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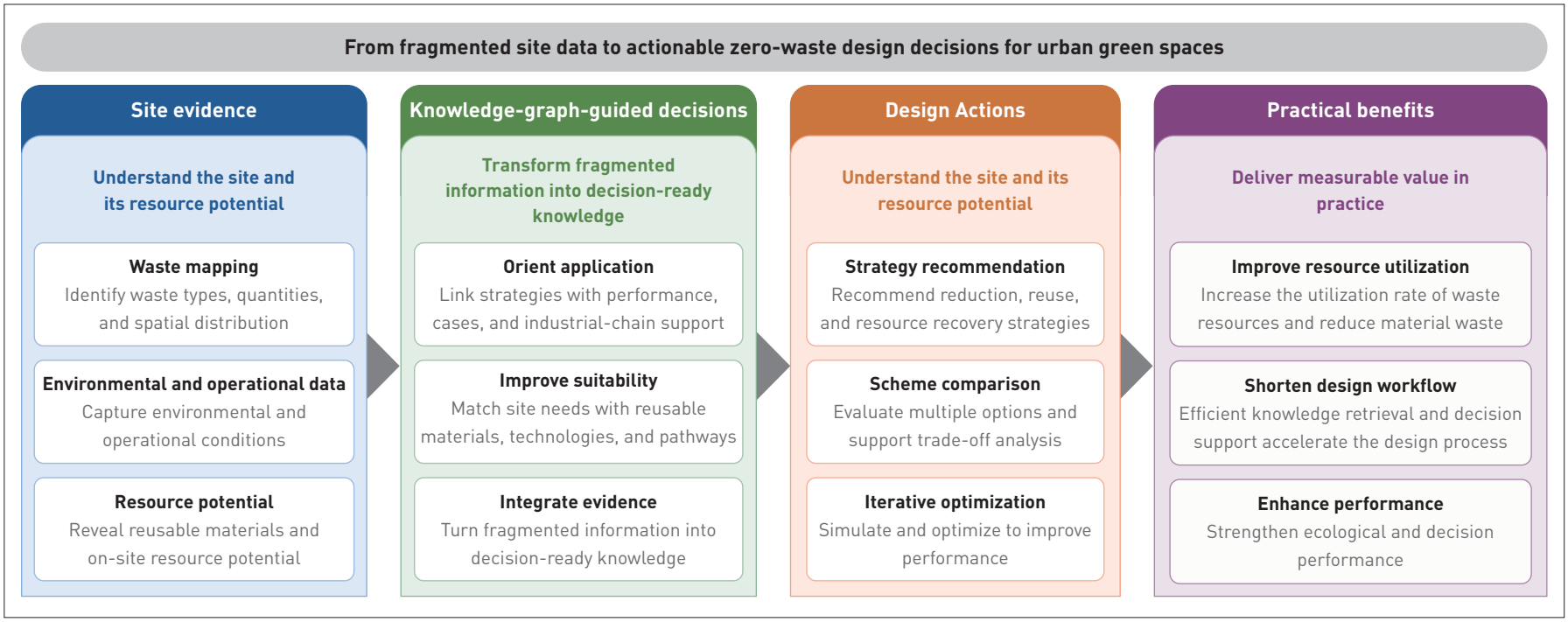
Knowledge-Graph Intelligent Auxiliary Decision-Making Tool for Zero-Waste Design of Urban Green Spaces Based on Multi-Source Sensing Data

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GRAPHICAL ABSTRACT



ABSTRACT

Urban green space zero-waste design faces challenges such as insufficient lifecycle waste reduction, inefficient interdisciplinary knowledge integration, disconnection between site data and design decision-making, and over-reliance on individual experience in design schemes. Traditional experience-driven design models are increasingly inadequate to support the demands for refined and intelligent transformation. To address these issues, this study proposes a Perception–Knowledge–Decision-Making framework driven by multi-source sensing data for the zero-waste design of urban green spaces. The framework collects multidimensional site data through drone imaging sensors, environmental sensors, and laser scanning technology. The study constructs a knowledge graph that semantically links four core entities: strategy, performance, case, and industrial-chain information. Stored in the Neo4j graph database, it enables dynamic knowledge association and efficient retrieval. An intelligent auxiliary decision-making tool is

developed by combining knowledge graph-enhanced retrieval and intelligent agent technologies, thereby improving the capabilities for identifying, reasoning, and matching strategies for complex design problems. A simulation-based case study at a community garden in Shanghai was conducted to demonstrate the feasibility of the proposed framework, revealing its potential to improve waste resource utilization matching, design efficiency, and resource utilization effectiveness. This study presents a proof-of-concept framework and provides a theoretical pathway and methodological exploration for sustainable landscape design supported by cutting-edge sensing technologies.

KEYWORDS

Urban Green Space; Knowledge Graph; Zero-Waste Design; Design Assistance; Intelligent Tool; Sensing Technology

HIGHLIGHTS

- Proposes a Perception–Knowledge–Decision-Making framework for urban green space zero-waste design
- Constructs a knowledge graph linking strategy, performance, case, and industrial-chain information
- Develops a GraphRAG-augmented intelligent agent for zero-waste strategy matching and design support

RESEARCH FUND

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1 Introduction

"Zero-waste design" can be understood as a design methodology that, from a full-lifecycle perspective, emphasizes waste reduction, resource circulation, and the improvement of ecological performance[1]. The construction of zero-waste cities represents a significant advance in China's ecological civilization development and serves as a promising direction for urban renewal[2]. As a vital component of urban ecosystems, green spaces integrate ecological regulation, safety protection, and spatial governance[3–4]. However, the construction and maintenance of green spaces generate increasing amounts of concrete fragments, discarded wood, and garden waste. Traditional management models still rely on end-of-pipe treatment methods such as landfilling and incineration, lacking full-lifecycle waste reduction and resource-oriented design strategies. The design decision-making approach remains singular and limited, resulting in low resource efficiency[5]. This not only exacerbates environmental pressures but also undermines the sustainable benefits of green spaces.

It is accurately against this backdrop that zero-waste design for urban green spaces has evolved beyond merely optimizing material substitution or end-of-pipe disposal, becoming a systemic issue involving full lifecycle management, multi-stakeholder collaboration, and data-driven decision-making. However, a significant disconnect persists between current design practices and technological means: site data collection, knowledge integration, and design decision-making have yet to form a traceable, inferable, and feedback-responsive closed-loop system. Zero-waste design for urban green spaces requires multi-agent collaboration across the lifecycle. Designers must integrate interdisciplinary knowledge from materials science, ecology, economics, and arts to optimize design strategies throughout the project lifecycle—yet are constrained by individual experience and knowledge barriers, making it difficult to efficiently address complex demands[6]. Moreover, community managers rely on traditional end-of-pipe treatment models, lacking emphasis on reduction strategies during the design phase, which leads to low resource efficiency[5]. Community residents have heightened expectations for green space functionality and well-being, while improper waste handling can undermine spatial experiences. The issues can be summarized into four core challenges. First, highly fragmented interdisciplinary knowledge makes it difficult for designers to apply efficiently[7]. Second, feedback from operation and maintenance to design decision-making remains insufficient, limiting the formation of a continuous closed-loop process. Third, the assessment of on-site waste distribution and resource reuse potential lacks precise data support[8–9]. Fourth, traditional experience-based decision-making struggles to achieve multi-objective collaborative optimization.

Recent advances in sensing technologies offer solutions. Drone imaging, environmental sensors, and LiDAR efficiently collect 3D point clouds, environmental parameters, and waste distribution data. Internet of Things (IoT)-enabled smart bins, equipped with built-in sensors, can monitor fill levels in real time and

transmit data to cloud platforms via communication networks, providing dynamic data for optimizing resource allocation and waste management[9–10]. Technologies such as image recognition and machine learning automate the identification and sorting of solid waste, significantly improving the accuracy and efficiency of waste processing[11]. The integration of these technologies with Artificial Intelligence (AI) further strengthens data analytics to support evidence-based decision-making[12]. Building on this, Zhonglong Chang and Yanqing Chang[13] constructed intelligent sorting via waste recovery data and big-data platforms. Teng Pan's team[14] developed an IoT-based hazardous waste tracking system, and a smart hazardous waste supervision platform for lifecycle monitoring has been created in Xuzhou, China[15]. These technologies form a comprehensive framework spanning data acquisition, processing, and management. However, massive data alone does not equate to usable knowledge. The point clouds, images, sensor records, and operational logs generated by multi-source sensing, if lacking unified semantic organization and structural representation, are difficult to directly support design decisions. Therefore, between the perception layer and the decision-making layer, it is necessary to construct an intermediary layer capable of completing "data semantic annotation—knowledge structuring—relationship networking," and the knowledge graph is a key technological pathway for achieving this transformation. Massive amounts of multidimensional data from sensing technologies underpin knowledge graphs, which structure information and enable intelligent reasoning to support zero-waste design, helping designers transcend cognitive boundaries and enhancing scientific decision-making for complex systems[16]. The application of knowledge graph-based intelligent decision support technology has achieved successful implementation in fields such as contaminated site management[17], meteorological simulation[18], and corporate sustainability[19].

However, current research predominantly focuses on the macro-management level, with insufficient attention paid to knowledge sharing and decision support for design practice. The construction of knowledge bases specifically for the zero-waste design of urban green spaces has not yet been reported[5,20]. Furthermore, existing research confirms that large language models (LLMs) can efficiently achieve precise extraction of structured information and entity relationships from scientific texts[21]. GraphRAG (Graph Retrieval-Augmented Generation) can accomplish multi-step reasoning and precise integration of complex knowledge through dynamic intelligent agents and adaptive retrieval strategies[22]. Generative AI has also demonstrated significant application value in decision support, multi-source data fusion, and multi-objective optimization throughout the urban design process[23–24]. These technological advancements crucially facilitate the construction of interdisciplinary knowledge integration and intelligent decision support system for the zero-waste design of urban green spaces.

How to intelligently and efficiently acquire multidimensional site data for dynamic sensing and monitoring and construct a scientific and AI-auxiliary decision-making system for the zero-waste design of urban green spaces has become a key research issue. Driven by multi-source sensing data and enhanced by knowledge graph technology, this study constructs a Perception–Knowledge–Decision-Making framework which links site perception, knowledge organization, and intelligent decision support within a single workflow, with particular emphasis on knowledge-graph-centered strategy association and decision support for zero-waste design.

2 Perception–Knowledge–Decision-Making Framework for Zero-Waste Design

To address the complex systemic requirements of zero-waste design in urban green spaces, this study constructs a Perception–Knowledge–Decision-Making framework (Fig. 1) through full-lifecycle feedback, which comprises three layers: the Perception Layer, the Knowledge Layer, and the Decision-Making Layer. These three layers are not parallel but rather follow a progressive logic from multi-source site data perception to knowledge organization and finally to intelligent decision-making support.

2.1 Perception Layer: Multi-Source Data Perception and Site Information Mapping

To construct a multi-source sensing system for the full lifecycle of zero-waste design in urban green spaces, high-precision and dynamic acquisition of comprehensive site data is achieved through four modules: 1) aerial and oblique photogrammetry image data of the site collected by drone imaging sensors; 2) 3D point cloud data of the site collected by LiDAR laser scanning systems; 3) dynamic time-series monitoring data of the site collected by environmental IoT sensor networks; and 4) operational and maintenance ledger data covering the entire site lifecycle. This enables high-precision and dynamic data collection on the spatial distribution and resource characteristics of site waste, ecological environmental parameters, spatial physical attributes, and operational performance.

To process the collected raw data, this study overcomes the

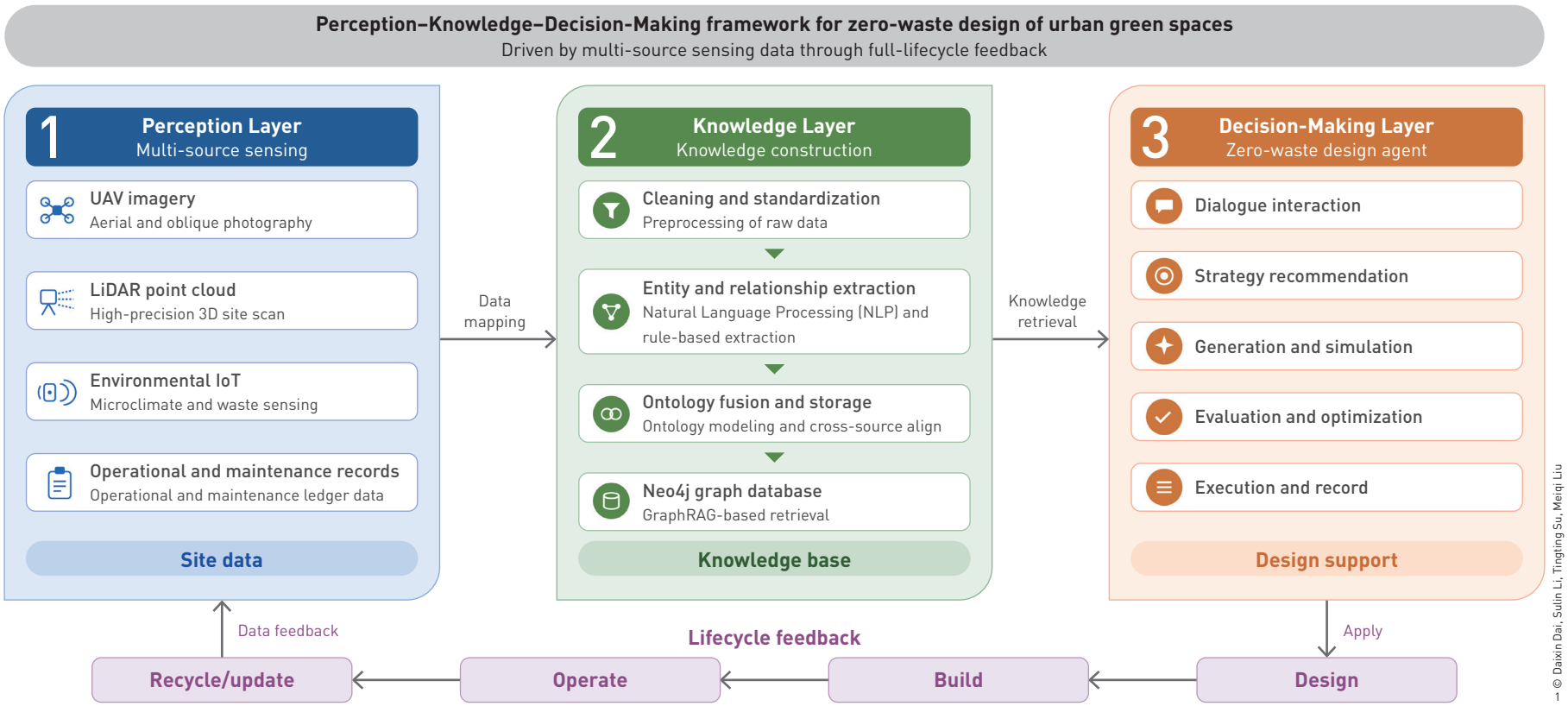


Fig. 1 Perception–Knowledge–Decision-Making framework for zero-waste design of urban green spaces.

technical limitations of traditional rule-based extraction and independent discriminative models. Based on the generative information extraction paradigm of the LLaMA 3 LLM[25], it completes the conversion of unstructured data into structured data through standardized preprocessing and semantic extraction processes, providing a normalized and unified input foundation for subsequent knowledge graph mapping. For domain-specific raw data, Python-based rules and regular expressions are further used for automated cleaning and standardized organization of entity instances. According to the characteristics of different data types, adapted technical pathways are employed to complete the structural conversion. For spatial data obtained from drone imagery and LiDAR laser scanning, Pix4Dmapper is used for image stitching and site 3D modeling, while CloudCompare is relied upon for point cloud data denoising, registration, and volume calculation. Simultaneously, the YOLO (You Only Look Once) deep learning algorithm is integrated to complete computer vision object detection, achieving automated identification and quantitative extraction of key features such as on-site solid waste type, spatial distribution, and volume. For unstructured textual data such as maintenance ledgers, a unified generative framework is used to perform end-to-end extraction of entities, attributes, and structured records.

Based on the structured dataset processed through the above standardization, a mapping route of "structured data → generative semantic extraction → entity nodes" is constructed, through which the system aligns core site elements from the structured dataset one-to-one with the conceptual framework defined by the domain ontology, transforming the standardized and extracted entities, attributes, and relationships into corresponding entity nodes, attribute fields, and relationship edges in the knowledge graph. After mapping, they are uniformly written into the Knowledge Layer, where the knowledge graph is instantiated and indexed. The foundational steps of the knowledge mapping process, such as data ingestion, standardized preprocessing, and graph database entry, are fully automated. For the core steps of knowledge transformation and association, a strategy of "LLM generative extraction as the main method, supplemented by manual review" is adopted. Manual verification and correction permissions are only opened for low-confidence entity alignments, relationship generation results, and anomalous samples. Designers can adjust the mapping results according to actual site conditions. Through this process, not only

can the precise pre-assessment of site waste resource potential be completed in the early design phase, establishing a real-time correspondence between design strategies and implementation performance, but a design closed-loop can also be formed through continuous feedback from full-cycle operational data, providing a solid and traceable data foundation for subsequent knowledge graph construction and intelligent decision-making output.

This study explicitly defines the workflow and knowledge mapping rules for multi-source sensing data. Drawing on entity–relationship modeling, this study organizes knowledge graph mapping outputs using an entity–relationship–attribute (ERA) structure, in which entities represent domain objects, relationships describe semantic associations between entities, and attributes characterize entity properties[26]. Table 1 specifically summarizes how such data are standardized and mapped from the Perception Layer into the Knowledge Layer.

2.2 Knowledge Layer: Construction of the Knowledge Graph

If the Perception Layer addresses the issue of "seeing the site," then the Knowledge Layer addresses the issue of "understanding the site." The former provides physical data, while the latter endows the data with semantics and associative structures, transforming it into knowledge units that can be reasoned upon, retrieved, and reorganized. Building on the ERA structure, this study develops the ontology design around the key tasks of the full-lifecycle and the theoretical framework proposed in the team's prior research[6], which links design requirements, prototypes, industrial chains and implementation pathways within a unified knowledge representation model. Leveraging design planning and parametric construction systems achieves synergy between waste reduction and landscape functionality.

On this basis, the Knowledge Layer organizes zero-waste design knowledge into a structured semantic network that enables dynamic associations between design elements. Using the ERA structure as the fundamental unit for technological innovation in zero-waste city construction[27], this theoretical framework for entity construction in the urban green space zero-waste design knowledge graph is established. Within this framework, the knowledge graph ontology is structured into three core components: hierarchical relationships, semantic relationships, and entity attributes. Adopting a dual logic of top-down ontology design and bottom-up knowledge graph implementation, zero-waste design information is mapped onto the ontology through entity identification and mapping, relationship extraction, and attribute extraction, followed by knowledge integration and association and storage in the Neo4j graph database (Fig. 2), where

Table 1: The workflow and mapping rules from the Perception Layer into the Knowledge Layer

Raw data format	Processing step	Semantic extraction method	Knowledge graph mapping output
Remote sensing aerial imagery; surveillance video	Denoising and filtering, geometric correction, and coordinate system unification	Object detection; instance segmentation; LLM-based semantic completion	· Entities: building, waste yard, recovery resource station · Relationships: recovery station → serves → surrounding waste generation area · Attributes: spatial coordinates, footprint area
LiDAR point clouds; topographic scanning data	Denoising and registration, elevation normalization, and invalid point removal	3D semantic segmentation; storage capacity calculation	· Entities: urban green space, resource recovery facility · Relationships: site → matched to → local resource recovery facility · Attributes: precise volume, waste inventory, site elevation, available capacity
IoT metering; monitoring time-series data	Outlier removal, missing value imputation, and time-series alignment	Time-series feature extraction; LLM-based anomaly event identification	· Entities: metering device, waste generation unit · Relationships: monitoring point → monitors → real-time waste yard environmental indicators · Attributes: waste generation amount, resource recovery rate
Waste generation reports; transfer and disposal ledgers	Format standardization, deduplication and cleaning, and field normalization	LLM-based generative information extraction	· Entities: waste generator/disposal enterprise, waste category · Relationships: disposal enterprise → provides resource recovery treatment for → solid waste · Attributes: enterprise qualification, waste treatment pathway

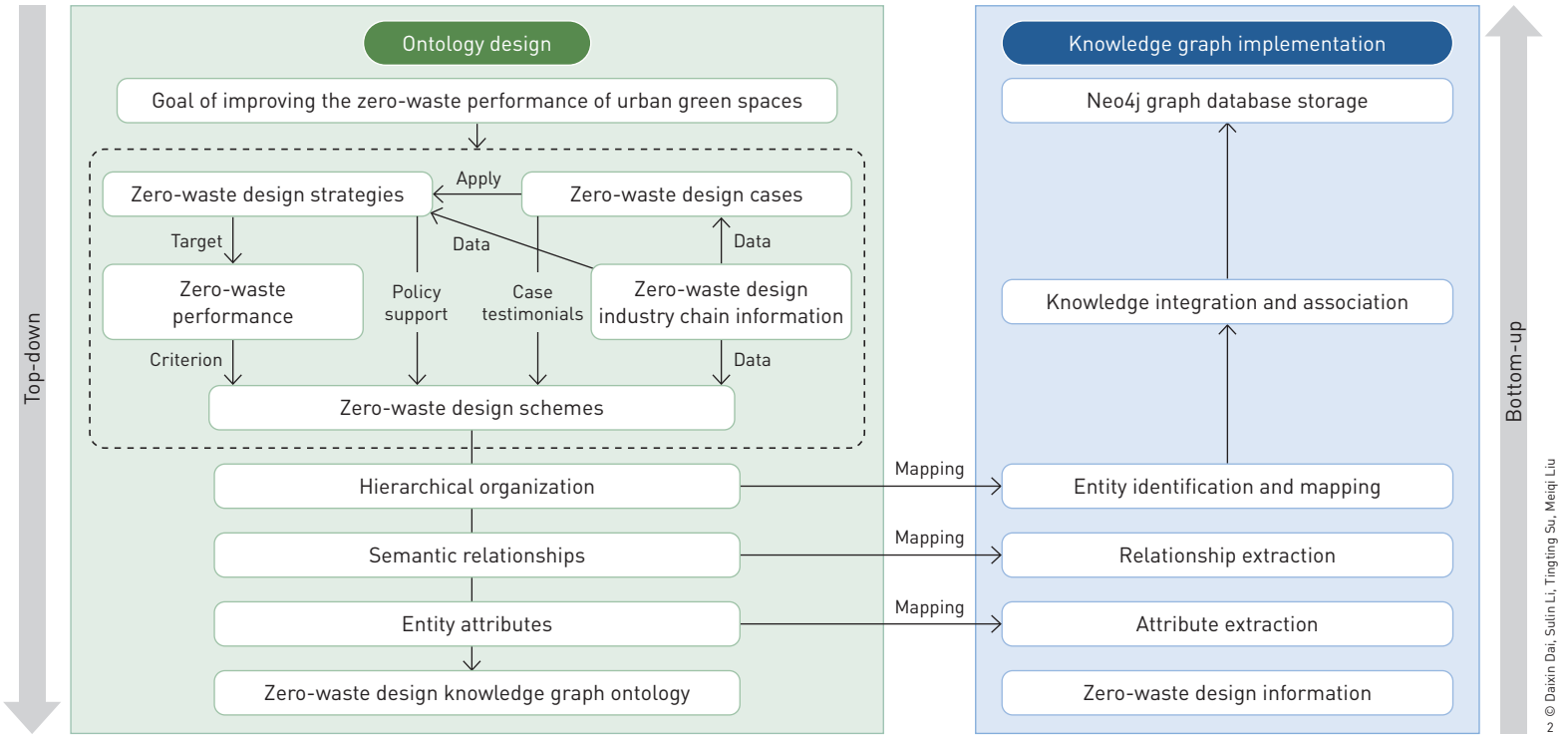


Fig. 2 The entity construction of knowledge graphs for the zero-waste design of urban green spaces.

the relationships between zero-waste design strategies and efficacy enhancement and the core entities are clarified.

The entities can be classified into four types: zero-waste performance, zero-waste design strategies, zero-waste cases, and industrial-chain information. For zero-waste performance, three sub-entities—reduction, recovery, and harmlessness—represent the objectives and criteria of zero-waste design. Zero-waste design strategies are hierarchically refined from a full-lifecycle perspective. The case studies correspond to specific strategies and include attributes such as location, construction time, and construction entity. Industrial-chain information encompasses secondary entities such as zero-waste enterprises, technologies, and products, providing data support for design strategies (Fig. 3). The knowledge graph is stored using the industry-standard Neo4j graph database, employing the Cypher query language to achieve efficient retrieval of complex graph structures and the Py2neo tool to complete the batch import of entity nodes, attribute fields, and relationship edges.

The Knowledge Layer improves the support capability for the design process through graph visualization presentation and interactive retrieval services. Its core value lies in using structured semantic associations to interconnect key elements throughout the entire design lifecycle. This enables designers, when screening strategies for specific problems, to simultaneously access information such as strategy direction, performance basis, case references, and supply support within the same knowledge graph interface. Thereby, it enhances the efficiency and consistency of interdisciplinary knowledge integration and provides a stable, explainable knowledge

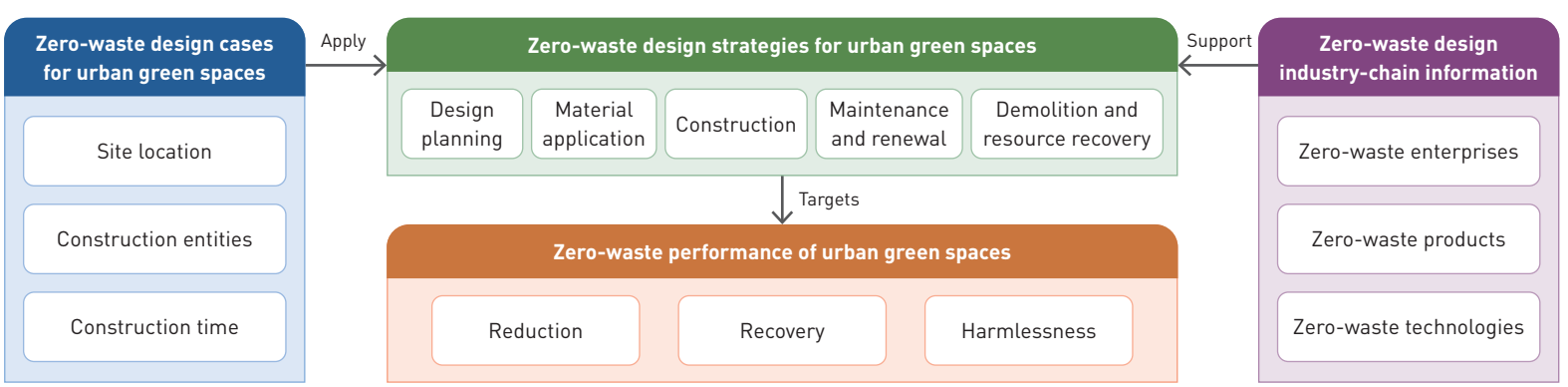


Fig. 3 Ontology design of the knowledge graph for the zero-waste design of urban green spaces.

foundation for subsequent intelligent recommendations and continuous optimization in the Decision-Making Layer.

2.3 Decision-Making Layer: Intelligent Auxiliary Decision-Making Tool

Although the knowledge graph achieves structured associations among strategies, performance, cases, and industrial-chain information, its essence remains a passive retrieval tool. To truly realize dynamic decision support within the design process, an active reasoning agent capable of understanding design tasks, integrating knowledge outcomes, and generating optimized solutions is required. Therefore, this study further constructs an intelligent agent for zero-waste design, upgrading the system from knowledge retrieval towards strategy generation and optimization. The intelligent agent operates along a task pipeline that links design demands, objectives, prototypes, and implementation paths. It adheres to the internationally recognized core architecture of "Perception–Memory–Planning–Action–Feedback" from cutting-edge agent research[28]. It integrates five functional modules—dialogue interaction, strategy recommendation, generative simulation, evaluation and optimization, and execution record—forming an active decision-making tool that covers the entire zero-waste design process.

1) The dialogue interaction module utilizes the open-source LLM ChatGLM3-6B. Leveraging its inherent natural language understanding and generation capabilities, it achieves precise parsing of design requirements and multi-turn natural language interaction, establishing a low-barrier communication channel between designers and the domain knowledge base.

2) The strategy recommendation module draws on the zero-waste design domain knowledge graph stored in the Neo4j graph database. It accomplishes knowledge recall through the GraphRAG component built into the LangChain framework, realizing strategy matching and recommendation tailored to site conditions and design objectives.

3) The generative simulation module supports the generation and simulation of candidate design schemes based on the recommended strategies, providing scheme alternatives for subsequent evaluation and optimization.

4) The evaluation and optimization module applies standardized and encapsulated Life-Cycle Assessment (LCA) models together with a multi-objective constraint scoring algorithm. Through the tool invocation capability of the LangChain framework, the module performs multi-dimensional performance calculations based on design scheme parameters and preset constraint goals, and outputs precise scheme evaluation results and targeted optimization suggestions.

5) The execution record module relies on the MySQL relational database to support decision traceability, version management, and experience accumulation throughout the entire design process.

The tool ultimately outputs standardized parametric design rules and core control indicators, which assist designers in constructing visual scheme prototypes through the Rhino + Grasshopper parametric design platform.

During the strategy-matching and scheme-optimization process, the intelligent agent performs multi-step logical reasoning using Few-shot Chain-of-Thought (CoT) prompt paradigm. Based on the actual site characteristics acquired by the Perception Layer and the associations among the four core entities in the knowledge graph, it provides designers with design strategy combinations tailored to site conditions and design objectives.

Unlike the templated recommendations of traditional tools, the intelligent agent can simultaneously consider multiple boundary conditions such as site waste characteristics, environmental parameters, economic cost constraints, and landscape functional requirements. It synchronously presents the expected performance, practical cases, and industrial-chain support information corresponding to the strategies, helping designers overcome the limitations of individual experience and knowledge barriers. Based on the recommended design strategies, the intelligent agent can integrate built-in simulation models to quantitatively assess the full-lifecycle zero-waste performance, ecological impact, and economic costs of different schemes. It then performs iterative optimization according to the core objectives set by the designer, ultimately outputting a comparable sequence of schemes and optimization suggestions that provides a basis for scheme comparison and selection.

During scheme design and implementation, the execution record module manages the entire process of the scheme generating and traces decision-making, while simultaneously storing the full-lifecycle decision data and scheme performance in the agent's long-term memory bank, providing experiential reference for subsequent design tasks of a similar type. Building on this, the intelligent agent establishes a closed-loop optimization mechanism of zero-waste design deeply interconnected with the Perception Layer and the Knowledge Layer. After a scheme is implemented, the operational feedback information collected by the Perception Layer flows back in two directions: on the one hand, it returns to the Knowledge Layer to dynamically update strategy performance, case practices, and industrial chain information; on the other hand,

it is fed back to the Decision-Making Layer to optimize the agent's strategy recommendation logic, scheme generation algorithms, and performance evaluation models. This ensures the framework continuously adapts to the technological developments and practical needs within the field of zero-waste design[29].

3 An Exploratory Application Scenario: The Yangshupu Road Community Gardening Center

Using the renovation design project of the Community Gardening Center on the Yangshupu Road, Yangpu District, Shanghai as an empirical case, this study demonstrates the practical application of the knowledge-graph intelligent auxiliary decision-making tool, from current performance assessment to optimized scheme implementation of zero-waste design of urban green spaces.

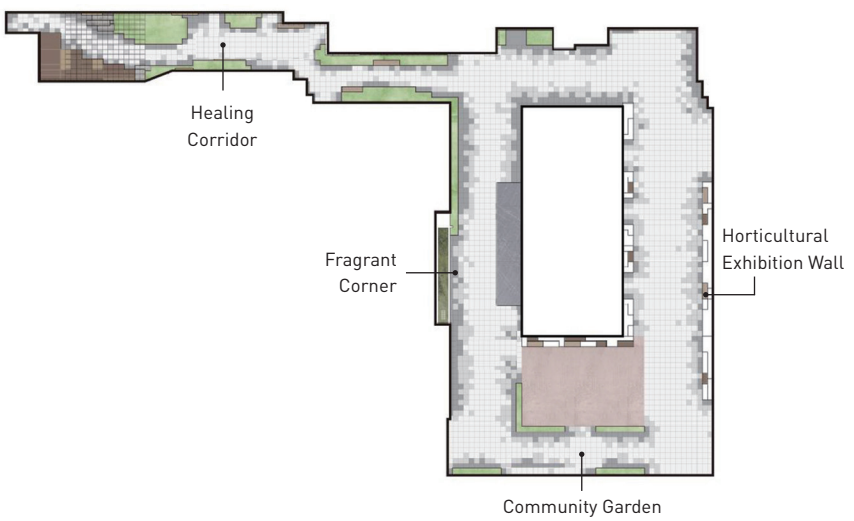
3.1 Case Overview

The site is located within the neighborhood center of Yangshupu Road, covering a total area of approximately 210 m^2, primarily serving surrounding elderly residents. The design scheme is centered on the core concepts of community co-creation and sustainable development, aiming to transform the site into a community public space that carries community memory, fosters neighborhood interaction, and provides gardening services. The overall layout is divided into four functional zones: Healing Corridor, Fragrant Corner, Horticultural Exhibition Wall, and Community Garden (Fig. 4).

Based on site investigations conducted around May 2024 with the design team, material suppliers, and construction personnel, five major waste streams were identified throughout the project lifecycle: discarded tree trunks, concrete blocks, discarded wooden boards from the Horticultural Exhibition Wall, waste concrete from road-surface demolition, and demolition waste from unauthorized and abandoned structures. According to the quantities adopted in the original performance calculation, these five waste streams amounted to a total of 77.3796 t. The zero-waste design strategies applied in the current design scheme primarily focus on reduction strategies, including the use of discarded tree trunks for the creation of landscape features and crushed concrete blocks as filling materials for gabion cages. However, most waste streams remain unutilized, including 1.6 t of discarded wooden boards from the Horticultural Exhibition Wall area, 35.5 t of waste concrete from road surface demolition, and 32.6 t of demolition waste from unauthorized and abandoned structures, which indicates significant potential for optimization.

The zero-waste performance evaluation model adopted in this study is constructed based on the evaluation system proposed in the team's prior work[30]. The ecological performance of the design scheme is calculated based on the quantity percentage of reduced waste to the total waste generated throughout the design lifecycle. Economic performance is expressed as the ratio of the total benefits generated by the implemented strategies to their total costs. For the initial design, 7.6796 t of waste were reduced out of a total of 77.3796 t, resulting in an ecological performance of 9.92%. The initial design achieved an economic performance ratio of 2.655. Since ecological performance is inherently bounded within the 0–100% range (a normalized ratio by definition), it requires no further scaling. After normalizing the economic performance using the modified Sigmoid function, ecological performance and normalized economic performance were assigned equal weights to calculate the overall zero-waste performance. The resulting overall zero-waste performance value for the initial design was 46%.

Fig. 4 Design plan of the case study site.



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3.2 Practical Application of the Knowledge-Graph Intelligent Auxiliary Decision-Making Tool

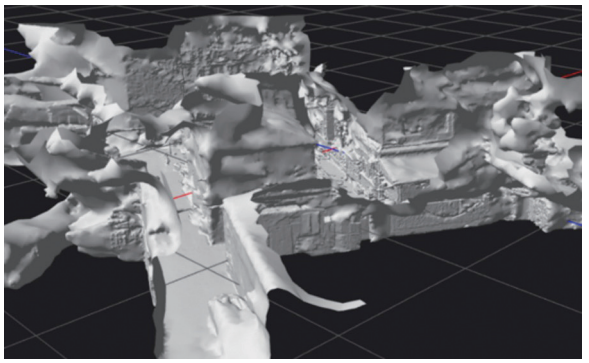
The designer first applied the Perception Layer to complete site information collection. Unmanned aerial vehicle (UAV) oblique images were processed in ContextCapture to reconstruct the site-scale 3D model and point cloud. Subsequently, waste objects in the oblique images were detected using a YOLOv8-based model and further refined into material sub-classes with support vector machine (SVM). The classified 2D results were then projected onto the reconstructed 3D point cloud using camera pose parameters,

followed by object-level point-cloud segmentation and 3D volume estimation. Figure 5 presents the reconstructed digital model, whereas Fig. 6 illustrates the workflow from 2D waste detection to 3D volume estimation.

Following the site-data acquisition, waste identification, and quantitative estimation described above, problem identification was conducted by comparing the identified waste inventory with the waste streams already utilized in the initial design. This comparison revealed the major underutilized waste streams, after which the designer used the framework's core knowledge graph component to retrieve relevant information and explore alternative design strategies through natural language interaction. The initial design incorporated only two on-site reuse strategies—the direct reuse of discarded tree trunks for landscape features and the use of crushed concrete blocks as gabion filling material, while three major waste streams remained unutilized, indicating a limited resource-recovery approach. By utilizing the knowledge-graph intelligent auxiliary decision-making tool for retrieval and comparison, the designer identified diversified resource recovery pathways. For example, the discarded wooden boards planned for off-site disposal could be retrieved via pathways such as wood-plastic composite transformation, composting, and garden organic mulch (Fig. 7). For the waste concrete, pathways such as recycled concrete blocks and recycled concrete bricks were retrieved. These recycled materials were then used for road and wall paving to enhance the level of resource recovery and economic benefits (Fig. 8).

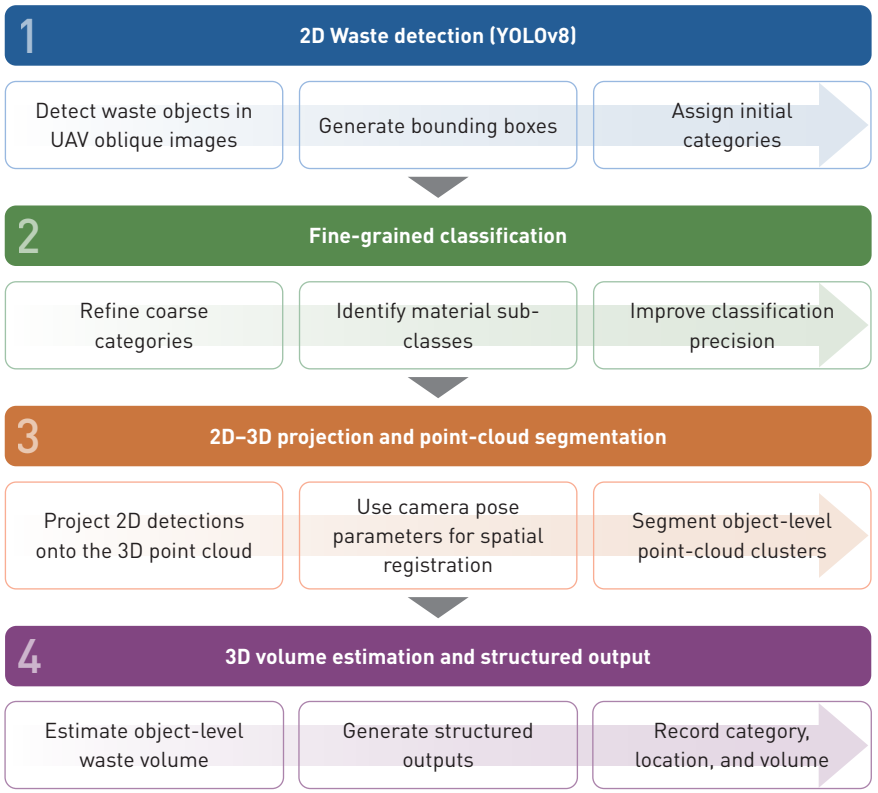
3.3 Quantitative Comparison of Core Indicators Before and After Renovation

To intuitively demonstrate the effectiveness of the knowledge-graph intelligent auxiliary decision-making tool in design practice, three key dimensions—design efficiency, waste resource recovery

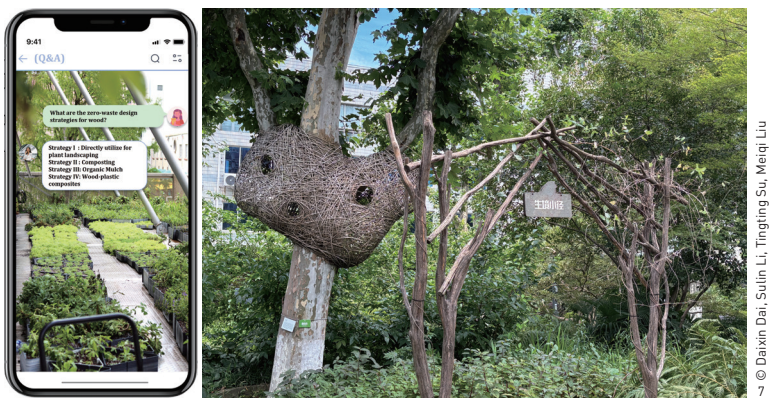


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5

Fig. 5 Digital model of the site.
Fig. 6 Workflow from 2D waste detection to 3D volume estimation.



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8

Fig. 7 Query interface of timber design strategy and the proposed recovery forms of waste timber, by the knowledge-graph intelligent auxiliary decision-making tool.
Fig. 8 Query interface of concrete design strategy and the proposed recovery forms of waste concrete, by the knowledge-graph intelligent auxiliary decision-making tool.

utilization, and zero-waste performance—were selected to conduct a quantitative comparison between the initial design and the optimized scheme (Table 2).

Design efficiency is measured by two types of time consumption: survey and waste statistics cycle and design cycle (sourced from the design team's work logs and survey records). Waste resource recovery utilization is measured by the total mass of resource-recovered waste. In terms of the zero-waste performance, ecological performance, economic performance, and overall zero-waste performance are calculated according to the existing evaluation model by the research team.

The results indicate that the zero-waste performance showed an overall improvement after the application of the knowledge-graph intelligent auxiliary decision-making tool. The Perception–Knowledge–Decision-Making framework constructed in this study forms a complete closed-loop for zero-waste design assistance, demonstrating its potential to effectively address common industry pain points in traditional design, such as insufficient precision in site data, low efficiency in strategy retrieval, and design thinking being limited by individual experience.

4 Discussion

This study presents a knowledge-graph intelligent auxiliary decision-making tool for zero-waste design of urban green spaces. It establishes semantic associations among four core entities—strategy, performance, case, and industrial-chain information—through ontology modeling, and conducts scenario simulations and preliminary proof-of-concept demonstration through an empirical case study.

First, at the theoretical level, this study breaks through the limitations of fragmented experience and singular technical optimization in existing zero-waste design research. It does not simply overlay sensing, knowledge graph, and AI technologies but organizes them into a hierarchical Perception–Knowledge–Decision-Making architecture with each layer addressing design complexity issues of different dimensions: the Perception Layer achieves standardized integration of multi-source site data; the Knowledge Layer accomplishes the externalization of tacit domain knowledge and the structuring of dispersed information; the Decision-Making Layer, through the intelligent agent for zero-waste design, realizes the transformation from structured knowledge to proactive design decisions. Building upon this, the study constructed a domain ontology encompassing four core entities and a knowledge network covering the full-lifecycle, addressing the gap in research on a unified knowledge architecture and standardized decision logic for zero-waste design of urban green spaces.

Second, at the level of technical implementation, this study achieved several technical contributions adapted to the landscape

Table 2: Quantitative comparison of key dimensions before and after applying the knowledge-graph intelligent auxiliary decision-making tool

Key dimension	Core indicator	Initial design scheme	Optimized scheme	Improvement amplitude
Design efficiency	Survey and waste statistics cycle	3–5 d	4–6 h	Efficiency increased by over 90.00%
	Design cycle	7–10 d	1–2 d	Efficiency increased by over 70.00%
Waste resource recovery utilization	Total mass of resource-recovered waste	7.68 t	46.28 t	Increased by 38.60 t
Zero-waste performance	Ecological performance	9.92%	58.67%	Increased by 48.75 percentage points
	Economic performance	2.66	2.59	Remained basically stable, both higher than the break-even point of 1.00
	Overall zero-waste performance	46.00%	66.00%	Increased by 20.00 percentage points

NOTE
The calculation methods for ecological performance and overall zero-waste performance are provided in the supplementary material.

architecture design context. It establishes standardized mapping rules between multi-source sensing data and knowledge graph entity nodes, achieving the normative transformation from unstructured data to structured knowledge. Moreover, based on GraphRAG knowledge-enhanced retrieval technology, it builds the core reasoning framework for the intelligent agent for zero-waste design, realizing a technological upgrade from passive knowledge retrieval to proactive strategy generation and scheme optimization, thereby addressing the pain point of traditional tools' insufficient adaptability to complex design requirements. Also, it constructed a full-lifecycle closed-loop optimization mechanism. A simulation-based proof-of-concept study suggests that the mechanism has the great potential to enhance waste reduction and resource recovery efficiency, though its real-world effectiveness remains to be validated through built projects, longitudinal monitoring, and multi-case empirical study.

5 Limitations and Outlook

It must be noted that this study has only presented the core conceptual framework and its exploratory proof-of-concept application in a single community green space, with four key limitations requiring further research.

First, tool integration is limited. The intelligent agent only supports one-way parametric rule output to Rhino + Grasshopper, lacking real-time bidirectional data linkage. Design modifications made by designers in Rhino + Grasshopper cannot yet be automatically fed back to the agent in real time for another round of evaluation and optimization. Therefore, a fully bidirectional loop has not yet been achieved. Second, data format standardization is insufficient. The system cannot directly parse non-standard data from heterogeneous sensors and operation ledgers, requiring manual preprocessing. Third, visualization interaction needs enhancement. The current knowledge graph only supports basic node-relationship display, lacking interactive features like multi-dimensional filtering and performance trend analysis. It cannot intuitively show the dynamic impact of design strategies on zero-waste performance. Fourth, practical implementation faces challenges. The framework relies on high-precision sensing equipment and professional data processing capabilities, which may incur high costs for small-to-medium projects. Furthermore, testing was conducted solely through a single community green space case, without incorporating users' evaluations and their behavioral evidence; thus, the comprehensive evaluation system requires further refinement.

Future research of zero-waste design of urban green spaces should focus on the full-lifecycle optimization of core architecture and empirical testing across multiple types and scales of practice cases. It should also integrate participatory mechanisms from community regeneration to supplement user-level evaluation and refine the multi-dimensional evaluation framework for assessing the practical effectiveness of the intelligent auxiliary decision-making tool, thereby further enhancing the generalizability and practical application value of the research framework.

ELECTRONIC SUPPLEMENTARY MATERIAL

Supplementary material is available in the online version of this article at https://doi.org/10.15302/J-LAF-2026-0045.

Competing interests | The authors declare that they have no competing interests.

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基于多源感知数据的城市绿地无废设计知识图谱智能辅助决策工具

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摘要

城市绿地无废设计面临全生命周期废弃物减量不足、跨学科知识整合效率较低、场地数据与设计决策脱节，以及设计方案过度依赖个体经验等问题，而传统经验驱动的设计模式则难以满足精细化与智能化转型需求。因此，本研究提出多源感知数据驱动的“感知－知识－决策”3层城市绿地无废设计框架。该框架通过无人机影像传感器、环境传感器及激光扫描技术获取多维场地数据；构建语义关联设计策略、绩效、案例和产业链信息4类核心实体的知识图谱，并将其存储于Neo4j图数据库中，实现知识的动态关联与高效检索。在此基础上，结合知识图谱增强检索与智能体技术，开发知识图谱智能辅助决策工具，以提升复杂设计问题中策略识别、推理与匹配能力。研究以上海市某社区花园为案例开展基于模拟，对所提出框架的可行性进行验证。结果表明，该框架具有提升废弃物资源利用匹配效率、设计效率及资源利用效能的潜力。本研究构建了一个概念验证性框架，为前沿感知技术支持下的可持续景观设计提供了理论路径与方法探索。

关键词

城市绿地；知识图谱；无废设计；设计辅助；智能工具；感知技术

文章亮点

- 提出面向城市绿地无废设计的“感知－知识－决策”框架
- 构建设计策略、绩效、案例与产业链信息4类核心实体关联的知识图谱
- 开发融合GraphRAG的智能体，实现无废设计策略匹配与设计辅助

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