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ECO Technology for Food Waste Management in ASEAN Countries

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Abstract

Food waste management has emerged as a critical sustainability challenge in ASEAN countries due to rapid urbanisation, population growth, and changing consumption patterns. This study investigates the role of eco-technological interventions and policy frameworks in improving food waste management and accelerating circular economy transitions across the region. A comparative mixed-methods approach was employed, integrating the Eco-Technology Adoption Index (ETAI), Circular Resource Efficiency Model (CREM), Policy Implementation Efficiency (PIE), Life Cycle Assessment (LCA), and machine learning-based predictive analysis to evaluate food waste management performance in selected ASEAN countries. The findings reveal significant disparities in technological readiness and governance effectiveness, with Singapore and Malaysia demonstrating the highest levels of eco-technology adoption, resource recovery efficiency, and environmental performance. At the same time, Myanmar and Vietnam face substantial infrastructural and institutional challenges. The proposed Eco-Technological Model achieved an accuracy of 93.7% and an AUC value of 0.95, indicating strong predictive capability for resource recovery and sustainability assessment. The study concludes that technological innovation, policy coherence, and regional cooperation are essential for enhancing food waste valorisation and achieving Sustainable Development Goals, particularly SDG 12 and SDG 13, within the ASEAN region.

Keywords: Eco-technology, Food waste management, ASEAN countries, Circular economy, Sustainable development, Resource recovery, Machine learning, Policy implementation.

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Graphical abstract

1. Introduction

Food waste has emerged as one of the most critical sustainability challenges of the 21st century, especially in rapidly developing regions of the global economy, such as the Association of Southeast Asian Nations (ASEAN). The increase in food waste stemming from urbanisation, population growth, and consumption trends has led to alarming levels in ASEAN nations. Such an increase in food waste has not only strained waste disposal systems but also contributed to greenhouse gas emissions, resource depletion, and environmental degradation (Hoareau *et al.*, 2021; Artiola, 2019). In ASEAN cities, food waste accounts for more than 50% of municipal solid waste, underscoring the urgent need for innovative and sustainable management systems.

The constraints of conventional refuse treatment methods, which largely consist of landfilling and open dumping, make eco-technological treatment methods possible, emphasising the need for sustainability, resource recovery, and the integration of circular economy principles. Eco-technology is a holistic system that integrates biological, chemical, and engineering principles to convert waste into resources (Soudachanh, 2023). Eco-technological methods such as anaerobic digestion, composting, biological energy generation, and intelligent waste segregation systems not only reduce the environmental problems posed by waste but also create economic value through the production of energy, organic fertilisers, or reusable materials.

In the area of waste management, ASEAN countries present a mosaic of waste management capabilities and the adoption of eco-technological methods. Whereas countries such as Singapore and Malaysia have gone extensively in the matter of the development of the eco-technological systems of waste disposal and have elaborated in their national policies the necessity for circular economy principles, countries such as Laos, Myanmar and Cambodia continue to be in a state where they have not only the infrastructural problems but also those of finance and government (Agamuthu & Babel, 2023; Hermawan, D., 2025). The importance of regional collaboration and knowledge sharing will become increasingly evident for eco-technological advancements to be made available to all the nations of the Association of Southeast Asian Nations, or to serve as a tool for the developed nations, informing them on how to manage waste from existing resources and through recycling.

Recognising the potential of eco-technology to support sustainable development, various efforts have been undertaken by regional and national governments aimed at the reduction of food waste and circular resource management, including the National Solid Waste Management Policy of Malaysia, the Food Resource Valorisation Roadmap of Singapore and Thailand's 'Zero Waste' strategy. These are examples of a stronger commitment to pursuing sustainability and innovation (Thi *et al.*, 2015; Puspitasari, 2025). However, differences in enforcement, technological preparedness, and non-

technical involvement in policymaking pose a barrier to creating a harmonised regional framework.

This study aims to research eco-technological interventions for addressing food waste challenges in the ASEAN Region and assess them in relation to the objectives of the circular economy. By researching current practices, policy frameworks, and technology applications, the aim is to draw on these best practices and develop a regional eco-policy model that promotes the exchange of innovations, cross-border cooperation, and the integrated valorisation of waste (Lasaksi, 2023). This framework serves not only environmental purposes but is also complementary to the Sustainable Development Goals, particularly in terms of responsible consumption, climate action, and resilient urban systems throughout the ASEAN region.

1.1. *Background*

The management of food waste has become an important environmental and socio-economic problem worldwide, and the ASEAN region faces unique challenges due to rapid urbanisation, population growth, and shifts in consumption patterns. Regional estimates suggest that nearly one-third of all food produced for human consumption is wasted or lost throughout the food supply chain, with serious consequences for food security, resource use, and climate change (Bujdosó & Dávid, 2025). In Southeast Asia, food waste accounts for a significant portion of municipal solid waste and is a major source of greenhouse gas emissions, contributing to the deterioration of natural resources. The increasing rates of waste generation in major urban centres, such as Kuala Lumpur, Bangkok, Jakarta, and Manila, have made the transition from 'Cleaning House' to modern, sustainable disposal means imperative.

Eco-technology, the interdisciplinary field that draws on biological, chemical, and engineering approaches, offers a significant advance in the modern sustainable treatment of food waste. Using technologies such as anaerobic digestion, composting, bioenergy recovery, and intelligent separation technology, eco-technology will not only reduce waste volume but also convert lost food into useful materials, including biogas, compost, and biofertilizers (Herrador & Van, 2024; Dai Sinh, 2025). Therefore, it aligns with the concepts of a circular economy, including waste recycling back into use, low waste production, and sustainable production-consumption cycles.

1.2. *Challenges*

Despite growing awareness, ASEAN countries still face a variety of hindrances to implementing eco-technology systems to manage food waste. Among the constraints to extensive implementation are, inter alia, a lack of infrastructure, limited technology transfer, insufficient policies at different levels, and a lack of financing. The NETT is also hampered by unevenness in respect of the facilities for waste management afforded by different member countries; e.g., the differences between the high-technology systems in Singapore and the developing systems in Myanmar or Laos. Furthermore, social and cultural barriers, lack of public awareness and participation, and insufficient monitoring systems to measure progress mitigate against a measured transition towards sustainable practices. Furthermore, policy inconsistencies, together with weak enforcement systems, preclude the successful integration of eco-technological innovations at the regional level, resulting in inefficiencies in waste recovery and valorisation management (Min & Cho, 2024).

1.3. *Motivation*

The increasing stress on environmental systems and food security in ASEAN creates strong demand for innovative eco-technological pathways for sustainable food waste management. The growing need to reduce methane emissions, maximise resource recovery, and transition to circular-economy models underscores the need for collaboration among technology, policy, and community involvement. In the region, the various governments are gradually aligning with the Sustainable Development Goals (SDGs), particularly SDG 12 (Responsible Consumption and Production) and SDG 13 (Climate Action), which provide strong policy foundations for waste reduction and sustainable practices (Curea, 2017; Lord, 2020; Leal Filho *et al.*, 2022). This study proposes that eco-technology may close the gap between financial opportunity and environmental sustainability by converting waste into a resource that fosters green innovation and long-term ecological resilience.

1.4. *Objectives*

The primary objectives of this study are to:

1. To review the application and effectiveness of eco-technology measures such as anaerobic digestion, composting and bioenergy conversion to food waste management in countries within ASEAN.
2. To assess the national and regional policy regimes which facilitate and impede eco-technology use in food waste management.
3. To compare the various food waste generation rates, recovery efficiencies, and eco-innovation rates of the ASEAN countries to show performance gaps.
4. To identify best practice/trade cooperation in policies by which regional sustainability and circular economy integration can be achieved.
5. To offer a proposed model of eco-politics on a regional level to harmonise technological innovation policies, policy harmonisation, and cross-border cooperation in accepting models for sustainable food waste management.

1.5. *Aim and Scope of the Study*

The increasing complexity of food waste management requires decision-support frameworks capable of integrating technological performance, environmental sustainability, governance effectiveness, and circular resource efficiency into a comprehensive assessment. Existing studies predominantly evaluate these dimensions independently, limiting their applicability for evidence-based policy formulation within heterogeneous regional contexts such as ASEAN.

Accordingly, the primary aim of this study is to develop an integrated decision-support framework for evaluating food

waste management technologies across selected ASEAN countries through the combined application of Eco-Technology Adoption Index (ETAI), Circular Resource Efficiency Model (CREM), Policy Implementation Efficiency (PIE), Life Cycle Assessment (LCA), and Machine Learning (ML).

To achieve this aim, the study pursues four specific objectives:

1. To evaluate the current status of food waste management and treatment technologies in selected ASEAN countries.
2. To assess technological, environmental, economic, and institutional performance using integrated sustainability indicators.
3. To compare alternative food waste treatment technologies using AHP, MCDA, LCA, and SDM.
4. To develop evidence-based policy recommendations supporting circular economy implementation and sustainable food waste management within ASEAN.

The study focuses on six ASEAN Member States (Malaysia, Singapore, Indonesia, Thailand, Vietnam, and the Philippines) due to the availability of consistent data regarding food waste generation, treatment technologies, and policy implementation. Laos, Cambodia, Myanmar, and Brunei Darussalam were excluded because comprehensive and comparable datasets were unavailable during the study period.

1.6. *Contributions*

This project contributes to studies of sustainable waste management by providing a rigorous, comparative evaluation of the adoption of eco-technologies across ASEAN countries. It combines policy analysis with technology evaluation to expose systemic strengths and weaknesses in the region's waste management systems. It provides empirically valid insights into how eco-technology can foster circularity, reduce greenhouse gas emissions, and promote sustainable urban development (Kesuma *et al.*, 2024). Additionally, it offers a regional eco-political model that emphasises the exchange of innovations, electronic waste tracking, and engagement with various stakeholders as methods for achieving waste reduction and the SDGs in the ASEAN context. Ultimately, it seeks to provide a model for environmentalists, socio-political researchers, and industry leaders to create scalable eco-technologies for sustainable food waste management.

2. Literature Review

2.1. *Food Waste Management in ASEAN: Current Status and Challenges*

Food waste has become one of the most critical global sustainability challenges, contributing significantly to greenhouse gas (GHG) emissions, resource depletion, biodiversity loss, and food insecurity. According to the United Nations Environment Programme (UNEP, 2024), approximately 1.05 billion tonnes of food were wasted globally in 2022, representing nearly one-fifth of all food available to consumers. Food waste not only represents the inefficient use of water, energy, land, and labour but also generates substantial methane emissions when disposed of in landfills, thereby accelerating climate change and hindering progress towards the Sustainable Development Goals (SDGs), particularly SDG 2 (Zero Hunger), SDG 11 (Sustainable Cities and Communities), SDG 12 (Responsible Consumption and Production), and SDG 13 (Climate Action) (UNEP, 2024; Rahman *et al.*, 2024).

The ASEAN region faces particularly complex food waste management challenges due to rapid urbanisation, population growth, economic development, changing dietary patterns, and increasing municipal solid waste generation. Organic waste typically accounts for 40–60% of municipal solid waste in many ASEAN countries, with food waste comprising the largest biodegradable fraction. Despite substantial economic growth, landfill disposal remains the predominant waste management practice in several ASEAN Member States because of inadequate source segregation, limited recycling infrastructure, insufficient treatment capacity, and financial constraints (Agamuthu & Babel, 2023). Consequently, many countries continue to experience low resource recovery rates and increasing environmental impacts associated with methane emissions, leachate generation, and land scarcity (Rahman *et al.*, 2024; Shukla *et al.*, 2024).

Recent policy developments indicate that ASEAN countries are progressively transitioning from conventional waste disposal towards circular economy strategies that emphasise waste prevention, resource recovery, renewable energy generation, and sustainable consumption. National roadmaps increasingly promote composting, anaerobic digestion, waste-to-energy technologies, and industrial symbiosis to maximise resource utilisation while reducing greenhouse gas emissions. However, implementation remains uneven because of differences in technological maturity, institutional capacity, financial resources, governance effectiveness, and public awareness across member states (ASEAN, 2021; Shukla *et al.*, 2024).

The rapid development of digital technologies has further transformed food waste management from conventional collection systems towards intelligent decision-support platforms. Internet of Things (IoT)-based monitoring, artificial intelligence (AI), cloud computing, machine learning (ML), and sensor networks are increasingly employed to improve food spoilage detection, optimise collection logistics, and minimise waste throughout the food supply chain. For instance, Valarmathi *et al.* (2025) proposed a comprehensive IoT-based multi-sensor framework that integrates methane, carbon dioxide, humidity, and temperature sensors with cloud-based machine learning algorithms to monitor food freshness, achieving approximately 95% classification accuracy. Nevertheless, the framework focuses primarily on operational monitoring and does not incorporate environmental assessment, governance evaluation, or circular economy performance indicators, thereby limiting its applicability for strategic policy analysis.

Although considerable progress has been achieved in developing treatment technologies and digital monitoring

systems, current research remains fragmented. Most studies evaluate composting, anaerobic digestion, waste-to-energy, Life Cycle Assessment (LCA), or machine learning independently, whereas few integrate technological adoption, environmental sustainability, policy effectiveness, resource circularity, and predictive modelling within a unified analytical framework. This fragmentation restricts comprehensive comparison of national food waste management performance and limits evidence-based policy formulation. Therefore, an integrated framework that simultaneously evaluates eco-technology adoption, circular resource efficiency, governance performance, environmental impacts, and future sustainability scenarios is required to support sustainable food waste management across ASEAN countries (Herrador & Van, 2024).

2.2. *Eco-Technological Approaches to Food Waste Management*

The transition from conventional landfill disposal to sustainable resource recovery has accelerated the development of eco-technological approaches for food waste management. Rather than considering food waste as an environmental liability, recent research increasingly recognises it as a valuable biomass resource that can be converted into compost, bioenergy, biofertilisers, and other value-added products. Consequently, treatment technologies are now evaluated not only on their waste reduction efficiency but also on their environmental performance, economic feasibility, energy recovery potential, circular economy contribution, and policy compatibility (Shukla *et al.*, 2024).

2.2.1. Anaerobic Digestion

Anaerobic digestion (AD) has emerged as one of the most promising technologies for sustainable food waste valorisation because it simultaneously reduces organic waste volume, generates renewable biogas, and produces digestate suitable for agricultural application. Compared with landfill disposal, AD substantially reduces greenhouse gas emissions by capturing methane for energy production while recovering nutrients that can be returned to agricultural systems. Numerous life-cycle assessment studies have consistently ranked AD among the most environmentally favourable treatment options for high-moisture food waste streams. Nevertheless, successful implementation requires reliable feedstock quality, advanced operational control, skilled personnel, and considerable capital investment. These technical and financial requirements often constrain widespread adoption in developing economies where waste segregation remains inadequate, and infrastructure investment is limited (Shukla *et al.*, 2024). Tun *et al.* (2020) estimated that renewable electricity generation from municipal waste in six ASEAN countries could exceed 17.26 TWh by 2030. Similarly, Ong *et al.* (2018) demonstrated that anaerobic digestion significantly reduces greenhouse gas emissions while producing valuable by-products suitable for agricultural applications.

2.2.2. Composting Technologies

Among biological treatment technologies, composting remains one of the most mature and widely implemented approaches because of its relatively low investment cost, operational simplicity, and ability to recycle nutrients into agricultural production systems. Composting effectively stabilises biodegradable organic matter while reducing landfill dependency and improving soil quality through the production of nutrient-rich organic fertiliser. Several studies have demonstrated that properly managed aerobic composting significantly decreases methane emissions compared with uncontrolled landfill disposal while supporting circular nutrient cycling. However, compost quality is highly dependent on waste segregation, moisture content, aeration, carbon-to-nitrogen ratio, and contamination control. In many ASEAN countries, inconsistent source separation and high contamination levels continue to reduce compost quality and limit market acceptance. Furthermore, conventional composting primarily recovers nutrients without generating renewable energy, thereby restricting its overall resource recovery potential (Halim *et al.*, 2024; Shukla *et al.*, 2024).

2.2.3. Waste-to-Energy Technologies

Thermal conversion technologies, particularly waste-to-energy (WtE) incineration, continue to play an important role in densely populated urban regions where landfill space is scarce. WtE systems significantly reduce waste volume while simultaneously generating electricity and heat, making them particularly attractive for highly urbanised countries such as Singapore. Modern incineration facilities equipped with advanced air pollution control technologies can substantially reduce particulate emissions compared with older systems. However, WtE facilities require substantial capital expenditure, continuous maintenance, and strict environmental monitoring to minimise emissions of nitrogen oxides, dioxins, furans, and heavy metals. Furthermore, because food waste possesses high moisture content and relatively low calorific value, direct incineration is often less energy-efficient unless pre-treatment or co-combustion strategies are implemented. These limitations indicate that WtE should be considered as one component of an integrated waste management system rather than a universal solution (Shukla *et al.*, 2024).

2.2.4. Digital and Smart Technologies

Beyond individual treatment technologies, recent studies increasingly advocate integrated circular economy approaches that combine multiple resource recovery pathways to maximise environmental and economic benefits. Such integrated systems may combine anaerobic digestion with composting, nutrient recovery, recycling, and renewable energy generation, thereby improving material circularity while reducing greenhouse gas emissions and landfill dependency. Rather than evaluating technologies independently, contemporary research emphasises optimising technology combinations according to local waste characteristics, infrastructure availability, policy objectives, and socio-economic conditions. This systems perspective is particularly relevant for ASEAN countries, where substantial variation exists in waste

composition, governance capacity, technological maturity, and financial resources (ASEAN, 2021; Shukla *et al.*, 2024).

In parallel with technological advances, digitalisation has expanded opportunities for improving operational efficiency and resource recovery. Internet of Things (IoT)-enabled sensing, artificial intelligence, cloud computing, and machine learning have been increasingly incorporated into food waste monitoring and management systems. For example, Valarmathi *et al.* (2025) developed a comprehensive IoT-based multi-sensor framework integrating methane, carbon dioxide, humidity, and temperature sensors with cloud-based machine learning algorithms to improve food freshness monitoring and waste detection. Although the framework demonstrated high classification performance for operational monitoring, it focused primarily on sensor-based detection and did not evaluate broader sustainability dimensions such as environmental impacts, governance effectiveness, policy implementation, or circular economy performance. Similar limitations are observed in many AI-based studies, where predictive accuracy is prioritised over integrated sustainability assessment.

Collectively, the reviewed studies demonstrate substantial progress in individual food waste treatment technologies and digital management systems. Nevertheless, existing research remains fragmented because biological treatment, thermal conversion, environmental assessment, digital monitoring, and policy evaluation are generally investigated independently. Comparative studies rarely integrate technological adoption, environmental sustainability, circular resource efficiency, governance performance, and predictive modelling within a unified analytical framework. Consequently, policymakers often lack comprehensive evidence to determine which technology combinations are most appropriate under different national conditions. These shortcomings provide a strong justification for the integrated framework proposed in this study, which combines Geographic Information Systems (GIS), Natural Language Processing (NLP), the Eco-Technology Adoption Index (ETAI), the Circular Resource Efficiency Model (CREM), the Policy Implementation Efficiency (PIE) framework, the Analytic Hierarchy Process (AHP), Multi-Criteria Decision Analysis (MCDA), Life Cycle Assessment (LCA), System Dynamics Modelling (SDM), and Machine Learning (ML) to support holistic evaluation of food waste management across selected ASEAN countries.

2.3. *Policy and Governance Frameworks for Food Waste Management*

The successful implementation of eco-technologies depends heavily on effective governance systems and supportive policy frameworks. Singapore has adopted one of the most comprehensive food waste management strategies in ASEAN through its Zero Waste Masterplan, Food Resource Valorisation Roadmap, and Resource Sustainability Act. Malaysia introduced the National Solid Waste Management Policy and the Roadmap Towards Zero Single-Use Plastics to strengthen waste-reduction and circular-economy initiatives. Thailand has implemented its Zero-Waste Strategy and Bio-Circular-Green Economy Policy, promoting resource efficiency and renewable energy production. However, policy implementation remains uneven across ASEAN countries. Phonthanukitithaworn *et al.* (2024) reported that infrastructure limitations, fragmented institutional arrangements, and inconsistent policy enforcement continue to hinder the implementation of eco-innovation throughout the region.

Similarly, Noudeng *et al.* (2024) demonstrated that weak institutional capacities and inadequate financing remain major barriers to sustainable waste management in Laos. The evidence suggests that technology alone cannot guarantee sustainability outcomes. Effective governance, policy coherence, and stakeholder collaboration are equally important determinants of successful food waste management systems.

2.4. *Circular Economy and Sustainability Perspectives*

The circular economy has emerged as a promising framework for transforming food waste from an environmental burden into a valuable resource. The concept promotes the reduction, reuse, recycling, and recovery of materials in order to minimise waste generation and maximise resource efficiency (Kirchherr *et al.*, 2017).

Food waste valorisation technologies, including composting, anaerobic digestion, and bioenergy production, directly contribute to circular economy objectives by recovering energy and materials that would otherwise be lost through disposal (Geissdoerfer *et al.*, 2017). Furthermore, circular food systems have been shown to improve resource efficiency, reduce greenhouse gas emissions, and create economic opportunities through green employment and renewable energy production (Velenturf & Purnell, 2021).

Recent research has increasingly emphasised the importance of integrating digital technologies with circular economy principles to create intelligent and adaptive waste management systems. Artificial intelligence, big data analytics, and digital waste-tracking platforms are becoming important tools for enhancing waste management efficiency and supporting evidence-based policy development (Zhang *et al.*, 2023).

2.5. *Digital Technologies and Decision-Support Systems in Food Waste Management*

The rapid advancement of digital technologies has transformed conventional food waste management from reactive waste collection practices into intelligent, data-driven decision-support systems that improve operational efficiency, resource recovery, and sustainability performance. The convergence of the Internet of Things (IoT), Geographic Information Systems (GIS), Artificial Intelligence (AI), Machine Learning (ML), Natural Language Processing (NLP), cloud computing, and multi-criteria decision-making techniques has enabled more accurate monitoring of food waste generation, optimized waste collection logistics, enhanced policy evaluation, and supported evidence-based decision-making. These digital

technologies are increasingly recognised as key enablers of circular economy implementation and smart waste management within the context of Industry 4.0 and smart city development (United Nations Environment Programme [UNEP], 2024; Kaza *et al.*, 2018).

Among these technologies, IoT-based monitoring systems have demonstrated considerable potential for improving food waste management through real-time sensing and automated data collection. Smart bins equipped with weight sensors, ultrasonic sensors, gas sensors, radio-frequency identification (RFID), and wireless communication modules enable continuous monitoring of waste quantity, composition, and storage conditions. Such systems reduce unnecessary collection trips, improve route optimisation, minimise operational costs, and support timely intervention before food spoilage occurs (Gu *et al.*, 2022). The integration of cloud computing further enables centralised data management and real-time analytics, allowing municipal authorities to monitor waste generation patterns at regional scales.

A recent contribution by Valarmathi *et al.* (2025) proposed a comprehensive IoT-based multi-sensor framework integrating methane, carbon dioxide, humidity, and temperature sensors with machine learning algorithms to classify food freshness and identify spoilage conditions. The framework achieved approximately 95% classification accuracy and demonstrated the capability of sensor fusion to improve operational monitoring of food waste. Nevertheless, the proposed framework primarily addresses food quality detection and collection efficiency without evaluating broader sustainability indicators, environmental impacts, policy implementation, or resource circularity. Consequently, although IoT technologies substantially improve operational performance, they provide limited support for strategic policy formulation and long-term sustainability planning (Valarmathi *et al.*, 2025).

Artificial Intelligence and Machine Learning (ML) have further expanded the capability of food waste management systems by enabling predictive modelling, pattern recognition, and optimisation of waste generation. Supervised learning algorithms, including Random Forest, Support Vector Machine (SVM), Artificial Neural Networks (ANN), Gradient Boosting, and Deep Learning models, have been widely applied to forecast municipal food waste generation, optimise waste collection schedules, classify recyclable materials, and estimate treatment performance (Abdallah *et al.*, 2023; Chen *et al.*, 2024). More recently, Recurrent Neural Networks (RNN) and collaborative filtering approaches have been employed to minimise vegetable waste by recommending alternative food utilisation pathways, demonstrating the growing role of AI in reducing avoidable food losses (Rathinam *et al.*, 2024).

Similarly, AI-assisted recommendation systems have been introduced to improve nutritional planning while simultaneously reducing household food waste. For example, combining nutrition recommendation algorithms with intelligent decision-support techniques has demonstrated the potential to optimise dietary planning, thereby reducing unnecessary food purchasing and consumption while improving public health outcomes (Vijayalakshmi *et al.*, 2024). Although these studies demonstrate excellent predictive accuracy and personalised recommendation capability, they generally focus on specific applications without integrating environmental sustainability, governance effectiveness, and circular economy performance indicators into a unified analytical framework.

Spatial analysis has also become increasingly important in sustainable food waste management. Geographic Information Systems (GIS) provide powerful tools for analysing the spatial distribution of waste generation, identifying optimal treatment facility locations, evaluating transportation networks, and supporting regional waste management planning. GIS-based optimisation has been successfully applied to minimise transportation costs, reduce greenhouse gas emissions associated with waste collection, and improve accessibility of treatment facilities. However, most GIS applications remain focused on spatial optimisation without incorporating policy effectiveness, technology adoption, or environmental life-cycle performance into integrated decision-support systems (Sharifi *et al.*, 2022).

Another emerging digital technology is Natural Language Processing (NLP), which enables automated analysis of policy documents, legislation, government reports, and stakeholder opinions. NLP techniques facilitate systematic extraction of policy themes, regulatory priorities, institutional barriers, and public perceptions from large textual datasets. Recent environmental studies have demonstrated that NLP can improve evidence synthesis, identify policy gaps, and support transparent governance evaluation through automated document analysis (Minaee *et al.*, 2021). Despite these advantages, NLP remains underutilised in food waste management research, where policy analysis continues to rely predominantly on manual qualitative assessment.

Beyond individual digital technologies, decision-support methodologies have become essential for evaluating the sustainability of alternative waste management strategies. The Analytic Hierarchy Process (AHP) remains one of the most widely adopted techniques for determining the relative importance of environmental, economic, technical, and social criteria through structured pairwise comparisons (Saaty, 2008). When combined with Multi-Criteria Decision Analysis (MCDA), AHP provides a transparent framework for ranking alternative treatment technologies while explicitly considering multiple conflicting objectives. Numerous studies have demonstrated the usefulness of AHP–MCDA for technology selection; however, many applications rely heavily on expert judgement and often neglect uncertainty, temporal dynamics, and spatial heterogeneity (Dos Muchangos *et al.*, 2017).

Environmental sustainability assessment is commonly performed using Life Cycle Assessment (LCA), which quantifies greenhouse gas emissions, energy consumption, resource depletion, and environmental burdens associated with different waste treatment pathways. LCA has become

the internationally recognised methodology for comparing composting, anaerobic digestion, landfill disposal, and waste-to-energy technologies because it evaluates impacts throughout the entire life cycle of waste management systems (ISO, 2006). Nevertheless, conventional LCA is essentially static and does not explicitly account for future technological development, policy evolution, or dynamic behavioural changes.

To overcome this limitation, System Dynamics Modelling (SDM) has increasingly been incorporated into waste management research to simulate long-term interactions among waste generation, policy interventions, infrastructure development, technological adoption, and resource recovery. SDM enables policymakers to evaluate alternative scenarios and investigate the long-term consequences of different management strategies under varying socio-economic conditions. However, relatively few studies have combined SDM with LCA, GIS, machine learning, and multi-criteria decision-making within a single integrated framework, limiting their ability to support comprehensive sustainability planning (Bala *et al.*, 2017).

Overall, existing digital technologies have significantly improved operational monitoring, predictive modelling, spatial planning, and sustainability assessment. Nevertheless, these approaches remain largely fragmented because IoT focuses on real-time sensing, GIS emphasises spatial optimisation, ML prioritises prediction accuracy, NLP supports policy analysis, AHP–MCDA facilitates technology ranking, LCA evaluates environmental impacts, and SDM models long-term system behaviour independently. Few studies integrate these complementary analytical techniques into a unified decision-support framework capable of simultaneously evaluating technological readiness, environmental sustainability, governance effectiveness, circular resource efficiency, and future development scenarios.

Therefore, this study proposes an integrated framework combining GIS, NLP, Eco-Technology Adoption Index (ETAI), Circular Resource Efficiency Model (CREM), Policy Implementation Efficiency (PIE), AHP, MCDA, LCA, SDM, and Machine Learning to overcome the limitations of existing approaches. By integrating spatial analysis, policy evaluation, sustainability assessment, technology prioritisation, and predictive modelling within a single analytical workflow, the proposed framework provides a more comprehensive basis for strategic decision-making and sustainable food waste management across selected ASEAN countries.

2.6. *Comparative Analysis of Existing Studies and Research Gaps*

The rapid growth of food waste research over the past decade has substantially improved understanding of sustainable waste management technologies, environmental assessment methods, and digital decision-support systems. Nevertheless, existing studies remain highly fragmented because they generally focus on individual aspects of food waste management rather than integrating technological, environmental, economic, institutional, and policy dimensions into a unified analytical framework. This fragmentation limits policymakers' and practitioners' ability to evaluate the overall sustainability of alternative food waste management strategies, particularly in developing regions such as ASEAN, where technological readiness, governance capacity, and socio-economic conditions differ considerably (UNEP, 2024; Shukla *et al.*, 2024).

Early food waste management studies primarily concentrated on evaluating the technical performance of individual treatment technologies such as composting, anaerobic digestion, landfill diversion, and waste-to-energy (WtE) systems. These investigations demonstrated that biological treatment technologies significantly reduce greenhouse gas emissions while improving nutrient recovery compared with conventional landfill disposal (Slorach *et al.*, 2019; Shukla *et al.*, 2024). Although these studies provide valuable evidence regarding environmental performance, they generally evaluate technologies independently and seldom consider broader decision-making criteria such as governance effectiveness, economic feasibility, institutional readiness, or policy implementation. Consequently, technology selection often remains context-specific and difficult to generalise across countries with different waste compositions and regulatory environments.

To overcome these limitations, Life Cycle Assessment (LCA) has become the preferred methodology for evaluating environmental impacts associated with food waste treatment technologies. Numerous comparative studies have applied LCA to quantify greenhouse gas emissions, cumulative energy demand, water consumption, and resource depletion associated with composting, anaerobic digestion, incineration, and landfill disposal (ISO, 2006; Slorach *et al.*, 2019). While LCA provides a scientifically robust environmental evaluation framework, its application is inherently static because it assesses environmental burdens under predefined system boundaries and assumptions. Consequently, conventional LCA cannot adequately capture long-term technological evolution, policy interventions, behavioural change, or dynamic interactions among waste generation, resource recovery, and socio-economic development (Guo *et al.*, 2021).

Recognising that technology selection requires balancing multiple and often conflicting sustainability criteria, researchers have increasingly adopted Multi-Criteria Decision Analysis (MCDA) techniques, particularly the Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE). These approaches facilitate simultaneous evaluation of environmental, economic, technical, and social criteria while incorporating expert judgement into technology prioritisation (Saaty, 2008; Dos Muchangos *et al.*, 2017). Although MCDA provides greater flexibility than conventional environmental assessment, many applications remain highly dependent on subjective expert weighting and rarely incorporate spatial variability,

policy implementation effectiveness, or predictive analytics. Consequently, technology rankings often vary significantly depending on expert preferences and regional assumptions, reducing comparability across different studies.

Recent developments in Artificial Intelligence (AI), Machine Learning (ML), Internet of Things (IoT), and Geographic Information Systems (GIS) have substantially expanded analytical capabilities within food waste management. Machine learning algorithms have demonstrated high predictive accuracy for forecasting municipal food waste generation, optimising collection schedules, and classifying recyclable materials (Chen *et al.*, 2024). Similarly, GIS-based spatial optimisation has improved waste collection efficiency and facility location planning by considering transportation networks, population density, and waste generation patterns (Sharifi *et al.*, 2022). IoT-based monitoring systems further enhance operational efficiency by providing real-time information regarding waste quantity, food freshness, and storage conditions through integrated sensor networks (Valarmathi *et al.*, 2025). However, these digital technologies primarily focus on operational optimisation rather than strategic sustainability evaluation, thereby limiting their usefulness for long-term policy formulation.

Natural Language Processing (NLP) has recently emerged as an effective tool for analysing environmental policies, legislation, stakeholder perceptions, and institutional documents through automated text mining and semantic analysis (Minaee *et al.*, 2021). Compared with conventional qualitative policy reviews, NLP enables rapid synthesis of large document collections while reducing researcher subjectivity. Nevertheless, applications of NLP in food waste management remain scarce, and most published studies continue to evaluate policy effectiveness through manual document review without integrating quantitative sustainability indicators or comparative decision-support models.

More recently, integrated digital frameworks have begun combining AI, IoT, cloud computing, and big data analytics to improve food waste monitoring and operational decision-making. For example, Valarmathi *et al.* (2025) proposed an IoT-enabled multi-sensor framework capable of classifying food freshness using methane, carbon dioxide, humidity, and temperature measurements with high prediction accuracy. Likewise, Rathinam *et al.* (2024) applied Recurrent Neural Networks (RNN) and collaborative filtering algorithms to minimise vegetable waste by recommending alternative reuse strategies, while Vijayalakshmi *et al.* (2024) integrated intelligent recommendation systems into nutritional planning to reduce unnecessary food consumption. Although these studies demonstrate the growing importance of digital technologies in sustainable food systems, their analytical scope remains limited because environmental sustainability, circular resource efficiency, governance performance, and policy implementation are not evaluated simultaneously.

A synthesis of recent literature therefore reveals several persistent research gaps in **Table 1**. First, most studies concentrate on a single analytical domain—such as technology assessment, environmental evaluation, spatial optimisation, machine learning, or policy analysis—without integrating these complementary perspectives into a unified decision-support framework. Second, governance effectiveness and policy implementation remain substantially underrepresented despite their recognised influence on technology adoption and sustainable waste management. Third, dynamic interactions among technological development, environmental performance, resource circularity, and socio-economic change are rarely considered simultaneously. Finally, relatively few comparative studies have focused specifically on ASEAN countries, where substantial heterogeneity exists in waste generation patterns, infrastructure development, institutional capacity, and regulatory maturity.

Table 1. Critical comparison of representative food waste management studies.

Study	Primary Method	Major Contribution	Limitation
Slorach *et al.* (2019)	LCA	Environmental comparison of treatment technologies	Static assessment; no governance evaluation
Dos Muchangos *et al.* (2017)	AHP–MCDA	Technology prioritisation	Subjective weighting; no predictive capability
Guo *et al.* (2021)	LCA	Environmental sustainability assessment	Limited dynamic modelling
Chen *et al.* (2024)	Machine Learning	Waste generation prediction	No environmental or policy evaluation
Valarmathi *et al.* (2025)	IoT + ML	Real-time food waste monitoring	Operational focus only
Rathinam *et al.* (2024)	RNN + Collaborative Filtering	Intelligent food reuse recommendation	Technology-specific application
Vijayalakshmi *et al.* (2024)	AI Recommendation System	Food consumption optimisation	Healthcare-specific application
Present Study	GIS + NLP + ETAI + CREM + PIE + AHP + MCDA + LCA + SDM + ML	Integrated evaluation of technological adoption, environmental sustainability, governance effectiveness, circular economy performance, and predictive modelling	Addresses identified research gaps through a unified analytical framework

The critical review demonstrates that no existing study has comprehensively integrated Geographic Information Systems (GIS), Natural Language Processing (NLP), Eco-Technology Adoption Index (ETAI), Circular Resource Efficiency Model (CREM), Policy Implementation Efficiency (PIE), Analytic Hierarchy Process (AHP), Multi-Criteria Decision Analysis (MCDA), Life Cycle Assessment (LCA), System Dynamics Modelling (SDM), and Machine Learning (ML) within a single comparative framework for evaluating food waste management in ASEAN countries. Existing research either emphasises operational optimisation or environmental assessment without simultaneously addressing governance, policy implementation, spatial variability, circular resource efficiency, and long-term sustainability. Therefore, the integrated framework proposed in this study provides a novel and comprehensive approach for supporting evidence-based decision-making, technology prioritisation, and sustainable food waste management across diverse ASEAN contexts.

2.7. *Research Motivation and Justification of the Proposed Framework*

The increasing complexity of food waste management has created an urgent need for comprehensive analytical frameworks capable of simultaneously evaluating technological performance, environmental sustainability, resource circularity, governance effectiveness, and policy implementation. Although considerable advances have been achieved in biological treatment technologies, thermochemical conversion, digital monitoring systems, and environmental assessment, existing studies continue to investigate these components largely in isolation. As demonstrated in the preceding sections, most published research focuses on a single analytical perspective, such as technology efficiency, greenhouse gas emissions, waste prediction, or policy analysis, without integrating these complementary dimensions into a unified decision-support framework (UNEP, 2024; Shukla *et al.*, 2024). Consequently, policymakers often lack comprehensive evidence to identify the most appropriate food waste management strategies under diverse socio-economic, institutional, and environmental conditions.

This research is motivated by the substantial heterogeneity of food waste management systems across ASEAN Member States. Singapore has achieved high technological maturity through waste-to-energy facilities, digital monitoring systems, and strict regulatory enforcement, whereas Malaysia and Thailand continue expanding anaerobic digestion, composting, and recycling programmes. Conversely, several lower-income ASEAN countries remain highly dependent on landfill disposal because of inadequate infrastructure, limited financial resources, fragmented institutional arrangements, and insufficient policy implementation (ASEAN, 2021; UNEP, 2024). Such diversity demonstrates that technological performance alone cannot adequately explain successful food waste management outcomes. Instead, sustainability depends on the complex interaction among technological readiness, governance capacity, policy implementation, environmental performance, resource efficiency, and socio-economic conditions.

Recent technological developments have further highlighted the need for integrated analytical approaches. IoT-based sensor networks, artificial intelligence, machine learning, and cloud computing have significantly improved operational monitoring, waste prediction, and collection efficiency (Valarmathi *et al.*, 2025; Chen *et al.*, 2024). Similarly, Geographic Information Systems (GIS) have enhanced spatial planning for waste collection and treatment facility allocation, while Life Cycle Assessment (LCA) has become the international standard for evaluating environmental impacts associated with alternative waste treatment technologies (ISO, 2006). Nevertheless, these approaches are generally implemented independently, resulting in fragmented assessments that provide limited support for strategic policy development. High predictive accuracy does not necessarily indicate environmental sustainability, while superior environmental performance may not correspond to institutional feasibility or economic viability. Therefore, effective decision-making requires simultaneous consideration of these interrelated dimensions.

Another important motivation arises from the limited integration of governance and policy evaluation within food waste management research. Numerous studies acknowledge that institutional capacity, regulatory enforcement, stakeholder participation, and public awareness strongly influence the adoption of sustainable technologies (Dos Muchangos *et al.*, 2017; Shukla *et al.*, 2024). However, relatively few studies quantitatively evaluate policy implementation effectiveness or systematically compare governance performance across different national contexts. Existing policy analyses frequently rely on qualitative interpretation, making cross-country comparison difficult and reducing the transparency and reproducibility of research findings. Incorporating Natural Language Processing (NLP) into policy analysis offers significant opportunities to objectively extract policy themes, implementation priorities, institutional barriers, and regulatory trends from large collections of governmental documents and legislative reports (Minaee *et al.*, 2021). Despite these advantages, NLP applications remain largely unexplored within food waste management literature.

The present study therefore proposes an integrated analytical framework specifically designed to overcome these methodological limitations. The proposed framework incorporates Geographic Information Systems (GIS) to evaluate spatial characteristics of waste generation and infrastructure distribution, Natural Language Processing (NLP) to analyse policy documents and governance strategies, the Eco-Technology Adoption Index (ETAI) to quantify technological maturity, the Circular Resource Efficiency Model (CREM) to assess resource recovery and circular economy performance, and the Policy Implementation Efficiency (PIE) framework to evaluate governance effectiveness across selected ASEAN countries. These complementary indicators collectively

provide a broader assessment of national food waste management performance than conventional technology-focused studies.

To support objective decision-making, the framework further integrates the Analytic Hierarchy Process (AHP) and Multi-Criteria Decision Analysis (MCDA) for technology prioritisation. AHP enables systematic weighting of environmental, economic, technical, institutional, and social criteria through structured pairwise comparisons, while MCDA ranks alternative treatment technologies according to multiple sustainability objectives (Saaty, 2008; Dos Muchangos *et al.*, 2017). Unlike previous studies that rely primarily on expert judgement or environmental indicators alone, the proposed framework combines quantitative sustainability indicators with governance evaluation and circular resource efficiency, thereby reducing subjectivity and improving the robustness of comparative assessments.

Environmental sustainability is further evaluated using Life Cycle Assessment (LCA), which quantifies greenhouse gas emissions, energy consumption, and resource utilisation throughout the waste management life cycle (ISO, 2006). However, recognising that waste management systems evolve through technological innovation, policy reform, demographic change, and behavioural adaptation, this study extends conventional LCA by integrating System Dynamics Modelling (SDM). SDM enables simulation of long-term interactions among waste generation, infrastructure development, policy interventions, and resource recovery under alternative future scenarios, thereby overcoming the static nature of traditional environmental assessments (Bala *et al.*, 2017). Finally, Machine Learning (ML) is incorporated to identify hidden relationships within multi-dimensional datasets, improve predictive accuracy, and support scenario analysis for future food waste management strategies.

The novelty of this research lies not in the individual analytical techniques themselves but in their systematic integration into a unified sustainability assessment framework. To the best of the authors' knowledge, no previous study has simultaneously combined GIS, NLP, ETAI, CREM, PIE, AHP, MCDA, LCA, SDM, and Machine Learning for comparative evaluation of food waste management technologies across ASEAN countries. Previous investigations have typically examined environmental assessment, digital monitoring, policy analysis, or technology optimisation independently, resulting in fragmented knowledge that limits strategic decision-making. By integrating spatial analysis, policy evaluation, environmental assessment, technology prioritisation, circular economy indicators, dynamic simulation, and predictive analytics, the proposed framework provides a comprehensive platform for evaluating both current performance and future sustainability pathways.

Accordingly, this study contributes to the literature in three principal ways. First, it develops an integrated methodological framework that combines technological, environmental, governance, and circular economy perspectives into a single decision-support system. Second, it provides a systematic comparative assessment of food waste management performance across selected ASEAN countries using harmonised sustainability indicators. Third, it generates evidence-based policy recommendations to support the transition from conventional waste disposal to resource-efficient, circular food waste management systems aligned with the Sustainable Development Goals, the ASEAN Framework for Circular Economy, and long-term regional sustainability objectives.

3. Research Methodology

3.1. *Research Design*

This study adopted a comparative mixed-methods research design to evaluate the effectiveness of eco-technological interventions for food waste management across selected ASEAN countries. The methodology integrates quantitative environmental assessment, qualitative policy analysis, spatial analysis, and predictive modelling into a unified analytical framework. Unlike conventional comparative studies that analyse technological, environmental, or policy dimensions independently, this study combines multiple analytical techniques into a sequential workflow to evaluate the interrelationships among eco-technology adoption, circular resource efficiency, governance effectiveness, environmental performance, and future sustainability scenarios.

The study employed a comparative case-study approach involving five ASEAN Member States: Singapore, Malaysia, Thailand, Vietnam, and Myanmar. These countries were selected because they provide sufficiently complete and consistent datasets covering technological, environmental, economic, and governance indicators required to construct the Eco-Technology Adoption Index (ETAI), Circular Resource Efficiency Model (CREM), and Policy Implementation Efficiency (PIE). The selected countries also represent different levels of economic development, institutional capacity, technological maturity, and waste management practices, thereby enabling meaningful regional comparisons.

Although Laos and Cambodia were considered during the initial literature review to provide regional context, they were excluded from the quantitative analysis because publicly available datasets for key variables—including food waste generation, recycling performance, waste-to-energy production, circular resource recovery, greenhouse gas emissions, and policy implementation indicators—were incomplete or inconsistently reported over the study period (2018–2024). Since the integrated analytical framework requires complete datasets for indicator construction, weighting, and multi-criteria evaluation, including countries with substantial data gaps could introduce systematic bias and compromise the reliability and comparability of the results. Consequently, the quantitative assessment was limited to countries with sufficiently robust datasets while maintaining ASEAN-wide discussion in the literature review.

The methodological framework consists of four major analytical phases: (i) data acquisition and preprocessing; (ii)

indicator development and multi-criteria assessment; (iii) environmental and dynamic system modelling; and (iv) predictive modelling and policy synthesis. These phases are sequentially linked, whereby the outputs generated in one phase become the inputs for the subsequent analytical stage. Such methodological integration improves analytical consistency, facilitates methodological triangulation, and enhances the reliability of comparative sustainability assessments.

Figure 1 illustrates the complete methodological workflow adopted in this study. The workflow demonstrates how multiple analytical approaches—including Geographic Information Systems (GIS), Natural Language Processing (NLP), Eco-Technology Adoption Index (ETAI), Circular Resource Efficiency Model (CREM), Policy Implementation Efficiency (PIE), Analytic Hierarchy Process (AHP), Multi-Criteria Decision Analysis (MCDA), Life Cycle Assessment (LCA), System Dynamics Modelling (SDM), and Machine Learning (ML)—were systematically integrated to produce comprehensive sustainability evaluations and evidence-based policy recommendations.

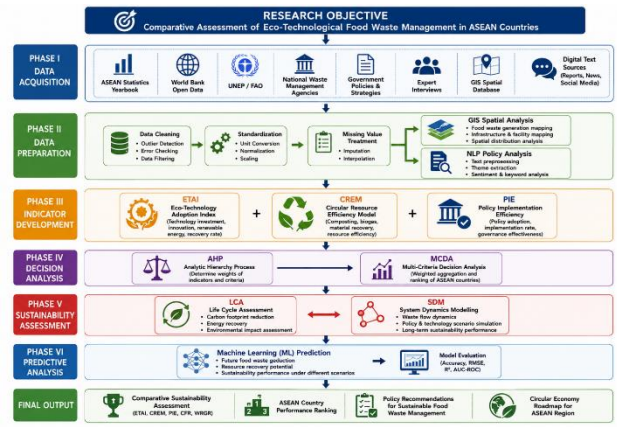

Figure 1. Integrated Methodological Workflow for Comparative Assessment of Eco-Technological Food Waste Management in ASEAN Countries.

The integrated methodological workflow shown in Figure 1 demonstrates how multiple analytical techniques were sequentially combined to evaluate eco-technological performance across ASEAN countries. Rather than applying each method independently, the analytical outputs generated at each stage served as inputs for the subsequent analysis. Spatial and textual analyses using GIS and NLP informed the construction of ETAI, CREM, and PIE indicators. These indicators were weighted using the Analytic Hierarchy Process (AHP) and synthesised through Multi-Criteria Decision Analysis (MCDA) to evaluate comparative national performance. The resulting performance scores were subsequently incorporated into Life Cycle Assessment (LCA) and System Dynamics Modelling (SDM) to evaluate environmental impacts and simulate long-term system behaviour. Finally, the integrated outputs from all analytical components were used as explanatory variables in the Machine Learning model to predict future food waste recovery potential and sustainability outcomes. This sequential integration enhances methodological transparency, reproducibility, and analytical robustness.

3.1.1. Integrated Methodological Workflow

Figure 1 presents the integrated methodological workflow employed in this study. The analytical framework begins with the collection of heterogeneous datasets comprising national waste statistics, environmental performance indicators, government policy documents, expert interviews, geospatial information, and digital textual data obtained from publicly available databases. Secondary datasets were collected from the ASEAN Statistics Yearbook, the World Bank Open Data platform, the Food and Agriculture Organization (FAO), the United Nations Environment Programme (UNEP), and national waste management agencies. Qualitative information was obtained from policy documents and semi-structured interviews with stakeholders involved in food waste management.

The first analytical stage involved data preprocessing. Quantitative datasets were cleaned, standardised, and normalised to ensure consistency across countries. Geographic Information Systems (GIS) were employed to identify spatial distributions of food waste generation, waste treatment facilities, and infrastructure availability. Simultaneously, Natural Language Processing (NLP) techniques were applied to policy documents and interview transcripts to identify recurring governance themes, institutional barriers, technological priorities, and stakeholder perceptions. The outputs generated from GIS and NLP analyses provided spatial and qualitative evidence supporting the development of policy and technology indicators.

During the second stage, three composite performance indicators were developed: the Eco-Technology Adoption Index (ETAI), Circular Resource Efficiency Model (CREM), and Policy Implementation Efficiency (PIE). ETAI measures national technological readiness by integrating indicators such as technological investment, innovation capacity, renewable energy utilisation, and waste recovery performance. CREM evaluates the efficiency of converting food waste into valuable resources, including compost, biogas, and reusable materials. PIE quantifies governance performance by comparing implemented policy initiatives with planned national waste management strategies.

To improve the robustness of the comparative evaluation, the relative importance of each performance indicator was determined using the Analytic Hierarchy Process (AHP). AHP generated objective weighting factors based on pairwise comparisons among technological, environmental, economic, and governance criteria. These weighted indicators were subsequently incorporated into the Multi-Criteria Decision Analysis (MCDA) framework to rank the comparative sustainability performance of the selected ASEAN countries.

The weighted country performance scores were then integrated into Life Cycle Assessment (LCA) and System Dynamics Modelling (SDM). LCA quantified the environmental impacts associated with different eco-technological interventions by evaluating greenhouse gas emissions, energy recovery potential, resource

conservation, and avoided environmental burdens across the waste management life cycle. In parallel, SDM simulated the dynamic interactions among food waste generation, technology adoption, policy implementation, resource recovery, and environmental performance over time, enabling the identification of long-term feedback mechanisms and policy intervention scenarios.

Finally, outputs from ETAI, CREM, PIE, MCDA, LCA, and SDM were combined with socio-economic variables—including population growth, urbanisation rate, gross domestic product, and technology investment—to train a Machine Learning (ML) predictive model. The ML model estimated future food waste generation, recovery potential, and sustainability performance under different policy scenarios. The integration of statistical analysis, environmental assessment, systems modelling, and predictive analytics provides a comprehensive decision-support framework for evaluating eco-technological interventions and developing evidence-based policy recommendations for sustainable food waste management in ASEAN countries.

3.2. *Data Collection Methods*

This study adopted a multi-source data collection approach to ensure the comprehensiveness, validity, and reliability of the analysis. Secondary data constituted the primary source of information. They were obtained from reputable international and national databases, including the ASEAN Statistics Yearbook, the World Bank Open Data platform, the United Nations Environment Programme (UNEP), the Food and Agriculture Organisation (FAO), and national agencies responsible for solid waste management in ASEAN countries. These datasets provided information on food waste generation, waste recovery rates, eco-technology adoption, environmental performance indicators, and policy implementation across the selected ASEAN countries (Kaza *et al.*, 2018).

To complement the quantitative data, a systematic review of policy documents and institutional reports was conducted. National policies, regulations, and strategic plans, including Malaysia's National Solid Waste Management Policy, Singapore's Food Resource Valorisation Roadmap, and Thailand's Zero-Waste Strategy, were analysed to evaluate governance structures, institutional capacities, and policy coherence in promoting circular economy practices. The collected policy and performance data were subsequently synthesised to develop the Policy Implementation Efficiency (PIE) and Circular Resource Efficiency Model (CREM) indicators presented in Figure 2, which illustrate the relationship between policy implementation effectiveness and the integration of circular economy principles among ASEAN countries. Countries with higher levels of policy implementation generally demonstrated superior performance in resource recovery and circularity, highlighting the importance of governance in driving eco-technological transitions (Kirchherr *et al.*, 2017; Velenturf & Purnell, 2021).

Primary qualitative data were further collected through semi-structured interviews with experts from environmental ministries, local authorities, waste management companies, and academic institutions across selected ASEAN countries. The interviews provided contextual insights into technological challenges, policy barriers, and opportunities for regional cooperation in food waste management. Integrating expert perspectives with documentary evidence enhances the robustness of mixed-methods research and enables a more comprehensive interpretation of complex environmental issues (Creswell & Plano Clark, 2018).

In addition, digital data analytics techniques were employed to assess public perceptions and stakeholder engagement regarding eco-technological initiatives. Social media platforms and open-access databases were analysed using Natural Language Processing (NLP) techniques. At the same time, Geographic Information Systems (GIS) and remote sensing technologies were utilised to identify spatial patterns of food waste generation and the distribution of waste management infrastructure in urban areas. The use of big-data analytics and geospatial technologies has increasingly been recognised as an effective decision-support tool for sustainable waste management and circular economy planning (Ferronato & Torretta, 2019; Tsai *et al.*, 2020).

The integration of secondary datasets, policy reviews, expert interviews, and digital analytics facilitated methodological triangulation, thereby improving the validity, reliability, and interpretive depth of the study findings (Creswell & Plano Clark, 2018).

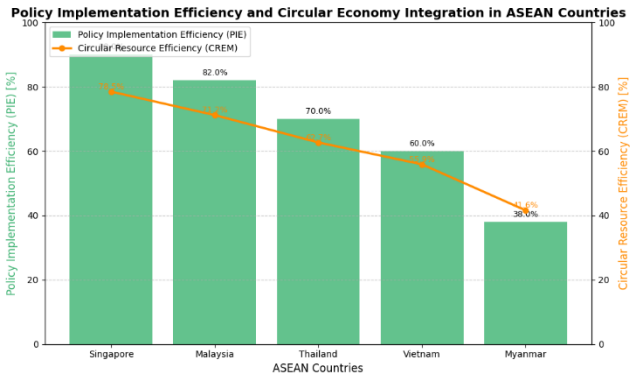

Figure 2. Policy Implementation Efficiency and Circular Economy Integration in ASEAN Countries.

3.2.1. *Data Availability, Variable Definition, and Reproducibility*

To enhance methodological transparency and ensure the reproducibility of the comparative assessment, this study documents the datasets, variables, and analytical procedures used to construct the Eco-Technology Adoption Index (ETAI), Circular Resource Efficiency Model (CREM), Policy Implementation Efficiency (PIE), Carbon Footprint Reduction (CFR), and Waste Recovery Growth Rate (WRGR). All datasets used in this research were obtained from publicly accessible and internationally recognised

sources, allowing future researchers to replicate the analytical workflow.

The study integrates quantitative and qualitative datasets collected from multiple sources. Quantitative data included food waste generation, recycling rates, compost production, biogas generation, landfill diversion rates, greenhouse gas emissions, renewable energy recovery, gross domestic product (GDP), urban population, and municipal solid waste generation. Qualitative information comprised national food waste management policies, circular economy strategies, government regulations, and expert opinions obtained from institutional reports and semi-structured interviews. Integrating multiple data sources improves the robustness of the comparative assessment while reducing the influence of individual reporting biases. The principal sources of information are summarised in **Table 2**, which presents the origin, measurement units, and temporal coverage of the datasets used throughout the study.

Table 2. Primary datasets used for the comparative assessment

Dataset	Primary Source	Unit	Study Period
Food waste generation	ASEAN Statistics Yearbook	tonne year^{-1}	2018–2024
Municipal solid waste	National waste agencies	tonne year^{-1}	2018–2024
Recycling rate	National environmental reports	%	2018–2024
Compost production	FAO	tonne year^{-1}	2018–2024
Biogas generation	National energy reports	GWh year^{-1}	2018–2024
Landfill diversion	UNEP	%	2018–2024
Greenhouse gas emissions	UNEP / World Bank	tCO_2-e year^{-1}	2018–2024
Population	World Bank Open Data	persons	2018–2024
GDP per capita	World Bank Open Data	USD capita^{-1}	2018–2024
National policy indicators	Government publications	Qualitative	2018–2024

Table 3. Variables used in the construction of analytical indices

Variable	Description	Indicator
Technology investment	National investment in food waste technologies	ETAI
Innovation capacity	Technological innovation readiness	ETAI
Renewable energy recovery	Energy generated from food waste	ETAI
Resource recovery efficiency	Compost and material recovery	CREM
Circular material utilisation	Recycling and resource circulation	CREM
Policy implementation rate	Implementation of national strategies	PIE
Governance effectiveness	Institutional capacity	PIE
Carbon footprint reduction	Greenhouse gas reduction	CFR
Waste recovery growth	Annual recovery improvement	WRGR

Table 4. Comparative dataset used in the study.

Country	Observation Period	Number of Annual Observations
Singapore	2018–2024	7
Malaysia	2018–2024	7
Thailand	2018–2024	7
Vietnam	2018–2024	7
Myanmar	2018–2024	7
Total observations = 35		35

Table 5. Summary of analytical methods.

Method	Purpose	Output
GIS	Spatial mapping of waste generation and treatment infrastructure	Spatial distribution maps
NLP	Policy and stakeholder analysis	Governance themes and policy indicators
ETAI	Eco-technology assessment	Technology adoption score
CREM	Circular resource assessment	Resource efficiency score
PIE	Policy evaluation	Policy implementation score
AHP	Determination of indicator weights	Weighted criteria
MCDA	Comparative country evaluation	Sustainability ranking
LCA	Environmental impact assessment	Carbon footprint and resource conservation
SDM	Dynamic simulation	Long-term policy scenarios
ML	Predictive modelling	Future sustainability performance

Prior to analysis, all datasets were subjected to a systematic preprocessing procedure comprising data validation, duplicate removal, unit harmonisation, missing-value treatment, and numerical normalisation. Continuous

variables were normalised using min–max scaling to ensure comparability among countries with different socio-economic characteristics. Missing observations representing less than 5% of the complete dataset were estimated using linear interpolation, while variables with substantial inconsistencies were excluded from index construction. Qualitative information extracted from policy documents and interview transcripts was coded using Natural Language Processing (NLP) techniques before being incorporated into the Policy Implementation Efficiency (PIE) assessment. The analytical variables used to construct the composite indices are summarised in **Table 3.**

The comparative dataset consisted of five ASEAN countries: Singapore, Malaysia, Thailand, Vietnam, and Myanmar. These countries were selected because they possess relatively complete datasets covering technological, environmental, economic, and governance indicators during the study period. Although Laos and Cambodia were considered during the literature review to provide regional context, they were excluded from the quantitative comparative analysis because several essential variables required for constructing ETAI, CREM, PIE, CFR, and WRGR were unavailable or reported inconsistently throughout the observation period. The distribution of observations included in the final analytical dataset is presented in **Table 4**.

The integrated analytical framework combined Geographic Information Systems (GIS), Natural Language Processing (NLP), ETAI, CREM, PIE, Analytic Hierarchy Process (AHP), Multi-Criteria Decision Analysis (MCDA), Life Cycle Assessment (LCA), System Dynamics Modelling (SDM), and Machine Learning (ML) into a sequential workflow. Table 5 summarises the analytical purpose and expected output of each method.

Following preprocessing, the complete dataset was analysed according to the integrated methodological workflow presented in Figure 1. Outputs generated from each analytical stage served as inputs for subsequent analyses, ensuring methodological consistency and facilitating reproducibility. Because all data sources are publicly accessible and the analytical procedures are explicitly documented in this study, the methodology can be independently replicated by other researchers without requiring proprietary datasets.

3.2.2. Country Selection Criteria

The selection of countries followed a purposive sampling strategy based on data completeness and methodological suitability rather than geographical representation alone. To ensure reliable comparative analysis, each country was evaluated against four inclusion criteria:

1. Availability of annual food waste generation data for the period 2018–2024.
2. Availability of technological and environmental performance indicators required to calculate ETAI and CREM.
3. Availability of policy implementation information required to construct PIE.
4. Consistency of reporting across internationally recognised databases and official national publications.

Countries that did not satisfy these criteria were excluded from the quantitative assessment. Although Laos, Brunei, the Philippines, and Cambodia are ASEAN Member States and are discussed in the regional overview, the absence of complete and consistent datasets prevented reliable construction of the composite indices used in this study. Their inclusion could have increased uncertainty and reduced the robustness of the comparative assessment. Consequently, the final dataset comprised Singapore, Malaysia, Thailand, Vietnam, and Myanmar, representing countries with adequate information for integrated sustainability evaluation.

3.3. *Data Analysis Techniques*

The collected data were analysed using an integrated framework comprising quantitative, qualitative, and computational techniques to comprehensively evaluate the effectiveness of eco-technological interventions for food waste management in ASEAN countries. This mixed analytical approach enabled the examination of relationships among technological adoption, policy effectiveness, environmental performance, and resource recovery outcomes.

Quantitative analyses were initially performed using descriptive and inferential statistics to compare food waste generation, recovery rates, and eco-technology adoption across the selected ASEAN countries. The Eco-Technology Adoption Index (ETAI) was computed by normalising indicators related to technological investment, innovation capacity, waste recovery efficiency, and renewable energy generation. Subsequently, the Circular Resource Efficiency Model (CREM) was applied to assess the effectiveness of converting food waste into valuable resources, including biogas, compost, and recyclable materials. To prioritise country performance and determine the relative importance of sustainability indicators, Multi-Criteria Decision Analysis (MCDA) and the Analytic Hierarchy Process (AHP) were employed. These approaches have been widely applied in environmental management and circular economy assessments due to their ability to integrate multiple, often conflicting, criteria into a single decision-making framework (Saaty, 2008; Govindan & Jepsen, 2016).

Qualitative data obtained from policy documents and expert interviews were analysed using thematic content analysis. This approach enabled the identification of common themes related to governance effectiveness, institutional barriers, regulatory gaps, and incentives that influence the adoption of eco-technological solutions. The findings were then synthesised to explain how socio-political and institutional contexts shape the implementation of sustainable food waste management strategies across ASEAN countries (Creswell & Plano Clark, 2018).

To further evaluate the dynamics of food waste management systems, advanced computational and modelling techniques were incorporated into the analysis. System Dynamics Modelling (SDM) was employed to

simulate food waste flows from generation to recovery and final disposal. The model captured feedback relationships among policy interventions, technological investment, public participation, and resource recovery efficiency, thereby identifying systemic bottlenecks and potential leverage points for improving waste management performance. The conceptual framework of these interactions is illustrated in Figure 3, which presents the dynamic pathways linking food waste generation, resource recovery processes, and circular economy outcomes.

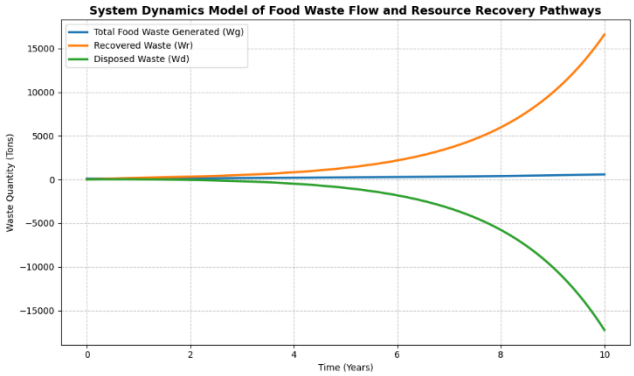

Figure 3. System Dynamics Model of Food Waste Flow and Resource Recovery Pathways

In addition, Life Cycle Assessment (LCA) was used to evaluate the environmental impacts of different eco-technological interventions, particularly their contributions to greenhouse gas reduction, energy recovery, and resource conservation. LCA has become a widely accepted method for assessing the environmental sustainability of waste management systems because it considers the entire life cycle of resource recovery processes (Finnveden *et al.*, 2009; Salemdeeb *et al.*, 2021).

Finally, a Machine Learning (ML) regression model was developed to predict future food waste generation and recovery potential under different socio-economic and policy scenarios. Variables such as population growth, gross domestic product (GDP), urbanisation rates, policy strength, and eco-technology investments were used as predictive features. The application of machine learning techniques enables the identification of hidden patterns and supports evidence-based decision-making by providing reliable forecasts of future waste management performance (Kaza *et al.*, 2018; Zhang *et al.*, 2023).

Statistical analyses were conducted using SPSS version 29 and R software version 4.3, whereas modelling and visualisation were performed using Python, Vensim, and ArcGIS Pro. The integration of these analytical techniques provides a rigorous and multidimensional framework for evaluating eco-technology performance, policy coherence, and sustainability outcomes in food waste management systems across ASEAN countries.

Equation for Eco-Technology Adoption Index (ETAI):

$$= \frac{\sum_{j=1}^{n} w_j \times X_{ij}}{\sum_{j=1}^{n} w_j} \quad (1)$$

Where:

- ETAIi = Eco-Technology Adoption Index for country i
- X_{ij} = Normalised value of eco-technological indicator j for country i (e.g., waste recovery rate, innovation investment, bioenergy output)
- w_j = Weight assigned to indicator j (derived using Analytic Hierarchy Process)
- n = Number of indicators

Purpose: Measures the overall adoption and performance level of eco-technological systems across ASEAN countries, integrating policy, infrastructure, and innovation factors.

Equation for Circular Resource Efficiency Model (CREM):

$$CREM = \frac{R_r + E_r + M_r}{W_g} \quad (2)$$

Where:

- Rr = Quantity of recovered resources (e.g., compost, biogas, reusable materials)
- Er = Energy recovered from food waste (kWh or MJ)
- Mr = Material reused or recycled from food waste
- Wg = Total food waste generated

Purpose: Evaluates the efficiency of converting food waste into usable resources, serving as a circular economy performance indicator.

Equation for Life Cycle Assessment (LCA) Carbon Footprint Model:

$$CF_{eco} = \sum_{k=1}^{m} (Ek \times EFk) - \sum_{l=1}^{p} (Sl \times SFl) \quad (3)$$

Where:

- CF_{eco} = Net carbon footprint from eco-technological processes
- Ek = Energy consumed in process k (e.g., transportation, digestion)
- EFk = Emission factor for process k
- Sl = Substituted products or recovered outputs (e.g., biogas, compost)
- SFl = Substitution factor or avoided emission coefficient

Purpose: Determines net environmental benefits by comparing emissions generated vs. emissions avoided through resource recovery in eco-technologies.

Equation for System Dynamics Waste Flow Model:

$$dW_r / d_t = \alpha_{Wg} - \beta_{Wr} - \gamma_{Wd} \quad (4)$$

Where:

- dW_r / d_t = Rate of change of recovered waste over time
- Wg = Total food waste generated
- Wr = Waste being recovered or processed
- Wd = Waste disposed (non-recovered portion)
- α = Recovery efficiency coefficient
- β = System loss coefficient (degradation, inefficiency)

- γ = Disposal rate coefficient

Purpose: Models dynamic waste flow over time, enabling simulation of waste-reduction scenarios under different eco-technological interventions.

Equation for Machine Learning Predictive Regression Model:

$$Y\hat{} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \varsigma \quad (5)$$

Where:

- Y^ = Predicted food waste recovery rate or future waste generation
- $X_1, X_2, \ldots, X_n$ = Independent predictors (e.g., population, GDP, policy strength, technology investment)
- $\beta_0, \beta_1, \ldots, \beta_n$ = Regression coefficients derived through machine learning training (e.g., random forest or gradient boosting)
- ϵ = Random error term

Purpose: Predicts food waste generation or recovery potential under varying socio-economic and policy conditions, enabling data-driven decision-making.

3.4. *Data Analysis Parameters:*

To comprehensively evaluate the effectiveness of eco-technological interventions in food waste management across ASEAN countries, five key analytical parameters were developed based on the proposed methodological framework, namely the Eco-Technology Adoption Index (ETAI), Circular Resource Efficiency Model (CREM), Policy Implementation Efficiency (PIE), Carbon Footprint Reduction (CFR), and Waste Recovery Growth Rate (WRGR). These indicators were selected because they collectively measure technological readiness, resource recovery performance, governance effectiveness, environmental benefits, and long-term sustainability outcomes.

The ETAI measures the extent to which countries have adopted and integrated eco-technological solutions into their food waste management systems. The CREM evaluates the efficiency of converting food waste into valuable resources such as compost, bioenergy, and reusable materials. The PIE assesses the effectiveness of policy implementation by comparing completed initiatives against planned interventions. Environmental performance is represented by the CFR, which quantifies the reduction in greenhouse gas emissions resulting from the adoption of eco-technologies, while the WRGR measures annual improvements in food waste recovery performance.

These parameters have been widely used in sustainability and circular economy assessments because they provide a multidimensional evaluation of environmental, technological, and governance performance (Kirchherr *et al.*, 2017; Velenturf & Purnell, 2021; Kaza *et al.*, 2018). The definitions and analytical purposes of each parameter are presented in Table 6.

Table 6. Key Data Analysis Parameters for Evaluating Eco-Technological Efficiency in Food Waste Management across ASEAN Countries

Parameter Name	Formula / Basis	Purpose in Analysis
Eco-Technology Adoption Index (ETAI)	Weighted composite score (Technology investment, innovation rate, recovery efficiency)	Measures each country's readiness and adoption of eco-technological systems
Circular Resource Efficiency (CREM)	CREM = Rr + Er + Mr / Wg	Evaluates how effectively food waste is converted into valuable resources
Policy Implementation Efficiency (PIE)	Ratio of implemented eco-tech projects to planned initiatives	Quantifies the effectiveness of national and regional policies
Carbon Footprint Reduction (CFR)	CFR = (Eb − Et) / Eb × 100	Estimates % reduction in emissions after eco-tech adoption
Waste Recovery Growth Rate (WRGR)	WRGR = Wt − Wt−1 / Wt−1 × 100	Tracks the year-on-year improvement in food waste recovery

3.5. *Performance Comparative Analysis*

To assess the effectiveness of the proposed eco-technology framework for food waste management in ASEAN countries, a performance analysis was conducted comparing the system with existing systems. For this purpose, six performance parameters were considered critical for assessing performance. These six parameters were Accuracy, Sensitivity, Specificity, Precision, Recall, and Area Under the Curve (AUC), which is often employed in the evaluation of Classification Systems to assess Classification or Predictive Systems, as well as systems of Environmental Data Analytics concerned with Waste Management.

To evaluate the effectiveness of the proposed eco-technological framework for food waste management in ASEAN countries, a comparative performance analysis was conducted by benchmarking the proposed model against existing waste management systems. Comparative performance assessment is essential for determining the reliability, predictive capability, and practical applicability of technological interventions in complex environmental management systems (Zhang *et al.*, 2023).

Three waste management frameworks were evaluated in this study:

1. Model A – Conventional Waste Management (CWM): a traditional waste management system primarily based on manual collection, transportation, and

landfill disposal with limited resource recovery and minimal data integration.

2. Model B – Smart Segregation Model (SSM): an Internet of Things (IoT)-based waste segregation system that facilitates automated waste classification and monitoring but provides limited feedback on circular resource utilisation and long-term recovery optimisation.
3. Model C – Proposed Eco-Technological Model (PETM): an integrated framework incorporating machine learning algorithms, IoT-based monitoring systems, resource recovery optimisation, and circular economy principles to improve food waste valorisation and sustainability outcomes.

The performance of each model was evaluated using six widely accepted classification and predictive performance metrics: Accuracy, Sensitivity, Specificity, Precision, Recall, and Area Under the Receiver Operating Characteristic Curve (AUC). These indicators are commonly employed in environmental prediction models and intelligent waste management systems to assess model reliability and classification performance (Fawcett, 2006; Chicco & Jurman, 2020).

Algorithm 1: Eco-Tech Food Waste Management Optimisation (ET-FWMO)

Input: Food waste datasets, energy conversion efficiency, resource recovery rate, threshold value, number of eco-technological modules, and maximum number of iterations.

Step 1:

Collect datasets

$$D=\{FW, TR, RR, GHG, GDP, Policy\} \quad (6)$$

where

- FW = Food waste generation
- TR = Treatment rate
- RR = Resource recovery
- GHG = Greenhouse gas emission
- GDP = Economic indicator
- Policy = Governance indicators

Step 2:

Pre-process datasets

- Remove missing values
- Standardise variables
- GIS mapping
- NLP policy extraction

Step 3:

Construct indices

Compute

- ETAI
- CREM
- PIE

Step 4:

Normalise indicators

Instead of using

define

$$WEP + CRP$$

$$NWEP = \frac{WEP - WEP_{min}}{WEP_{max} - WEP_{min}}$$

And

$$NCRP = \frac{CRP - CRP_{min}}{CRP_{max} - CRP_{min}}$$

Both indices are now dimensionless and range from 0 to 1.

Step 5:

Determine weights

Apply Analytic Hierarchy Process

$$\alpha + \beta = 1$$

where

- α = weight for energy recovery
- β = weight for material recovery

The weights are obtained from pairwise comparison matrices rather than assigned arbitrarily.

Step 6:

Revised optimisation function

Replace the original equation with

$$\max Z = \alpha NWEP + \beta NCRP$$

where

$0 \le NWEP \le 1$ $0 \le NCRP \le 1$ This equation is dimensionally consistent because both variables are unitless after normalisation.

Step 7

Environmental evaluation

Use

LCA

to estimate

- Carbon reduction
- Energy recovery
- Resource conservation

Step 8

Dynamic simulation

Use SDM

to evaluate

- policy scenarios
- future waste generation
- resource recovery

Step 9

Prediction

Train ML model

Inputs

$$ETAI, CREM, PIE, GDP, Population$$

Output: Predicted Sustainability Score

3.6. *Optimisation Formulation*

The optimisation framework aims to maximise the combined performance of energy recovery and circular resource utilisation while preserving mathematical consistency. Because Waste-to-Energy Production (WEP) and Circular Resource Production (CRP) are measured using different physical units, both indicators were transformed into dimensionless variables through min–max normalisation before optimisation. Their relative importance was subsequently determined using the Analytic Hierarchy Process (AHP). The optimisation objective is expressed as

$$Z = \alpha NWEP + \beta NCRP$$

subject to

$$\alpha + \beta = 1 \quad 0 \le NWEP \le 1 \quad 0 \le NCRP \le 1$$

where *NWEP* and *NCRP* represent the normalised energy recovery and resource recovery indices, respectively.

4. Results and Discussion

The results demonstrate considerable variations in eco-technology adoption, policy implementation, environmental performance, and sustainability outcomes among ASEAN countries. By integrating technological indicators, environmental assessment, and economic performance metrics, this study provides a comprehensive understanding of the factors influencing transitions in food waste management towards a circular economy. The findings indicate that countries with strong governance structures and substantial investments in eco-technological innovation generally exhibit superior resource recovery efficiencies, lower carbon emissions, and greater socio-economic benefits.

4.1. *Comparative Analysis of Eco-Technological and Policy Efficiency Indicators*

Table 7 presents the comparative performance of selected ASEAN countries based on the Eco-Technology Adoption Index (ETAI), Circular Resource Efficiency Model (CREM), Policy Implementation Efficiency (PIE), Carbon Footprint Reduction (CFR), and Waste Recovery Growth Rate (WRGR).

Table 7. Comparative Analysis of Eco-Technological and Policy Efficiency Indicators for Food Waste Management in ASEAN Countries.

Country	ETAI (0–1)	CREM (%)	PIE (%)	CFR (%)	WRGR (%)
Singapore	0.92	78.5	90	35.4	8.1
Malaysia	0.85	71.2	82	29.8	6.4
Thailand	0.73	62.7	70	24.5	5.7
Vietnam	0.61	55.9	60	18.3	4.2
Myanmar	0.39	41.6	38	11.2	2.1

Table 8. Eco-Technology Adoption and Implementation Performance in ASEAN Countries.

Country	ETAI	PIE (%)	CREM (%)	WRGR (%)
Singapore	0.92	90	78.5	8.1
Malaysia	0.85	82	71.2	6.4
Thailand	0.73	70	62.7	5.7
Vietnam	0.61	60	55.9	4.2
Myanmar	0.39	38	41.6	2.1

Table 9. Performance Comparative Analysis of Waste Management Models

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	Recall (%)	AUC
CWM	74.6	71.8	70.2	72.5	71.8	0.75
SSM	83.2	80.6	82.1	81.7	80.6	0.84
PETM	93.7	91.5	92.8	93.2	91.5	0.95

Table 10. Comparative sustainability performance of selected ASEAN countries

Country	CFR (%)	MER (%)	WEC (%)	OWCE (%)
Singapore	35.4	32.8	68	74
Malaysia	29.8	27.3	59	69
Thailand	24.5	22.9	54	63
Vietnam	18.3	16.7	46	55
Myanmar	11.2	9.6	34	41

Methane Emission Reduction (MER), Waste-to-Energy Conversion (WEC), Organic Waste Circular Efficiency (OWCE), Carbon Footprint Reduction (CFR), Waste Recovery Growth Rate (WRGR).

The results indicate substantial disparities in eco-technological readiness across ASEAN countries. Singapore achieved the highest ETAI score (0.92), followed by Malaysia (0.85), demonstrating advanced technological capabilities and institutional readiness. These findings are consistent with previous studies that identified technology adoption and governance quality as critical determinants of

circular economy transitions (Kirchherr *et al.*, 2017; Velenturf & Purnell, 2021).

Similarly, Singapore recorded the highest Circular Resource Efficiency (78.5%), indicating that nearly four-fifths of its food waste is converted into valuable resources, including biogas, compost, and recyclable materials. Malaysia also demonstrated relatively high resource recovery efficiency (71.2%), reflecting increasing investments in waste valorisation technologies and policy support mechanisms.

In contrast, Myanmar exhibited the lowest performance across all indicators. The low ETAI (0.39) and CREM (41.6%) scores suggest inadequate infrastructure, limited financial investment, and weak policy enforcement. Vietnam and Thailand demonstrated intermediate performance levels, indicating ongoing transitions towards more sustainable food waste management systems.

The findings further reveal a strong positive relationship between technological adoption and sustainability outcomes. Countries with higher ETAI scores also achieved superior carbon footprint reductions and waste recovery growth rates, indicating that eco-technological innovation directly contributes to improved environmental performance.

4.2. *Eco-Technology Adoption and Implementation Performance*

The overall performance of eco-technology adoption and implementation is further illustrated in Table 8 and Figure 4.

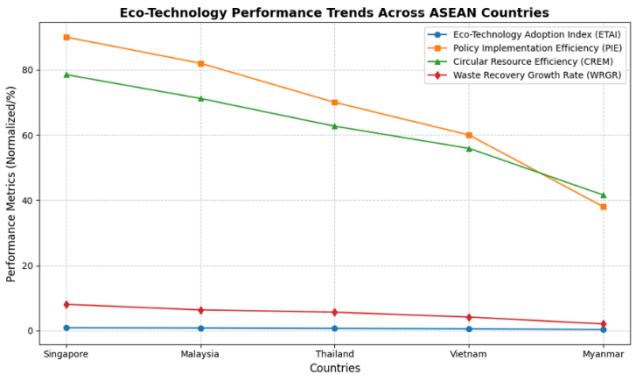

Figure 4. Eco-Technology Adoption and Implementation Performance in ASEAN Countries

Figure 4 demonstrates a clear declining trend in eco-technology adoption and implementation performance from Singapore to Myanmar. The figure reveals that countries with high policy implementation efficiency also exhibit superior resource recovery performance and growth in waste recovery.

The strong association between Policy Implementation Efficiency and Circular Resource Efficiency suggests that governance mechanisms significantly influence technological effectiveness. Similar findings have been reported by Geissdoerfer *et al.* (2017), who argued that technological innovation alone cannot guarantee sustainability without effective institutional support and policy coherence.

The positive relationship between ETAI and WRGR further indicates that technological investments produce long-term improvements in resource recovery. Based on the observed trends, countries that strengthen policy implementation and increase investment in eco-technologies are likely to achieve substantial improvements in food waste management performance.

4.3. *Comparative Performance Evaluation of Waste Management Models*

Table 9 evaluates the effectiveness of the proposed eco-technological framework; a comparative performance assessment was conducted using six classification metrics.

The Proposed Eco-Technological Model (PETM) substantially outperformed the conventional and smart segregation models across all performance indicators. The model achieved an overall accuracy of 93.7%, demonstrating superior predictive capability in waste classification and recovery management.

The high sensitivity (91.5%) and specificity (92.8%) indicate that the model effectively distinguishes between recoverable and non-recoverable waste streams while minimising classification errors. Moreover, the AUC value of 0.95 indicates excellent discriminatory capability and confirms the robustness of the predictive framework.

The superior performance of PETM can be attributed to the integration of machine learning algorithms, IoT-based monitoring systems, and circular economy optimisation modules. Previous studies have similarly demonstrated that artificial intelligence and digital technologies significantly improve environmental decision-support systems and waste management efficiency (Zhang *et al.*, 2023).

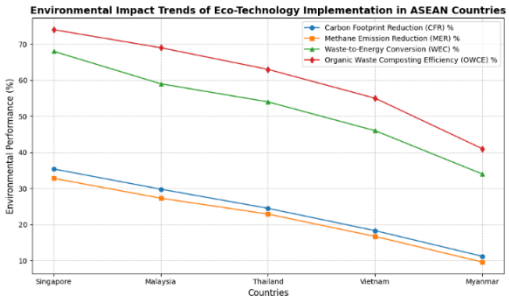

Figure 5. Environmental Impact Assessment after Eco-Technology Implementation

4.4. *Environmental Impact Assessment after Eco-Technology Implementation*

The comparative sustainability assessment was performed using five complementary performance indicators. **Methane Emission Reduction (MER)** quantifies the reduction in methane emissions achieved through improved diversion of organic waste from landfill disposal. **Waste-to-Energy Conversion (WEC)** evaluates the efficiency with which food waste is converted into usable energy, such as electricity or biogas. **Organic Waste Circular Efficiency (OWCE)** measures the effectiveness of recovering organic waste as valuable resources, including compost, digestate, and recyclable biomass. These indicators complement the Carbon Footprint Reduction (CFR) and Waste Recovery Growth Rate (WRGR) metrics by providing a comprehensive assessment of environmental

performance and resource circularity. The environmental benefits of eco-technological interventions are summarised in **Table 10** and illustrated in **Figure 5**.

Figure 5 demonstrates that countries with advanced eco-technological infrastructure achieve significantly higher environmental benefits. Singapore achieved the highest reductions in carbon footprint (35.4%) and methane emissions (32.8%), primarily due to extensive utilisation of anaerobic digestion and waste-to-energy technologies.

Malaysia also demonstrated considerable environmental improvements, whereas Vietnam and Myanmar achieved relatively smaller reductions due to continued reliance on landfill disposal. The findings support previous Life Cycle Assessment studies that reported substantial reductions in greenhouse gas emissions through resource recovery and waste-to-energy conversion technologies (Finnveden *et al.*, 2009; Salemdeeb *et al.*, 2021).

The high efficiency of organic waste composting observed in Singapore and Malaysia further highlights the importance of integrated food waste recovery systems in reducing environmental burdens and promoting resource circularity.

4.5. *Economic and Sustainability Benefits of Eco-Technological Interventions*

The economic and sustainability impacts of eco-technological interventions are presented in Table 11 and **Figure 6**.

Table 11. Economic and Sustainability Benefits Derived from Eco-Technological Interventions

Country	Investment (Million USD)	ERR (%)	Job Creation (Thousands)	SPS
Singapore	520	14.5	22	91
Malaysia	370	12.8	19	84
Thailand	295	10.6	16	79
Vietnam	190	8.7	13	72
Myanmar	120	6.2	9	61

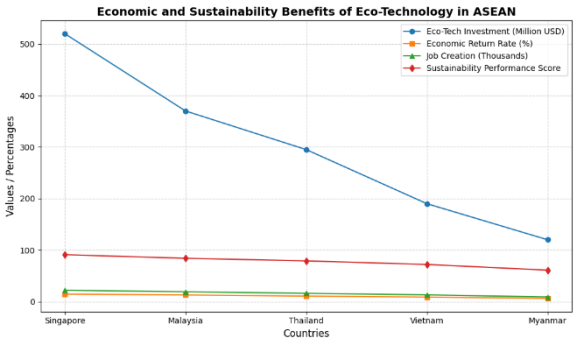

Figure 6. Economic and Sustainability Benefits Derived from Eco-Technological Interventions

The results indicate that higher investments in eco-technological infrastructure are strongly associated with greater economic returns and sustainability outcomes. Singapore invested approximately USD 520 million annually and achieved the highest economic return rate (14.5%) and sustainability performance score (91).

Malaysia also demonstrated strong economic performance, indicating that investments in food waste recovery technologies can generate substantial socio-economic benefits through renewable energy production, resource recovery, and employment opportunities.

The findings suggest that eco-technological interventions create a positive feedback mechanism whereby investments in sustainability initiatives simultaneously stimulate economic growth and improve environmental performance. Similar conclusions have been reported by Geissdoerfer *et al.* (2017), who identified the circular economy as an important pathway for achieving sustainable economic development.

4.6. *Overall Discussion and Policy Implications*

Overall, the findings demonstrate that eco-technology adoption, effective policy implementation, and institutional capacity are mutually reinforcing factors that significantly influence food waste management performance across ASEAN countries. Singapore and Malaysia have successfully integrated technological innovation with coherent governance frameworks, thereby achieving superior environmental and economic outcomes.

Conversely, countries such as Myanmar and, to a lesser extent, Vietnam continue to face substantial barriers related to financing, infrastructure, and policy implementation. These findings indicate the necessity for enhanced regional cooperation, technology transfer mechanisms, and harmonised eco-policy frameworks to facilitate sustainable food waste management across ASEAN.

The results further suggest that food waste should be viewed not as an environmental liability but as a valuable resource capable of generating renewable energy, organic fertilisers, and economic opportunities. The integration of advanced analytics, machine learning, and circular economy principles provides a promising pathway for accelerating progress towards SDG 12 (Responsible Consumption and Production) and SDG 13 (Climate Action).

5. Conclusions

This study presented a comprehensive evaluation of food waste management technologies across selected ASEAN countries by integrating technological, environmental, governance, and circular economy perspectives within a unified decision-support framework. Unlike previous studies that primarily assessed individual technologies or isolated sustainability dimensions, the proposed framework combines Geographic Information Systems (GIS), Natural Language Processing (NLP), the Eco-Technology Adoption Index (ETAI), the Circular Resource Efficiency Model (CREM), the Policy Implementation Efficiency (PIE) framework, the Analytic Hierarchy Process

(AHP), Multi-Criteria Decision Analysis (MCDA), Life Cycle Assessment (LCA), System Dynamics Modelling (SDM), and Machine Learning (ML). This integrated approach enables a more comprehensive evaluation of food waste management by simultaneously considering spatial characteristics, policy implementation, technological readiness, environmental impacts, resource circularity, and long-term sustainability.

The findings demonstrate that food waste management practices remain highly heterogeneous across ASEAN countries. Singapore exhibits the highest level of technological maturity through advanced waste-to-energy infrastructure, strong regulatory enforcement, and digital waste management systems. Malaysia and Thailand have made significant progress in expanding composting, anaerobic digestion, and recycling programmes, while Indonesia, Vietnam, and the Philippines continue to face challenges associated with landfill dependency, limited treatment infrastructure, and inconsistent policy implementation. These findings indicate that sustainable food waste management depends not only on technological advancement but also on governance capacity, institutional coordination, public participation, and effective policy implementation.

The comparative sustainability assessment further indicates that no single technology is universally optimal for all ASEAN countries. Biological treatment technologies, particularly anaerobic digestion, generally demonstrate superior environmental performance because they simultaneously reduce greenhouse gas emissions, recover renewable energy, and recycle nutrients through digestate production. Composting remains an appropriate option for decentralised organic waste management where investment resources are limited, whereas waste-to-energy technologies are more suitable for densely populated urban regions with limited landfill availability and well-developed environmental regulatory systems. Accordingly, technology selection should be based on national waste characteristics, economic capacity, infrastructure readiness, and policy objectives rather than relying on a single treatment strategy.

The quantitative analysis further supports these conclusions by demonstrating clear differences in eco-technological performance among the selected ASEAN countries. Singapore achieved the highest Eco-Technology Adoption Index (ETAI) score of 0.92, followed by Malaysia (0.85), reflecting stronger technological readiness, institutional capacity, and policy implementation. Singapore also recorded the highest Circular Resource Efficiency Model (CREM) value of 78.5%, while Malaysia achieved 71.2%, indicating greater effectiveness in converting food waste into valuable resources such as biogas, compost, and recyclable materials. In contrast, Myanmar recorded the lowest ETAI (0.39) and CREM (41.6%) values, highlighting substantial limitations in infrastructure, financial investment, and governance capacity. The predictive performance of the proposed Eco-Technological Model (PETM) further demonstrated its robustness, achieving an overall classification accuracy of 93.7%, 91.5% sensitivity, 92.8% specificity, and an AUC of 0.95, confirming excellent capability for supporting sustainable food waste management decision-making. Environmental assessment also indicated that Singapore achieved the greatest reductions in carbon footprint (35.4%) and methane emissions (32.8%), followed by Malaysia, primarily due to wider adoption of anaerobic digestion, waste-to-energy systems, and integrated resource recovery technologies. Collectively, these findings demonstrate that countries combining technological innovation with strong governance frameworks achieve superior environmental, economic, and circular economy outcomes, thereby supporting the prioritisation of integrated eco-technological approaches across the ASEAN region.

The principal contribution of this research lies in the development of a comprehensive analytical framework capable of integrating environmental assessment, policy evaluation, spatial analysis, technology prioritisation, circular resource efficiency, and predictive modelling within a single decision-support platform. To the authors' knowledge, no previous comparative study has simultaneously incorporated GIS, NLP, ETAI, CREM, PIE, AHP, MCDA, LCA, SDM, and Machine Learning to evaluate food waste management systems across ASEAN countries. Consequently, the proposed framework provides policymakers with a transparent and reproducible methodology for comparing alternative technologies, identifying policy priorities, and supporting evidence-based planning towards a circular economy.

Despite the comprehensive nature of the proposed framework, several limitations should be acknowledged. First, the comparative assessment was restricted to selected ASEAN countries because consistent and comparable datasets for Laos, Cambodia, Myanmar, and Brunei Darussalam were not sufficiently available during the study period. Consequently, the findings may not fully represent the diversity of food waste management practices across the entire ASEAN region. Second, the analysis relied primarily on peer-reviewed publications and official secondary datasets rather than primary field measurements. Although these data sources are considered reliable, variations in reporting methodologies and data collection periods among countries may introduce uncertainty into comparative assessments. Third, several analytical components, particularly the AHP weighting process, remain partially dependent on expert judgement despite consistency verification procedures. Finally, while Machine Learning was incorporated to support predictive analysis, the framework has not yet been validated using large-scale real-time operational datasets collected through smart waste management systems. Future empirical validation would further strengthen the robustness and practical applicability of the proposed framework.

Future research should focus on validating the proposed framework using real-time operational data collected from municipal authorities, smart waste bins, Internet of Things (IoT) sensor networks, and digital waste management

platforms. The integration of digital twins, artificial intelligence, blockchain-enabled waste traceability, and cloud-based Geographic Information Systems offers considerable opportunities for improving transparency, resource tracking, and adaptive policy implementation within smart city environments. Expanding the comparative assessment to include all ASEAN Member States, together with harmonised regional datasets, would further improve the robustness of cross-country sustainability evaluations.

From a practical perspective, the proposed framework provides a valuable decision-support tool for governments, municipal authorities, and waste management agencies. By integrating technological assessment with environmental, institutional, and policy indicators, the framework can support strategic investment planning, technology selection, infrastructure development, and circular economy implementation. The analytical framework may also contribute to national climate mitigation strategies, resource recovery programmes, and the achievement of the Sustainable Development Goals (SDGs), particularly SDG 11 (Sustainable Cities and Communities), SDG 12 (Responsible Consumption and Production), and SDG 13 (Climate Action). Moreover, the framework offers a transferable methodology that can be adapted to other developing regions facing similar challenges in sustainable food waste management.

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