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Machine Learning Modeling in Waste-to-Energy Project Financing Schemes

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Abstract

The increasing global challenges of waste accumulation, energy transition, and climate resilience have positioned Waste-to-Energy (WtE) systems as an important pathway for sustainable resource recovery. However, the complexity and uncertainty of WtE processes require advanced modeling approaches capable of capturing nonlinear relationships and improving predictive accuracy. Machine Learning (ML) has emerged as a promising tool for optimizing WtE operations; however, existing studies remain fragmented and are largely focused on technical performance rather than broader conceptual, methodological, and sustainability dimensions. This study aims to systematically examine the development, trends, methodological characteristics, and research gaps in ML applications for WtE systems. A Systematic Literature Review (SLR) was conducted using the PRISMA framework by analyzing relevant publications indexed in Scopus from 2020 to 2025. From the initial search results, 42 studies were selected for qualitative thematic analysis using structured coding to identify technological domains, geographic patterns, theoretical foundations, and methodological approaches. The findings indicate that ML applications in WtE are predominantly focused on optimization, prediction, gasification, and energy recovery modeling. However, the field remains characterized by geographical concentration, limited theoretical integration, insufficient interdisciplinary perspectives, and inconsistent consideration of governance, policy, and socio-environmental factors. The review highlights that future ML-based WtE research should incorporate stronger theoretical frameworks, improve data diversity, enhance model transparency, and integrate sustainability-oriented assessments. In conclusion, ML provides significant opportunities for advancing WtE systems; however, its transformative potential depends on moving beyond algorithmic accuracy toward holistic, equitable, and context-sensitive sustainability solutions.

INTRODUCTION

Worldwide debates on climate resilience, energy transitions, and unsustainable waste accumulation have elevated Waste-to-Energy (WtE) technologies from a niche engineering solution to a central pillar of contemporary sustainability discourse. However, as WtE systems become increasingly complex, traditional modeling approaches have struggled to capture the nonlinear and multivariate interactions that influence system performance. This challenge has created opportunities for Machine Learning (ML), which has gained prominence due to its ability to manage uncertainty, identify hidden patterns, and generate more reliable predictive outputs. Recent empirical studies have demonstrated that ML-based models outperform classical statistical techniques in tasks such as calorific value estimation, biogas production forecasting, and gasification process optimization (Taki & Rohani, 2022; Zhang et al., 2024). However, despite these advancements, the literature has often presented ML applications as isolated technical achievements rather than as components of a broader, system-level transformation in WtE research.

Despite the rapid growth of ML-oriented publications since 2020, the field remains theoretically underdeveloped and methodologically inconsistent (Gülhan, 2026; Santamaria-Pedrón et al., 2026). Many studies have adopted ML as a computational tool without clearly explaining the conceptual rationale behind model selection, the implications of algorithmic assumptions, or the criteria used to evaluate model generalizability. Moreover, previous reviews, although valuable, have primarily focused on related topics such as WtE technologies, circular economy policies, or AI-based waste classification (Rezania et al., 2023; Fotovvatikhah et al., 2025). A comprehensive synthesis examining how ML is reshaping WtE research agendas, where research activities are geographically concentrated, and why methodological fragmentation persists across studies remains limited. The absence of such a synthesis obscures important dynamics, including regional disparities in knowledge production, the dominance of specific algorithmic approaches, and limited engagement with sustainability theories and systems-thinking frameworks.

These gaps are significant because they hinder the development of a coherent scientific trajectory in the field. For instance, the lack of comparative evaluations across ML techniques limits the ability to determine which models are most robust under different waste compositions and operational conditions. Similarly, limited attention to policymaking, governance, and socio-environmental considerations indicates a disconnect between ML-driven optimization and practical sustainability objectives. Such limitations raise critical questions regarding whether current research genuinely advances WtE as a sustainable energy pathway or primarily reinforces a technocentric perspective that overlooks structural and contextual challenges.

Against this background, the present review seeks to provide a more critical and integrative perspective. By systematically synthesizing ML-based WtE research published between 2020 and 2025, this study not only maps empirical trends but also examines the conceptual, methodological, and geographical characteristics of the field. Three research questions guide the analysis: What global technological, methodological, and spatial patterns characterize the evolution of ML in WtE research? What thematic domains and research approaches underpin current ML applications? More importantly, what conceptual limitations and methodological inconsistencies remain, and how can addressing these challenges contribute to the future development of ML-enabled WtE systems?

The review follows a PRISMA-based protocol, followed by descriptive and thematic analyses, and concludes with a critical discussion highlighting implications for theory, methodology, and sustainability practice. Through this approach, the study aims to move beyond simple classification of existing research and contribute to a more reflective and strategically oriented research agenda for ML applications in WtE systems.

Research on waste management and renewable energy has undergone substantial transformation over the past decade, shifting from conventional modeling practices toward more advanced, data-driven analytical approaches. Earlier studies frequently relied on traditional frameworks, including statistical analysis and qualitative policy assessments. For example, Gao and Zhao (2018) applied system dynamics and evolutionary game theory to investigate strategic interactions between governments and private investors in public–private partnership (PPP)-based energy projects. Similarly, Khan et al. (2022) conducted a rapid review identifying policy and infrastructure barriers that continue to restrict WtE adoption in developing countries. These studies established important foundations; however, their explanatory capabilities remained limited, particularly in addressing prediction, optimization, and large-scale system variability.

As WtE and renewable energy systems became increasingly technologically complex, researchers adopted modeling techniques capable of capturing nonlinear relationships and dynamic feedback mechanisms. Mathematical and hybrid computational approaches emerged as transitional methods between conventional qualitative assessments and advanced ML-based approaches. Liu et al. (2023), for example, developed a two-stage recycling–remanufacturing model to examine compensation mechanisms within waste-related PPP projects. In parallel, research on circular economy transitions emphasized the importance of positioning WtE within broader sustainability frameworks. Rezania et al. (2023) highlighted that integrating WtE into circular economy strategies is essential for reducing waste generation and recovering valuable resources, although implementation remains uneven due to fragmented regulations and differences in technological readiness across regions.

Within this evolving research landscape, ML and artificial intelligence (AI) have increasingly become central analytical approaches. A growing body of research has demonstrated that ML techniques can outperform conventional models in forecasting, optimization, and classification tasks relevant to WtE operations. Studies by Zhang et al. (2024) and Kulisz et al. (2024), for example, showed that ML can improve syngas prediction and energy recovery modeling. Meanwhile, hybrid modeling approaches, such as integrating response surface methodology with ML (Masoomi et al., 2025) or combining Monte Carlo simulation with neural networks (Ng et al., 2025), indicate that single-method approaches are often insufficient for capturing the multidimensional uncertainties inherent in WtE processes.

ML has also transformed waste classification and system optimization. Deep learning models reported by Castro-Bello et al. (2025) significantly improved wastetype identification accuracy, while Baez-Barron et al. (2025) applied AI-based multi-objective optimization to model biomass gasification with greater generalizability than previous deterministic approaches. Collectively, these studies demonstrate a transition from descriptive analysis toward predictive, prescriptive, and adaptive modeling, consistent with broader digital transformation trends in environmental analytics.

Another research direction integrates ML with environmental governance and policy evaluation. Guo et al. (2025), using double machine learning, examined the causal effects of China's "Zero-Waste City" initiative and provided insights into how policy interventions influence urban energy consumption patterns. However, despite these advances, many ML-based studies remain predominantly technocentric, with limited consideration of social, institutional, and behavioral factors that influence the success of WtE implementation in practice.

Overall, the literature reveals several converging yet uneven research trajectories. There has been a clear methodological transition toward hybrid and data-intensive approaches, stronger alignment between WtE and circular economy principles, and increasing interest in ML-based optimization and forecasting. Nevertheless, several research gaps remain. Many ML-based studies rely on geographically limited datasets, raising concerns regarding model transferability and generalizability. Comparative assessments of algorithm performance remain insufficient, leaving uncertainty regarding which ML approaches perform most reliably under varying waste compositions and policy environments. Furthermore, interdisciplinary integration, particularly the incorporation of socio-economic and governance factors into ML-driven analyses, remains limited despite its importance for successful WtE deployment.

Overall, although the literature demonstrates considerable progress, it also highlights the need for a more comprehensive research agenda that incorporates diverse datasets, encourages cross-regional comparisons, and bridges the gap between technological innovation and the social and institutional contexts required for sustainable WtE implementation.

METHOD

This review adopted a Systematic Literature Review (SLR) approach guided by the PRISMA framework, which has been widely recognized for promoting methodological transparency and analytical rigor (Moher et al., 2009; Panic et al., 2013). PRISMA was selected because it provides a structured procedure for refining a broad body of literature into a focused and defensible collection of studies. The overall review process is illustrated in Figure 1, which presents the sequential stages used to identify, screen, assess, and select relevant studies.

The process began with the identification stage, during which a comprehensive search was conducted using the Scopus database. Scopus was selected due to its rigorous indexing standards and broad coverage of high-quality academic publications, which was important given the rapid growth of research at the intersection of machine learning and waste-to-energy (WtE). Using the keywords "Waste to Energy AND

Machine Learning: PPP AND BOT: Project Feasibility Analysis," 103 records were initially identified. No duplicate records were found during this stage. Studies outside the predefined publication period were excluded (39 records), along with articles that did not meet journal-quality criteria (10 records) or lacked abstracts. This refinement ensured that the selected dataset remained relevant and methodologically appropriate.

The screening stage involved a detailed assessment of titles, abstracts, and keywords. At this stage, one article was excluded due to insufficient relevance to the research focus. During full-text retrieval, although 53 articles were identified as potentially eligible, 39 articles could not be accessed. To address this limitation, an additional 34 sources were identified through citation chaining to complement the initial dataset.

During the eligibility stage, all accessible articles were evaluated based on their alignment with the research objectives, methodological quality, and contribution to understanding ML applications in WtE systems. Only studies providing substantial analytical, empirical, or theoretical contributions were included to ensure that the synthesis was based on a coherent and relevant evidence base.

The final inclusion stage resulted in 42 studies that met all selection criteria. These studies were subsequently analyzed using qualitative thematic analysis to identify patterns related to machine learning applications, technological domains, methodological approaches, and research contexts. Systematic coding and theme identification were supported by the Watase analytical system (Wahyudi, 2024), which facilitated structured analysis and organization of emerging themes.

Overall, the PRISMA-guided process provided a transparent and systematic approach for analyzing the expanding research landscape of machine learning applications in WtE systems. The approach enabled the review to narrow a broad collection of publications into a curated set of studies that supported the development of theoretical insights and practical implications for ML-based WtE research.

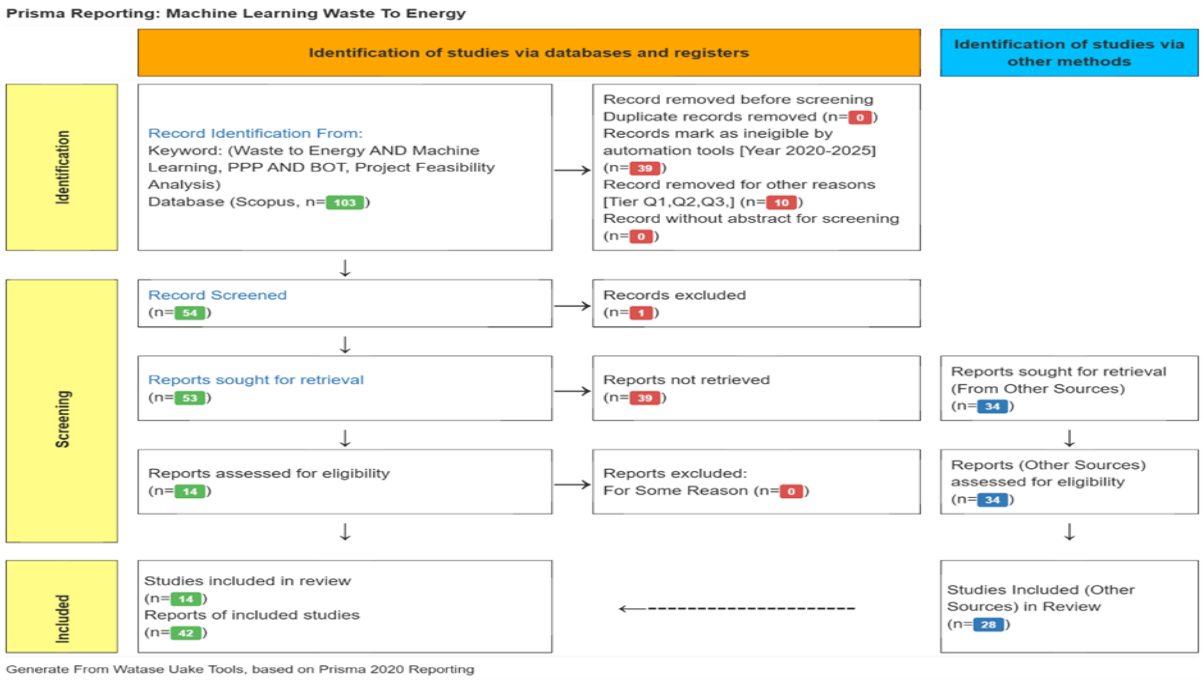

Figure 1. PRISMA Statement

RESULTS AND DISCUSSION

The synthesis of 42 publications included in this review offers a dynamic yet uneven portrayal of how machine learning (ML) has been integrated into waste-to-energy (WtE) research. To contextualize the patterns discussed later, the order of accompanying visuals is first outlined. A keyword-derived word cloud reveals the conceptual language dominating the literature, followed by tables that depict geographic concentration, journal rankings, citation performance, theoretical grounding, and methodological structures. Finally, several classification matrices highlight how researchers conceptualize ML within WtE systems. These visuals act as the empirical scaffolding for the more critical and interpretive analysis that unfolds in the subsequent discussion.

Figure 2, the word cloud, for instance, offers an intuitively accessible yet indicative snapshot of the dominant discourse in ML WtE literature. Recurring terms such as *optimization*, *gasification*, *biogas*, *neural networks*, *prediction*, and *sustainability* appear prominently, reflecting a research ecosystem primarily oriented toward enhancing process performance and mitigating environmental impact. This aligns well with the increasing global emphasis on waste valorization and energy recovery, particularly in countries experiencing high waste-generation pressure. Interestingly, several terms related to governance such as *feasibility*, *PPP*, or *investment* appear far less frequently, quietly flagging a thematic asymmetry that resurfaces across deeper layers of analysis.

Figure 2. Wordcloud

While figure 3 maps the geographical distribution of studies, revealing striking regional asymmetries. The geographical distribution of research highlights a strong concentration of publications in Asia, particularly China, India, Iran, and Bangladesh. This overrepresentation is understandable given the demographic pressures and waste generation levels in these regions, yet it simultaneously reveals deeper systemic blind spots. For instance, the near absence of contributions from African and Latin American countries underscores a structural inequity in research capacity and digital infrastructure, which may ultimately skew global understanding of ML-WtE dynamics. In contrast, European contributions though fewer tend to exhibit greater methodological sophistication, integrating system-level energy modeling or high-resolution environmental assessment. Notably, however, these advanced methods rarely migrate to high-need regions, limiting their transformative potential. Citation analysis further illustrates unevenness: highly cited works (such as Taki & Rohani, 2022, or Zhang et al., 2024) often emerge from technically mature research ecosystems, whereas many publications from resource-constrained contexts remain uncited. This does not necessarily indicate lower quality but rather reflects global imbalances in visibility, publication networks, and citation flows. Taken together, the journal ecosystems reveal a field that enjoys high publication placement 17 studies appear in Q1 journals, yet citation maturity remains limited. This paradox suggests a field that is academically promising but still fragmented. High-impact placement signals the acceptance of ML-WtE research within top-tier scholarly communities, while low citation uptake reflects limited interdisciplinary integration. Many studies emphasize computational performance but rarely engage with environmental economics, political ecology, or socio-technical transition theory, which restricts their resonance across disciplinary boundaries. Interestingly, this methodological insularity may partly explain why the field's conceptual vocabulary remains relatively narrow.

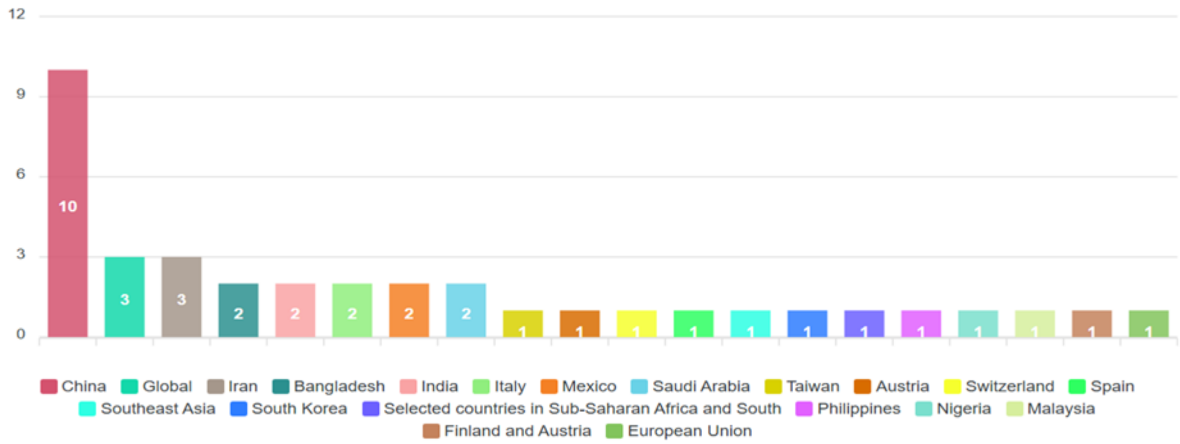

Figure 3. The geographical distribution of studies

Based on the data in Table 1, research on ML-WtE appears across journals with differing levels of impact, though a noticeable share has already entered high-quality publication venues. This pattern suggests that the topic, despite its relatively recent emergence, has gained early traction within reputable scholarly platforms. Notably, citation performance varies widely: the study by Taki and Rohani (2022) stands out with 67 citations, followed at some distance by Zhang et al. (2024) with 14. However, a considerable portion of the literature remains minimally cited, with 15 articles receiving no citations at all (Kulisz et al., 2024; Ali et al., 2025; Soni et al., 2025; 2024; Liu & Wang, 2024; Baez-Barron et al., 2025; Fotovvatikhah et al., 2025). Interestingly, this uneven distribution does not signal a weakness in the research itself but rather reflects the nascent and rapidly evolving nature of the field. The trajectory implied by these trends indicates that considerable space remains for strengthening theoretical depth, methodological innovation, and broader interdisciplinary integration. As global attention increasingly shifts toward sustainable energy transitions and smarter waste management systems, ML-based WtE research is positioned to grow in influence. Consequently, ongoing work in this area holds the potential not only to respond to current scientific and technological challenges but also to shape future directions in sustainable technology development and environmental systems research.

Table 1. Summarizes journal classifications and citation

Authors	Year	Title	Journal	Citation
Taki, Morteza; Rohani, Abbas	2022	Machine learning models for prediction the Higher Heating Value (HHV) of Municipal Solid Waste (MSW) for waste-to-energy evaluation,	*Case Studies in Thermal Engineering*	67
Zhang, Yulan; Aldosky, Abdulrahman Jaffar; Goyal, Vishal; Meqdad, Maytham N.; Nutakki, Tirumala Uday Kumar; Alsenani, Theyab R.; Nguyen, Van Nhanh; Dahari, Mahidzal; Nguyen, Phuoc Quy Phong; Ali, H. Elhosiny	2024	A machine learning study on a municipal solid waste-to-energy system for environmental sustainability in a multi-generation energy system for hydrogen production,	*Process Safety and Environmental Protection*	14
Kulisz, Monika; Kujawska, Justyna; Cioch, Michal; Cel, Wojciech; Pizon, Jakub	2024	Comparative Analysis of Machine Learning Methods for Predicting Energy Recovery from Waste,	*Applied Sciences (Switzerland)*	13
Andayesh, Mohammad; Florez-Orrego, Daniel Alexander; Germanier, Reginald; Gatti, Manuele; Marschal, Francois	2023	Improved Waste Heat Management and Energy Integration in an Aluminum Annealing Continuous Furnace Using a Machine Learning Approach,	*Entropy*	7
Anjum, Tahsin; Parvez Mahmud, M. A.; Kumar, Laveet; El Haj Assad, Mamdouh; Ehyaei, M. A.	2024	Feasibility analysis of hybrid photovoltaic, wind, and fuel cell systems for onâ€“off-grid applications: A case study of housing project in Bangladesh,	*Energy Science and Engineering*	6
Liu, Mengkai; Yan, Acai	2022	Feasibility analysis of water resources market transaction of water diversion project based on evolutionary game,	*Water Science and Technology: Water Supply*	6
Iweka, Sunday Chukwuka; Ighofiomoni, Michael Oghale; Falowo, Olayomi Abiodun; Oladunni, Atilade A.	2024	Biogas production from Udara seeds inoculated with food waste digestate and its optimal output for energy utilities: Central composite design and machine learning approach,	*Energy Science and Engineering*	4

Guo, Bingnan; Qian, Yuren; Guo, Xinyan; Zhang, Hao	2025	Impact of Zero-Waste City Pilot Policies on Urban Energy Consumption Intensity: Causal Inference Based on Double Machine Learning,	*Sustainability*	4
Shim, Heecheoul; Kim, Jaehwan	2022	Determinants of the Economic and Financial Feasibility of Real Estate Development Projects: A Comparative Analysis between Public and Private Development Projects in South Korea,	*Sustainability*	3
Jiang, Haotong; Yao, Liuyang; Bai, Xueru; Li, Hua	2023	Dynamic Analysis and Simulation of the Feasibility and Stability of Innovative Carbon Emission Reduction Projects Entering the Carbon-Trading Market,	*Sustainability*	1

A further limitation concerns the theoretical foundations of the reviewed studies. In most cases, ML itself functions implicitly as the theoretical frame guiding inquiry, despite being primarily a methodological tool. Only a small subset of studies, such as those drawing on Evolutionary Game Theory (Liu & Yan, 2022; Liu & Wang, 2024), attempt to situate their analyses within broader conceptual frameworks. Even promising conceptual labels such as "Digital-AI Optimization" remain analytically underdeveloped. This theoretical thinness constrains interpretive depth and hinders the development of cumulative knowledge. Without more robust theoretical scaffolding whether from the circular economy, socio-technical transition theory, or energy governance studies ML-WtE scholarship risks becoming method-driven rather than insight-driven, as also illustrated in Table 2.

Table 2. Citation theory

Theory	Count	Citation	Author
Thermodynamics	1	67	Taki and Rohani, 2022
Evolutionary Game Theory	2	6	Liu and Yan, 2022 Liu and Wang, 2024

The methodological landscape, unsurprisingly, is dominated by quantitative approaches (67.5%). Yet, what is more revealing is how unevenly these studies address the challenges inherent in ML modeling. Several papers rely on localized or incomplete datasets, compromising the generalizability of their conclusions. Although some studies employ hybrid models combining ML with Monte Carlo simulations or RSM few articulate the conceptual rationale behind these integrations. In practice, this creates an impression that hybridization is driven more by methodological novelty than by analytical necessity. Moreover, a strong focus on maximizing predictive accuracy tends to overshadow equally important considerations such as interpretability, fairness, transparency, or long-term system robustness. These omissions could pose significant risks when ML models are deployed in real WtE infrastructures, where decision errors have tangible socio-environmental consequences. Methodological orientations are presented in figure 4.

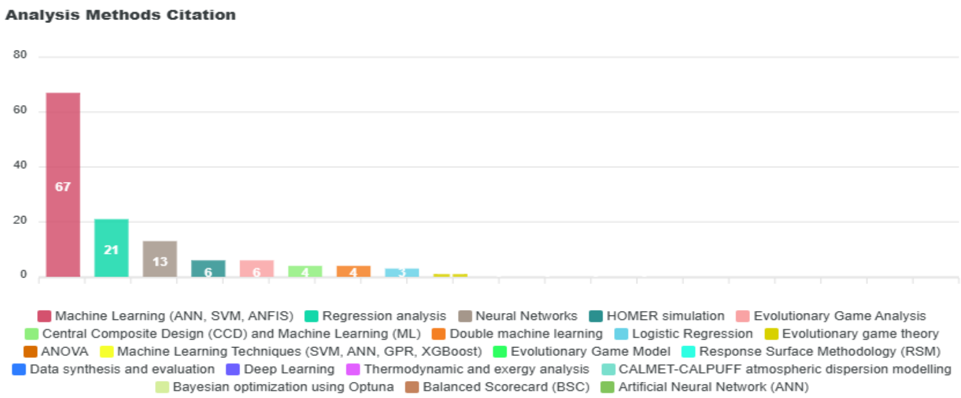

Figure 4. Analysis methode

Across thematic categories, several revealing patterns emerge. Studies classified under project implementation (Category 1) tend to equate "success" with technical and operational efficiency. However, history shows that WtE projects often fail not because of technological malfunction but due to governance challenges, financial risk asymmetries, public resistance, and policy discontinuity dimensions largely missing in these analyses. Optimization-focused studies (Category 2) dominate the field but rarely acknowledge trade-offs between energy maximization and environmental or social externalities. Deep learning and other advanced AI approaches (Category 3) offer impressive computational capabilities yet often lack discussions of cybersecurity, workforce readiness, or digital infrastructure disparities factors that determine whether automated systems can be sustainably deployed. Environmental-policy interaction studies (Category 4) provide some of the most conceptually rich insights, yet they remain underrepresented relative to the significance of policy dynamics in determining WtE project feasibility, as also illustrated in Figure 5.

Figure 5. Category classification (CIMO)

The temporal trajectory of ML-WtE scholarship reveals rapid acceleration since. Early papers focused on relatively narrow tasks, such as predicting calorific value or biogas yield. More recent work engages with multi-objective optimization, hybrid architectures, and system-level energy transition modeling. Yet despite this encouraging methodological evolution, thematic depth has not grown at the same pace. Few studies engage with life-cycle sustainability assessment, socio-economic trade-offs, or political economy barriers to WtE adoption. Interestingly, the studies that do address these dimensions tend to be more theoretically grounded, highlighting the potential benefits of interdisciplinary integration.

Synthesizing these patterns leads to several overarching insights. ML has clearly reshaped WtE research by enabling more sophisticated modeling and optimization. However, this computational progress risks overshadowing the structural challenges that determine whether WtE projects succeed in practice. Without attention to governance quality, regulatory stability, financial mechanisms, and public acceptance, even the most accurate models may have limited real-world impact. A second insight concerns data asymmetry: the regions with the greatest waste management needs often lack high-quality datasets, raising ethical and practical questions about algorithmic fairness and global research equity. A third insight centres on the field's persistent method-centrism, which limits its capacity to engage with broader system-level transitions such as the circular economy or climate-oriented energy reforms.

Taken together, these findings align strongly with the research questions and novelty claims of this review. They show that while ML-WtE scholarship has expanded rapidly, it remains characterized by methodological fragmentation, theoretical thinness, and geographical imbalance. The contribution of this review, therefore, lies not simply in synthesizing the literature, but in highlighting the structural blind spots and conceptual gaps that must be addressed to deepen the field's scientific and practical relevance. In doing so, the review offers a roadmap for future research that aspires not only to improve computational performance but also to meaningfully support sustainable, just, and context-responsive WtE transitions.

The findings of this review reveal a rapidly developing yet uneven body of work on machine learning (ML) applications in waste-to-energy (WtE) systems. While the expanding use of ML is broadly in line with earlier studies documenting the rise of data-driven modeling in the renewable energy domain (Taki & Rohani, 2022; Zhang et al., 2024), the present synthesis suggests a more complex picture one that is not fully captured by earlier analyses. Interestingly, although technological advancements occupy a central position in prior reviews (Rezania et al., 2023), this study shows that the evolution of ML-WtE research is shaped as much by conceptual omissions and geographic asymmetries as by modeling breakthroughs. Such findings call for a more layered interpretation of how ML contributes to WtE transitions, beyond the conventional celebration of computational accuracy.

The dominance of keywords related to optimization, prediction, and feasibility echoes themes highlighted in previous engineering-oriented literature. However, the present review adds nuance by revealing that such conceptual clustering may inadvertently narrow the intellectual boundaries of the field. Many studies reference sustainability aspirations, yet only a small subset operationalizes these claims with measurable indicators or theoretical frameworks. This pattern stands in contrast to the assumption common in previous WtE reviews that methodological innovation naturally aligns with environmental benefits. The findings here suggest that this alignment is far from automatic; improvements in predictive accuracy do not inherently resolve deeper governance, financing, or infrastructural barriers that shape real-world WtE performance.

The geographic distribution of research also reflects both continuity and divergence from earlier analyses. Studies consistently note the dominance of Asia especially China, India, Iran, and Bangladesh in WtE innovation (Khan et al., 2022). This review confirms that trend but extends its implications. Notably, regional clusters not only affect where research is produced but also shape how ML is conceptualized. For instance, studies from emerging economies tend to emphasize operational optimization or feasibility modeling, whereas European contributions more frequently incorporate policy sensitivity, environmental impact pathways, or hybrid analytical frameworks. This divergence underscores how local infrastructural realities influence methodological choices. At the same time, the near absence of African and Latin American contributions highlights a long-standing research inequity that earlier reviews have not fully addressed. Such imbalance limits the development of ML models capable of generalizing across diverse regulatory and socio-technical contexts.

Journal classification and citation patterns also reveal noteworthy tensions. Consistent with earlier bibliometric mapping, this review finds that ML-WtE studies are well represented in Q1 journals such as Applied Energy and Journal of Cleaner Production. However, while prior studies often interpret Q1 representation as an indicator of field maturity, the present results suggest otherwise. A surprisingly large proportion of studies, including those published in prestigious outlets, remain minimally cited. This pattern is not unusual in emerging interdisciplinary domains, yet it indicates that research visibility does not always translate into conceptual consolidation. In contrast to expectations formed by earlier reviews, the present study shows that ML-WtE scholarship is expanding faster than it is integrating, leading to methodological fragmentation and limited cross-disciplinary dialogue.

A particularly striking finding relates to theoretical engagement or rather, its scarcity. Earlier studies have noted that ML research tends to be method-driven, but this SLR demonstrates just how pervasive the lack of theoretical framing is within WtE scholarship. Aside from a few notable exceptions using Evolutionary Game Theory to examine PPP configurations (Liu & Yan, 2022; Liu & Wang, 2024), most studies rely on ML as a computational tool detached from broader conceptual perspectives. This absence is not merely an academic concern; without theoretical guidance, ML models risk being interpreted narrowly, focusing on numerical improvements rather than system-level implications. The present review therefore extends prior critiques and highlights the need for conceptual frameworks drawn from socio-technical transitions, circular economy theory, or environmental governance to deepen the interpretive richness of ML-WtE research.

Methodologically, although the dominance of quantitative approaches in ML–WtE research was anticipated, the implications revealed by this review warrant closer scrutiny. A substantial number of studies rely on localized or limited datasets, whose provenance and reliability are not always clearly articulated, raising concerns about model generalizability. While some papers employ validation techniques such as cross-validation or Monte Carlo simulation, these practices are applied inconsistently and are rarely accompanied by explicit methodological justification. Moreover, the prevailing emphasis on predictive accuracy often eclipses critical issues such as transparency, fairness, and uncertainty quantification dimensions that are increasingly central in responsible AI discourse. Rather than merely cataloguing model types, this review demonstrates how methodological norms intersect with structural data constraints, particularly in regions characterized by fragmented data ecosystems.

The thematic synthesis further illustrates how the intellectual architecture of ML–WtE research has been shaped. Studies centered on project implementation frequently equate success with technical efficiency, leaving governance dynamics, policy continuity, and financing mechanisms underexplored. This contrasts with earlier reviews that implicitly treated technical performance as the primary determinant of WtE success. Similarly, optimization-oriented studies dominate the literature, yet their framing often prioritizes internal system performance without adequately considering external constraints or socio-environmental trade-offs. The present review highlights that optimization is not value-neutral; prioritizing energy output or efficiency may inadvertently exacerbate environmental or social inequities when contextual variables are ignored.

AI-driven process innovation represents some of the most technically advanced work in the field. However, a notable blind spot persists limited attention to institutional readiness, including cybersecurity, workforce capacity, and infrastructure compatibility. Environmental and policy-oriented studies, though fewer in number, provide conceptually rich insights into how ML can support governance and environmental monitoring, yet they remain marginalized within WtE scholarship.

Taken together, these patterns depict a field that is rapidly evolving but lacks conceptual cohesion. This review contributes a novel, integrative perspective by foregrounding the structural, theoretical, and geographic dynamics that constrain ML–WtE's transformative potential. It underscores the need for theory-informed, interdisciplinary, and governance-aware research agendas capable of translating ML innovation into sustainable and socially robust WtE solutions.

CONCLUSION

This review synthesized a rapidly expanding yet uneven body of research on machine learning (ML) applications in waste-to-energy (WtE) systems, providing a more critical perspective on the current state and future direction of the field. While previous studies have emphasized the improvements in predictive accuracy and process optimization enabled by ML (Taki & Rohani, 2022; Zhang et al., 2024), the present synthesis revealed a more complex research landscape. The value of ML in WtE research was found to extend beyond algorithmic capabilities, as it was also influenced by the structural conditions shaping model development and implementation. The findings indicated that methodological fragmentation, geographical concentration, and limited theoretical integration continued to constrain the broader interpretive and practical contributions of the field.

This review contributed to the existing literature by providing an integrated assessment that connected conceptual, methodological, and contextual dimensions of ML-based WtE research. By demonstrating how research activities were concentrated in specific regions, how optimization-oriented studies often dominated over system-level analyses, and how policy-oriented and theory-driven investigations remained limited, this review provided a more comprehensive understanding of current research patterns. These findings suggested not a lack of progress but rather a maturing research landscape in which existing limitations could serve as opportunities for future development. Instead of merely summarizing previous findings, this review emphasized the importance of aligning ML innovation with governance frameworks, data ecosystems, and long-term sustainability objectives.

Several research directions should receive greater attention in future studies. Researchers should expand empirical investigations by incorporating underrepresented regions, particularly areas experiencing significant waste management and energy challenges. The adoption of interdisciplinary frameworks, such as socio-technical transition theory and circular economy models, could provide deeper interpretations of ML outcomes within institutional, environmental, and social contexts. Furthermore, stronger emphasis should be placed on model transparency, uncertainty analysis, and data governance, particularly in environments where data availability and quality vary substantially. Integrating ML-based optimization with life-cycle sustainability assessments could provide a more comprehensive evaluation of trade-offs that are often overlooked. In addition, closer collaboration among engineers, policymakers, and social scientists is necessary to translate algorithmic insights into practical, resilient, and socially acceptable WtE solutions.

In conclusion, this review demonstrated that although ML offers substantial potential for advancing WtE systems, its transformative impact depends on the ability of researchers and practitioners to move beyond purely technical objectives. By identifying both the achievements and limitations of current research, this study provides a foundation for developing a more coherent, inclusive, and sustainability-oriented trajectory for ML-supported WtE development.

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