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Explainable AI Framework for Optimizing Urban Waste Management Toward Sustainable Smart Cities

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ABSTRACT

Rapid urbanization and increasing waste generation have created significant challenges for urban waste management, particularly in improving collection efficiency, waste classification, recycling, and environmental monitoring. Although Artificial Intelligence (AI) offers promising solutions, the lack of transparency in AI-driven decisions may reduce stakeholder trust and limit its broader implementation. **This study aims** to develop an Explainable Artificial Intelligence (XAI) framework for optimizing urban waste management and supporting environmental resilience and sustainable smart cities. **This study employs** a conceptual framework development approach by integrating AI-based waste prediction, automated waste classification, collection route optimization, and environmental monitoring with explainability mechanisms. The framework emphasizes transparent and interpretable AI-generated recommendations for supporting stakeholder decision-making. **The proposed framework** indicates that XAI can improve operational efficiency, optimize resource allocation, support recycling processes, and enhance the transparency of waste management decisions. Explainable insights also enable governments, waste management operators, and communities to better understand and evaluate AI-based recommendations. **Integrating XAI** into urban waste management can create a more intelligent, transparent, and adaptive system. The proposed framework contributes to environmental resilience and supports the transition toward sustainable and data-driven smart cities.

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1. INTRODUCTION

Rapid urbanization, population growth, and changing consumption patterns have significantly increased the volume and complexity of municipal waste generated in urban areas [1]. The growing amount of waste creates substantial challenges related to collection, transportation, sorting, recycling, treatment, and final disposal. When these processes are managed inefficiently, they can contribute to environmental pollution, excessive resource consumption, greenhouse gas emissions, and declining urban environmental quality [2]. These challenges highlight the importance of developing more efficient and sustainable waste management

systems that can respond to dynamic urban conditions. This issue is closely related to the Sustainable Development Goals (SDGs), particularly SDG 11, which promotes sustainable cities and communities, and SDG 12, which emphasizes responsible consumption and production through waste reduction, recycling, reuse, and efficient resource utilization [3].

The advancement of AI has created new opportunities for improving urban waste management through waste generation prediction, automated waste classification, optimized collection routes, real time monitoring, and data driven resource allocation [4]. By processing large volumes of data from sensors, waste collection systems, and urban infrastructure, AI can support faster and more adaptive decision making. However, the increasing use of AI also presents challenges related to transparency and accountability [5]. Many AI models operate as black box systems, making their predictions and recommendations difficult for governments, waste management operators, and communities to understand and evaluate. This lack of interpretability may reduce stakeholder trust and limit the effective adoption of AI based systems [6]. Therefore, XAI is increasingly important because it can provide transparent and interpretable insights into how AI systems generate predictions and recommendations.

Accordingly, this study proposes an explainable AI framework for optimizing urban waste management toward environmental resilience and sustainable smart cities [7]. The proposed framework integrates AI based waste prediction, intelligent classification, collection optimization, environmental monitoring, and explainability mechanisms to support transparent and accountable decision making. Beyond improving operational efficiency, the framework is expected to strengthen collaboration among governments, waste management operators, communities, and other relevant stakeholders by making AI generated insights easier to understand and evaluate [8]. This study contributes primarily to SDG 11 by supporting sustainable and resilient urban management, SDG 12 by encouraging efficient resource use and improved waste management practices, and SDG 13 by supporting efforts to reduce the environmental and climate impacts associated with inefficient waste systems [9]. By integrating AI capabilities with explainability, this study provides a foundation for developing urban waste management systems that are more intelligent, transparent, adaptive, and environmentally resilient while supporting the broader transition toward sustainable smart cities [10].

2. LITERATURE REVIEW

Urban waste management has become an important area of research due to increasing waste generation and the growing complexity of urban environments. Conventional waste management systems often face limitations in predicting waste generation, monitoring waste conditions, optimizing collection activities, and improving recycling processes [11]. Previous studies have demonstrated that AI can address these challenges through predictive analytics, intelligent waste classification, smart monitoring, and route optimization. AI technologies can improve operational efficiency and support more responsive waste management systems, particularly when integrated with sensors, internet of things technologies, and urban data infrastructures [12].

Despite these developments, the implementation of AI in waste management still faces several challenges. Existing studies frequently focus on specific applications, such as waste forecasting, waste sorting, smart bins, or vehicle routing, rather than developing an integrated approach across the broader waste management process [13]. In addition, data quality, system scalability, infrastructure readiness, and governance remain important barriers to practical implementation. Another significant limitation is the black box nature of many AI models, where the process underlying predictions and recommendations is difficult for users and decision makers to understand [14]. This lack of transparency may affect trust, accountability, and the willingness of stakeholders to adopt AI supported waste management systems.

XAI provides a potential approach to address these limitations by improving the interpretability and transparency of AI generated decisions [15, 16]. Through explainability mechanisms, stakeholders can better understand the factors influencing predictions, classifications, and optimization recommendations, allowing AI systems to function not only as automated technologies but also as transparent decision support tools [17]. However, the integration of explainability with a comprehensive urban waste management framework remains limited within existing research. Therefore, this study develops an explainable AI framework that integrates waste prediction, classification, collection optimization, environmental monitoring, and transparent decision making [18]. This approach is expected to strengthen environmental resilience while supporting the development of sustainable and intelligent smart cities.

3. RESEARCH METHOD

This study employed a structured conceptual approach to develop an explainable AI framework for urban waste management. The research process involved literature analysis, identification of key dimensions, framework development, and conceptual validation to establish the relationships among AI capabilities, explainability, stakeholder decision making, and sustainability outcomes.

3.1. Research Design

This study employed a conceptual framework development approach supported by a structured literature analysis [19]. The research was designed to identify the major challenges, technological applications, and transparency issues associated with AI in urban waste management [20, 21]. The analysis focused on understanding how AI can support different stages of waste management, including waste generation prediction, waste classification, collection optimization, recycling, environmental monitoring, and decision making.

The conceptual development process was selected because the existing literature has extensively discussed individual applications of AI in waste management, while the integration of explainability, environmental resilience, and sustainable smart city objectives remains fragmented [22]. Therefore, this study synthesized relevant concepts and findings to establish relationships among AI capabilities, explainability mechanisms, stakeholder decision making, and sustainability outcomes. The resulting framework was designed as an integrative model rather than as a technical comparison of individual algorithms [23].

3.2. Literature Identification and Selection

Relevant literature was identified through a structured search of academic publications related to AI, explainable AI, urban waste management, environmental resilience, and sustainable smart cities [24]. The search focused on studies examining AI applications in waste prediction, classification, monitoring, collection, routing, recycling, and environmental management. Potentially relevant publications were initially identified and subsequently screened based on their titles, abstracts, and full text content [25]. Studies that focused on unrelated technological applications or lacked sufficient relevance to urban waste management and explainability were excluded. The selected publications were then analyzed based on their conceptual relevance, methodological contribution, technological capabilities, implementation challenges, and identified research gaps [26]. This process provided the theoretical and conceptual foundation for developing the proposed explainable AI framework.

Table 1. Literature Analysis Dimensions

Dimension	Focus of analysis	Contribution to framework
Waste prediction	Estimation of waste volume and generation patterns	Supports planning and resource allocation
Waste classification	Identification and sorting of waste categories	Improves recycling and treatment processes
Collection optimization	Route and schedule optimization	Improves operational efficiency
Environmental monitoring	Monitoring of waste conditions and environmental impacts	Supports adaptive management
Explainability	Interpretation of AI predictions and recommendations	Improves transparency and trust
Sustainability outcomes	Environmental resilience and sustainable urban development	Connects technological outcomes with SDGs

Table 1 presents the main analytical dimensions used to examine the selected literature and establish the foundation for framework development. These dimensions connect specific AI applications with explainability requirements and broader sustainability outcomes while providing a structured basis for identifying how individual technological capabilities can be integrated within a comprehensive urban waste management framework [27]. Rather than examining each AI application independently, the analysis considers the relationship between operational functions, transparent decision making, stakeholder involvement, and environmental sustainability, enabling the proposed framework to address both technological performance and the broader requirements of sustainable smart city development [28].

3.3. Framework development

The proposed framework was developed through a synthesis of the key dimensions identified during the literature analysis, beginning with the identification of major input elements required for intelligent urban waste management, including waste generation data, environmental information, sensor data, collection records, and relevant urban infrastructure data [29, 30]. These inputs enable AI to generate predictions, classifications, and optimization recommendations across different waste management functions, including waste prediction, classification, collection optimization, and environmental monitoring [31]. The framework subsequently integrates explainability mechanisms to provide understandable interpretations of AI generated outputs, enabling decision makers and other stakeholders to evaluate the factors influencing recommendations and supporting more transparent, accountable, and informed decision making [32].

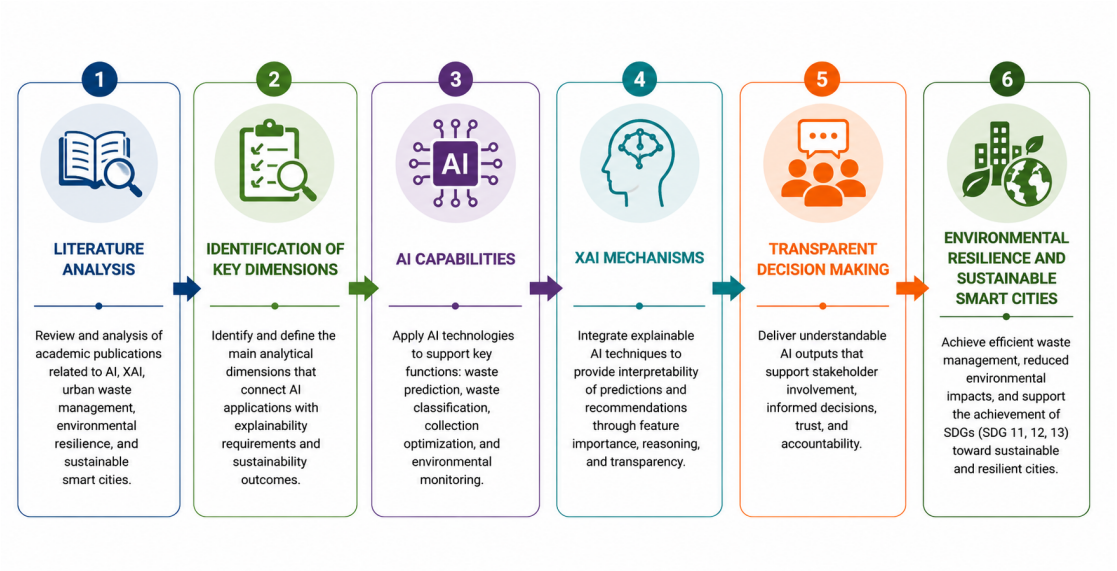


Figure 1. Research Framework Development Process

Figure 1 illustrates the overall process used to develop the proposed framework. The process begins with the analysis of relevant literature and the identification of key dimensions associated with urban waste management [33]. These dimensions are then integrated into AI capabilities and XAI mechanisms to create a transparent decision support process. The final outcomes of the framework emphasize environmental resilience and sustainable smart city development [34]. This structure demonstrates that explainability is positioned as an essential component that connects AI generated insights with stakeholder understanding and decision making, rather than functioning as an isolated technological feature.

3.4. Framework validation and expected outcomes

The proposed framework was evaluated through conceptual validation based on its consistency with the major findings and challenges identified in the literature [35]. The validation focused on whether the framework adequately integrated the key functions of urban waste management with explainability, transparency, stakeholder decision making, and sustainability objectives [36]. This process ensured that the proposed relationships among the framework components were theoretically supported by existing knowledge in the fields of AI, waste management, and sustainable urban development.

The expected outcomes include a comprehensive framework that can guide future research and practical implementation of explainable AI in urban waste management [37]. The framework is expected to support more efficient resource allocation, improved waste collection and classification, enhanced transparency of AI generated recommendations, and stronger stakeholder trust. In addition, the framework is aligned with SDG 11 through sustainable urban management, SDG 12 through improved resource efficiency and waste management, and SDG 13 through the reduction of environmental impacts associated with inefficient urban waste systems [38].

4. RESULT AND DISCUSSION

The findings reveal several key dimensions that shape the development of an explainable AI framework for urban waste management. The results highlight the integration of AI capabilities, explainability, and sustainability considerations to support more efficient, transparent, and adaptive waste management practices.

4.1. Key dimensions of intelligent urban waste management

The literature analysis identified six key dimensions that form the foundation of the proposed framework, namely waste prediction, waste classification, collection optimization, environmental monitoring, explainability, and sustainability outcomes [39]. These dimensions represent interconnected functions within urban waste management, where each dimension contributes to improving the efficiency, responsiveness, and sustainability of waste related activities. Waste prediction supports the estimation of future waste generation, while waste classification facilitates the identification and separation of waste according to its characteristics. Collection optimization contributes to more efficient transportation and resource allocation, whereas environmental monitoring provides continuous information regarding waste conditions and environmental impacts [40].

The identified dimensions demonstrate that intelligent urban waste management requires an integrated approach rather than the implementation of isolated technological applications. The combination of operational capabilities with explainability and sustainability considerations allows AI to support not only waste management efficiency but also transparent and responsible decision making. Based on this analysis, the relationship among the identified dimensions provides the foundation for integrating AI capabilities with XAI mechanisms and sustainability objectives within the proposed framework [41].

Table 2. Key Dimensions of Intelligent Urban Waste Management

Dimension	Primary function	Expected outcome
Waste prediction	Estimate waste generation patterns	Improved planning
Waste classification	Identify waste categories	Improved sorting and recycling
Collection optimization	Optimize routes and schedules	Higher operational efficiency
Environmental monitoring	Monitor waste and environmental conditions	Adaptive management
Explainability	Interpret AI predictions and recommendations	Transparency and stakeholder trust
Sustainability outcomes	Support environmental and urban sustainability	Environmental resilience

Table 2 summarizes the relationship between the main dimensions identified through the literature analysis, their primary functions, and their expected outcomes. The table demonstrates that each dimension addresses a specific requirement of urban waste management while contributing to a broader integrated system. The inclusion of explainability and sustainability outcomes also demonstrates that the proposed framework considers both technological and environmental requirements.

4.2. Integration of AI capabilities

The proposed framework integrates AI as the primary analytical component for processing information generated from urban waste management activities. AI capabilities can support waste prediction by identifying patterns in historical and current waste generation data, while classification techniques can assist in recognizing different waste categories [42]. AI can also optimize collection routes and schedules by considering factors such as waste volume, collection locations, traffic conditions, and available resources. Furthermore, environmental monitoring can utilize AI to analyze information from sensors and other urban data sources to identify changing environmental conditions.

The integration of these capabilities enables waste management systems to move from conventional reactive processes toward more adaptive and data informed management. Instead of relying solely on fixed schedules or manual assessments, decision makers can use AI generated insights to anticipate waste generation, prioritize collection activities, improve resource allocation, and identify potential environmental risks [43]. However, these capabilities also increase the importance of understanding how AI produces its outputs.

Therefore, the framework incorporates XAI mechanisms to ensure that AI supported recommendations can be interpreted and evaluated by relevant stakeholders.

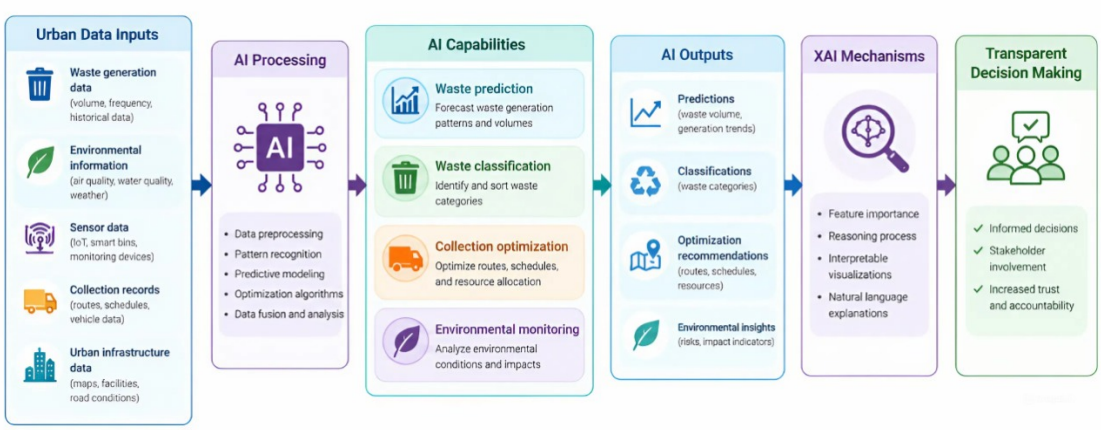


Figure 2. AI capabilities in urban waste management

Figure 2 illustrates how AI capabilities are integrated into the proposed urban waste management system. Various data sources are processed through AI techniques to generate predictions, classifications, optimization recommendations, and environmental insights. The resulting outputs are subsequently connected with XAI mechanisms to improve their interpretability before being used as decision support for relevant stakeholders. This structure emphasizes that AI functions as an analytical component, while XAI facilitates the transition from complex computational outputs to understandable decision support.

4.3. The role of explainable AI in transparent decision making

A central finding of the proposed framework is that XAI plays an important role in connecting AI generated outputs with stakeholder understanding. Conventional AI systems can provide predictions and recommendations for various urban waste management activities, but the reasoning behind these outputs may be difficult for users to interpret. XAI addresses this limitation by providing understandable information about the factors, patterns, and features that influence AI outputs. In urban waste management, these explanations can help stakeholders understand the reasons behind waste generation predictions, waste classifications, collection route recommendations, and environmental assessments. This interpretability allows AI outputs to become more meaningful and useful for stakeholders who may not have advanced technical knowledge [44].

The integration of XAI also strengthens transparency and accountability in AI supported decision making. Governments, waste management operators, communities, and other stakeholders can evaluate AI recommendations more effectively when the underlying reasoning is clearly presented and understandable. Greater interpretability can increase confidence in AI systems and support more responsible adoption within urban waste management practices [45]. Therefore, explainability in the proposed framework is positioned not as an independent technological component, but as a connecting mechanism between AI capabilities, human interpretation, stakeholder participation, and accountable decision making. This integration supports the development of waste management systems that are not only intelligent and efficient but also transparent, trustworthy, and aligned with sustainable urban development.

4.4. Environmental resilience and sustainable smart city outcomes

The integration of AI and XAI within urban waste management provides several potential outcomes for improving environmental resilience, operational efficiency, and the adaptability of urban waste systems. More accurate waste prediction can support better planning and resource allocation by enabling waste management operators to anticipate changes in waste generation and adjust operational capacity accordingly [46]. Intelligent waste classification can improve the identification and separation of waste materials, supporting more effective sorting, recycling, and material recovery processes. Collection optimization can improve transportation efficiency by supporting the selection of appropriate routes and schedules while reducing unnecessary travel, fuel consumption, and operational costs. Meanwhile, environmental monitoring can continuously analyze waste conditions and relevant environmental information to identify potential risks and changes in urban

conditions at an earlier stage. The integration of these capabilities enables different waste management activities to operate as interconnected functions rather than isolated processes, allowing information generated from one function to support decisions in another [47]. Consequently, the proposed framework can enhance the ability of urban waste management systems to respond to changing waste volumes, environmental conditions, infrastructure limitations, and operational requirements, thereby supporting more adaptive, efficient, and environmentally resilient urban waste management.

Table 3. Expected Outcomes of the Proposed Framework

Capability	**Management function**	**Expected outcome**
Waste prediction	Waste planning	Improved planning and resource allocation
Waste classification	Waste sorting and recycling	Improved material recovery
Collection optimization	Waste transportation	Reduced unnecessary transportation
Environmental monitoring	Environmental assessment	Early identification of environmental risks
XAI	Decision support	Improved transparency and stakeholder understanding
Integrated framework	Urban waste management	Greater adaptability and environmental resilience

Table 3 summarizes the expected outcomes generated by the integration of AI and XAI capabilities within the proposed framework. Each capability contributes to a specific waste management function while producing an outcome that supports operational efficiency, environmental monitoring, transparency, or system adaptability. The table demonstrates that the framework does not focus on a single AI application, but combines several capabilities to address different requirements of urban waste management [48].

The proposed framework demonstrates that the combination of AI capabilities and explainability can extend the role of technology beyond operational automation toward more adaptive and responsible urban management. Transparent AI generated insights can support stakeholders in identifying problems, evaluating alternatives, and responding to changing environmental conditions. This integration can improve the ability of urban waste management systems to anticipate potential risks, optimize available resources, and maintain effective operations under changing circumstances [49]. Consequently, the framework provides a foundation for developing waste management systems that are more intelligent, adaptive, transparent, and resilient while supporting the long term development of sustainable smart cities.

5. MANAGERIAL IMPLICATION

The proposed framework provides several implications for managers and decision makers involved in urban waste management. Managers can utilize AI capabilities to improve operational planning by integrating waste generation data, collection records, sensor information, environmental conditions, and urban infrastructure data. Waste prediction can help managers anticipate changes in waste volume and determine appropriate resource requirements, while collection optimization can support more efficient route and schedule planning. The integration of these capabilities can reduce inefficient resource utilization and enable managers to make decisions based on timely and comprehensive information rather than relying primarily on conventional procedures.

The framework also highlights the importance of explainability when implementing AI within urban waste management operations. Managers should not focus only on the predictive performance of AI systems but also consider whether the resulting recommendations can be understood and evaluated by their users. By incorporating XAI mechanisms, managers can obtain clearer explanations of the factors influencing waste predictions, classifications, collection recommendations, and environmental assessments. This can support greater transparency and accountability while helping operational staff and other stakeholders understand the basis of AI supported decisions. Organizations should therefore establish appropriate processes for reviewing AI outputs and explanations before they are incorporated into operational decisions.

From a strategic perspective, managers can use the proposed framework as a foundation for devel-

oping more adaptive and resilient waste management systems. The integration of AI, XAI, environmental monitoring, and stakeholder involvement can support continuous improvement by allowing managers to identify operational problems, evaluate alternative actions, and respond to changing urban conditions. Successful implementation also requires adequate data infrastructure, staff capabilities, system integration, and organizational readiness. By balancing technological capabilities with human oversight and transparent decision making, managers can improve operational efficiency while developing waste management practices that are more responsive, accountable, and aligned with the long term sustainability of urban environments.

6. CONCLUSION

This study developed an explainable AI framework for optimizing urban waste management toward environmental resilience and sustainable smart cities. The findings indicate that the integration of waste prediction, waste classification, collection optimization, and environmental monitoring can strengthen the efficiency, adaptability, and responsiveness of urban waste management systems. The framework also demonstrates that explainable AI can improve the interpretation of AI outputs by providing understandable information regarding the factors and patterns underlying predictions and recommendations. Through this integration, AI capabilities can support operational planning while XAI strengthens transparency, stakeholder understanding, and accountable decision making.

The main novelty of this study lies in the integration of AI capabilities and XAI mechanisms into a unified framework that connects operational waste management functions with transparent decision making and environmental resilience. Rather than treating prediction, classification, collection, monitoring, and explainability as separate applications, the proposed framework positions them as interconnected components within an integrated decision support system. This perspective extends existing discussions of AI in waste management by emphasizing not only technological efficiency but also interpretability, human understanding, and responsible decision making. The proposed framework therefore provides a conceptual foundation for developing intelligent urban waste management systems that are more transparent, adaptive, and resilient.

For future research, the proposed framework can be empirically validated through implementation in different urban environments using real time waste management data. Future studies can examine the predictive performance of specific AI models, compare different XAI techniques, and evaluate the accuracy, interpretability, and usability of AI supported recommendations among managers and other stakeholders. Further research can also integrate Internet of Things sensors, geographic information systems, and real time environmental data to strengthen the framework's ability to respond to dynamic urban conditions. Such empirical validation would help determine the practical effectiveness of the framework and support its refinement toward scalable and sustainable smart city applications.

7. DECLARATIONS

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7.2. Author Contributions

Conceptualization: QA; Methodology: NA; Software: DA; Validation: AD and QA; Formal Analysis: NA and DA; Investigation: AD; Resources: QA; Data Curation: NA; Writing Original Draft Preparation: DA and AD; Writing Review and Editing: QA and NA; Visualization: DA; All authors, DA, QA, NA and AD have read and agreed to the published version of the manuscript.

7.3. Data Availability Statement

In line with our commitment to research transparency, the dataset underlying this study has been archived in the Zenodo Repository https://doi.org/10.5281/zenodo.22703733.

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7.5. Declaration of Conflicting Interest

The authors declare that they have no conflicts of interest, known competing financial interests, or personal relationships that could have influenced the work reported in this paper.

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