidence from Nigeria also indicates that informal waste-sector actors already contribute substantially to collection, sorting, upcycling, resource recovery and recycling activities.

5. **Resource Productivity:**
   Recovering materials from waste reduces the need to obtain equivalent quantities of virgin resources and can therefore contribute to more efficient use of materials within the economy.

c. Economic Value Equation

At the conceptual level, the framework can express net economic value as:

Net Economic Value = Recovered-Material Revenue + Avoided Costs + Operational Savings − Technology and Processing Costs

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Where:

1. **Recovered-Material Revenue** represents income from recyclable or reusable materials;
2. **Avoided Costs** represent costs that would otherwise be incurred through disposal or inefficient operations;
3. **Operational Savings** represent reductions arising from AI-supported collection, transportation and processing;
4. **Technology and Processing Costs** include investments in sensors, computing infrastructure, AI systems, sorting equipment, maintenance and other operational requirements.

This equation is intended as a **decision-support model**, not as an empirical estimate of Nigeria's total economic value. Its purpose is to enable future implementations of the framework to compare alternative waste-management strategies using actual local data.

d. Evidence of Economic Potential in Nigeria

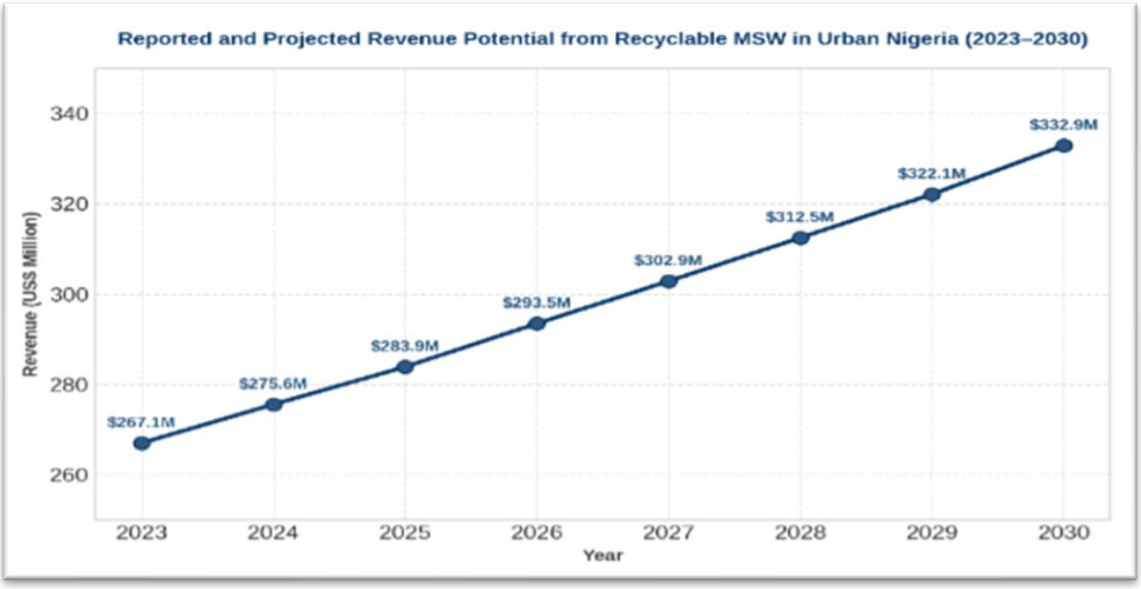
The economic potential of circular waste management is supported by recent Nigerian evidence. Omokaro et al. (2026) estimated that urban Nigeria generated approximately **29.5 million tonnes of municipal solid waste in 2023**, including about **7.68 million tonnes of recyclable materials**. Their analysis estimated revenue of approximately **U267.05 million** from the recyclable materials collected and processed in 2023 and projected increasing revenue as waste generation and material recovery expand.

The same study projects recyclable-material revenue to increase from approximately **US267.05 million in 2023 to U332.93 million by 2030**, illustrating the potential economic significance of improved material recovery. These figures are projections from the study rather than observed national revenue and should therefore be interpreted as an indication of potential rather than a forecast guaranteed to occur.

This figure should be presented as a **line chart** showing the study's reported/projection series:

Year	Projected revenue (US million)
2023	267.05
2024	275.60
2025	283.92
2026	293.52
2027	302.91
2028	312.51
2029	322.14
2030	332.93

Source: Ezeudu and Ugochukwu (2026)



Source: Author`s computation/construct (2026)

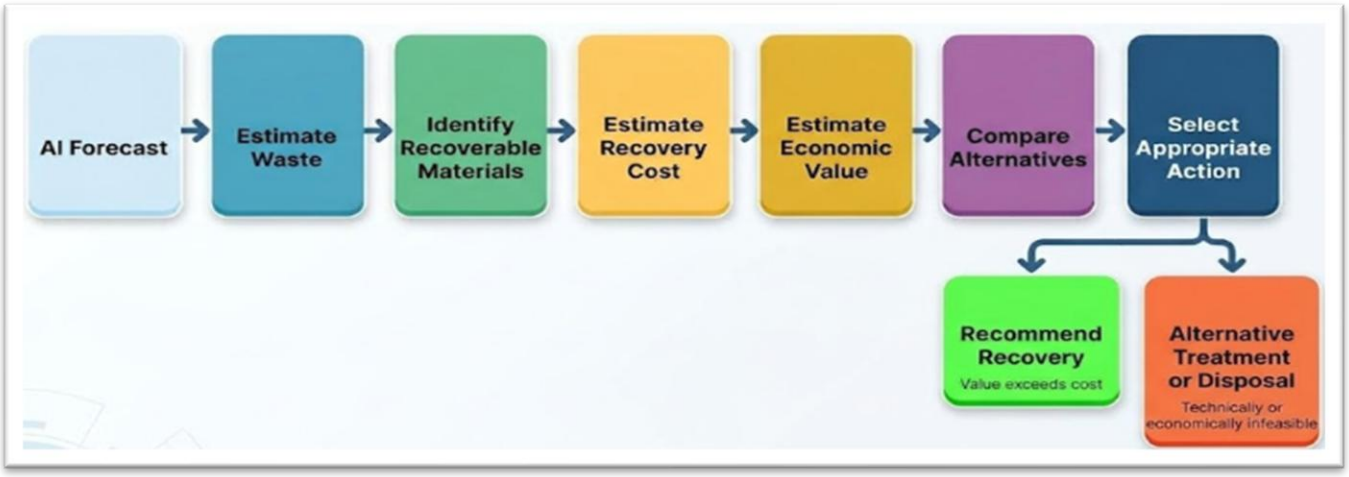
Figure 5: Reported and Projected Revenue Potential from Recyclable Municipal Solid Waste in Urban Nigeria, 2023–2030

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The chart demonstrates why economic value should be explicitly incorporated into the proposed AI framework. If AI-supported systems improve the identification, collection and recovery of recyclable materials, the resulting increase in material recovery can potentially strengthen the economic contribution of the circular waste sector. However, actual economic outcomes will depend on material prices, collection efficiency, processing capacity, technology costs, market demand and institutional conditions.

e. Economic Decision Logic

The proposed framework applies the following decision logic:



Source: Author`s elaboration based AI-enabled Circular waste management framework (2026)

Figure 6: AI-Enabled Waste management Decision Logic

Explanation: Main Sequential Flow: The core pipeline maps the step-by-step decision process starting from AI Forecast through estimating waste, identifying recoverable materials, evaluating recovery costs and economic values, comparing options, and selecting an appropriate action.

Decision Pathways: At the final step (Select Appropriate Action), the logic splits into two pathways:
Recommend Recovery: Triggered when the estimated value of the recoverable material exceeds the cost of collection and processing.

Alternative Treatment or Disposal: Recommended when recovery is determined to be technically or economically infeasible.
Core Principle: The framework demonstrates that not every technically recoverable material is necessarily economically recoverable. It ensures AI predictions are paired with economic cost-value considerations before generating a recommendation.
For example, where the estimated value of recoverable material exceeds the additional cost of collection and processing, the system can recommend recovery. Where recovery is technically or economically infeasible, the system can recommend an alternative treatment or disposal pathway.

This approach introduces an important economic principle into AI-enabled waste management: **not every technically recoverable material is necessarily economically recoverable**. Consequently, the proposed framework combines AI predictions with cost and value information before generating a recommendation.

f. Economic Performance Indicators

The framework will use several indicators for future implementation:

Indicator	Interpretation
Material recovery value	Monetary value of recovered materials
Collection cost	Cost of collecting waste
Transportation cost	Cost associated with waste movement
Processing cost	Cost of sorting and recovering materials
Revenue from recovered materials	Income generated from recovered resources
Avoided disposal cost	Disposal expenditure avoided through recovery
Operational savings	Savings generated through improved decisions
Return on investment (ROI)	Economic return relative to investment
Cost-benefit ratio	Relationship between benefits and costs
Employment potential	Jobs/value-chain opportunities created

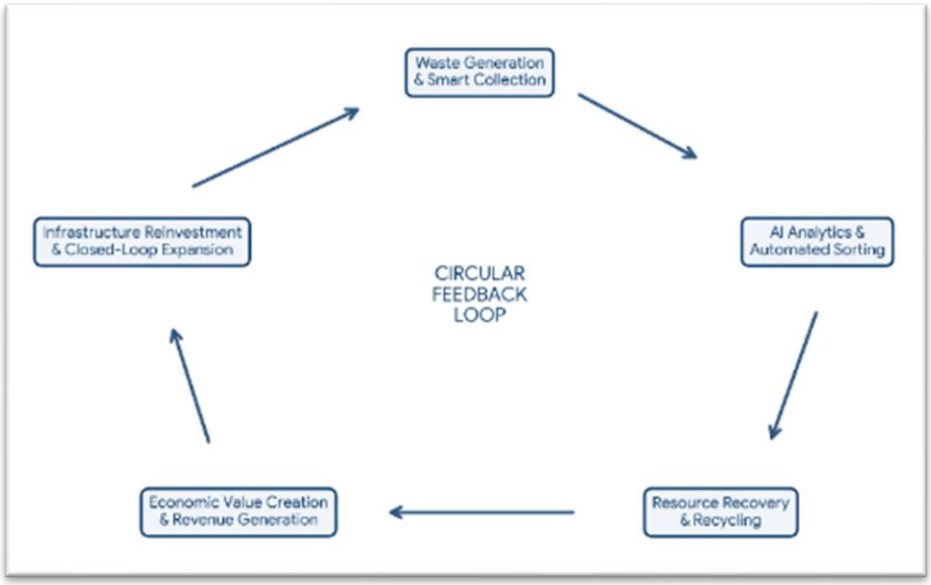
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These indicators provide a bridge between the technical performance of the AI system and the economic outcomes expected from circular waste management.

g. Circular Waste–Economic Value Loop

The economic model operates not as a static calculation, but as a continuous, dynamic feedback system in which digital intelligence and financial returns reinforce one another. Rather than treating monetary evaluation as an isolated post-disposal activity, the proposed framework integrates circular material flows directly into a closed economic loop.

Figure 3 illustrates the **Circular Waste–Economic Value Loop**, detailing the cyclical interaction between smart technological interventions and economic value creation.



Source: Authors' conceptualisation based on the proposed framework.(2026)

Figure 7: Circular Waste–Economic Value Feedback Loop

As shown in Figure 3, the loop begins with **Smart Waste Generation and Collection**, where IoT sensors and mobile reporting capture real-time waste volumes and spatial distribution. This operational data feeds directly into **AI Analytics & Automated Sorting**, where machine learning algorithms optimize dynamic fleet routes and computer vision systems classify recyclable streams with high purity. The sorted materials advance to **Resource Recovery & Recycling**, supplying secondary raw materials to local manufacturing and processing industries.

The resulting **Economic Value Creation & Revenue Generation** yields tangible financial outcomes, including secondary material sales, reduced collection fuel expenditure, and avoided landfill tipping fees. Crucially, a proportion of these economic gains is directed into **Infrastructure Reinvestment & Closed-Loop Expansion**. This reinvestment finances additional IoT sensor deployment, edge computing hardware, and local recycling facility upgrades, thereby expanding system capacity and restarting the feedback loop. By converting waste management from a traditional municipal expense into a self-funding economic catalyst, this circular loop ensures long-term operational and financial sustainability.

h. Economic Inclusion of the Informal Waste Sector

An important component of the Nigerian model is the integration of informal waste-sector participants. Recent evidence indicates that informal waste workers contribute significantly to collection, transportation, sorting, upcycling, resource recovery and recycling in Nigeria.

The proposed framework therefore does not assume that digitalisation should replace existing human actors. Instead, digital platforms could potentially connect waste pickers and small recycling enterprises with collection information, material markets, sorting facilities and municipal systems. This could improve traceability while enabling informal actors to participate more effectively in formal circular value chains.

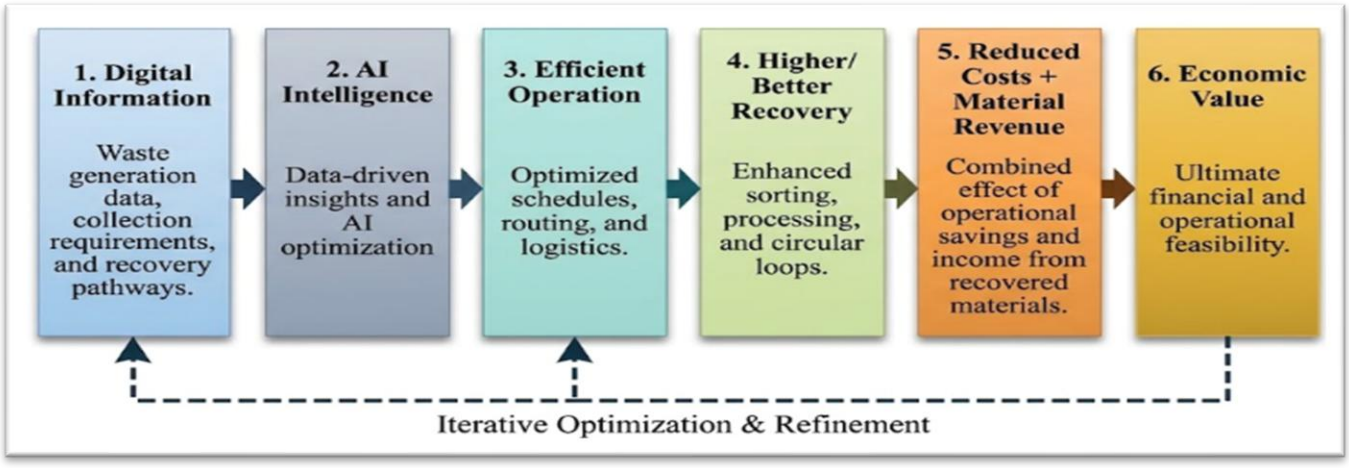
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i. Economic Implication of the Proposed Model

The central economic proposition of the framework is that **better information can support better resource-allocation decisions**. AI improves information about where waste is generated, what materials are present, when collection is required and which recovery pathways may be appropriate. Economic analysis then determines whether the proposed action is financially and operationally justified.

The resulting model can therefore be represented as:

Digital Information → AI Intelligence → Efficient Operation → Higher/Better Recovery → Reduced Costs + Material Revenue → Economic Value



Source: Author`s Conceptualization (2026)

Figure: Economic Implication of the proposed model

A brief breakdown of the Economic Implication of the Proposed Model sequence:

1. Digital Information: Captures critical data on where waste is generated, what materials are present, when collection is required, and which recovery pathways may be appropriate.

2. AI Intelligence: Uses algorithms to analyze the digital information, helping to make more informed, data-driven decisions on resource allocation.

3. Efficient Operation: Optimizes waste logistics, transport routes, and scheduling, based on AI insights, to eliminate waste and reduce unnecessary movements.

4. Higher/Better Recovery: Enables superior sorting and processing, channelling a higher percentage of quality recyclables back into the circular economy.

5. Reduced Costs + Material Revenue: Directly lowers fuel, labour, and operational expenses while simultaneously capturing new revenue from the sale of recovered materials.

6. Economic Value: Results in a financially and operationally justified model, yielding tangible value through increased savings, new resource revenue, and job opportunities.

7. Iterative Optimization & Refinement: Operates as a continuous loop, using feedback from operations to further refine data and intelligence, maximizing economic returns over time

8. This integration distinguishes the proposed framework from conventional smart-waste systems that focus primarily on collection efficiency. It positions waste management as part of a broader circular economic system in which environmental improvement and economic value creation can be considered simultaneously.

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VI. DISCUSSION

The proposed framework demonstrates how artificial intelligence (AI) and digital innovation can connect waste-management operations with circular-economy and economic-value objectives. Rather than treating waste simply as a disposal problem, the framework positions waste as a potential source of recoverable materials, business opportunities and employment. This is consistent with recent studies that identify digital technologies, intelligent sorting and data-driven decision-making as important enablers of circular waste-management systems (Fang et al., 2023; Dawar et al., 2025).

The framework integrates **data acquisition, AI analytics, smart operations and resource recovery** into a continuous process. IoT devices, smart bins, cameras and GPS/GIS technologies can provide operational data, while machine learning and computer vision can support waste classification, demand prediction and route optimisation. Such integration can reduce operational inefficiencies and improve the identification of recyclable materials. In developing contexts such as Nigeria, where fragmented waste systems and limited infrastructure remain significant challenges, the integration of these technologies provides a basis for more coordinated waste-management decisions (Omokaro et al., 2026; Olawade et al., 2026).

The economic dimension is particularly important. AI-enabled optimisation can potentially reduce collection and transportation costs, while improved sorting and recovery can increase the quantity and quality of materials entering recycling and reuse markets. The Nigerian evidence reported by Omokaro et al. (2026) illustrates this potential, with recyclable municipal solid waste associated with substantial present and projected revenue opportunities. **Figure 2** therefore provides an evidence-based illustration of the economic potential of recyclable materials rather than an assumed or simulated economic projection.

Figure 3 emphasises that economic value creation is not a final stage but part of a **feedback loop**. Revenue from recovered materials and savings from improved operations can support further investment in collection infrastructure, digital technologies and recycling enterprises. This creates an iterative relationship between technological efficiency, resource recovery and economic activity.

The framework also recognises the role of informal waste workers, who constitute an important part of Nigeria's existing recovery and recycling ecosystem. Integrating rather than displacing these actors can support inclusive circular-economy development while improving traceability, safety and market participation (Omokaro et al., 2026).

Overall, the framework provides a conceptual bridge between **Computer Science and Economics** by demonstrating how AI-generated intelligence can influence operational decisions and, ultimately, economic outcomes. Its principal contribution is therefore not the introduction of a single technology, but the integration of digital intelligence, circular resource recovery and economic value creation within a Nigerian waste-management context.

VII. RECOMMENDATIONS

Based on the proposed framework, the following recommendations are made:

1. **Adopt AI-enabled waste management:** Government and waste-management authorities should progressively introduce AI, IoT, GPS/GIS and digital platforms for waste monitoring, collection and resource recovery.

2. **Develop integrated waste-data platforms:** Standardised digital systems should be established to support real-time collection, analysis and sharing of waste-management information among relevant stakeholders.

3. **Promote circular-economy enterprises:** Policies should encourage recycling, reuse, repair, remanufacturing and other businesses capable of converting waste into economic resources.

4. **Support local technology development:** Nigerian universities, researchers and technology enterprises should develop affordable and locally maintainable AI and IoT solutions suited to Nigerian conditions.

5. **Include informal waste workers:** Existing waste pickers and other informal actors should be integrated into formal circular-economy programmes through training, safer working conditions and access to organised markets.

6. **Strengthen public–private partnerships:** Government should collaborate with technology companies, recycling firms, investors and research institutions to finance and scale intelligent waste-management infrastructure.

7. **Measure economic performance:** Implementation should track indicators such as operational savings, recovered-material revenue, avoided disposal costs, employment generation and return on investment to ensure that technological interventions produce measurable economic value.

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VIII. FUTURE RESEARCH

Future studies should move beyond the conceptual framework by developing and experimentally validating a **working AI-enabled waste-management prototype** in selected Nigerian cities. Such studies could collect real-time data from IoT-enabled bins, cameras, GPS/GIS systems and recycling facilities to evaluate prediction accuracy, routing efficiency and waste-classification performance.

Further research should also examine the **economic performance** of the framework using real operational costs, recovered-material prices, revenue, employment and return-on-investment data. Comparative studies across Nigerian cities could determine how infrastructure, waste composition and local market conditions influence implementation outcomes.
Finally, future researchers should investigate advanced AI models, edge computing, blockchain-enabled traceability and digital marketplaces for recovered materials. Such extensions could strengthen transparency, scalability and integration across Nigeria's circular waste-management ecosystem.

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