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EXPLORATIVE AI FOR CONCEPTUAL DESIGN AND SPECIFICATION ENGINEERING OF A MULTI-FUNCTIONAL AUTONOMOUS ROBOTIC PLATFORM FOR SMART URBAN SERVICES

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Abstract: *The design of autonomous robotic systems involves selecting and integrating components while ensuring feasibility across functional and environmental constraints. This study introduces an Explorative AI-driven methodology for generating and refining modular robotic platform configurations. The AI model analyzed millions of design configurations, identifying over 1400 feasible variants based on mobility constraints, energy consumption, subsystem compatibility, operational scalability, and regulatory compliance. A multi-objective optimization process refined these variants, ensuring compatibility across subsystems while minimizing integration conflicts. From these, a final optimized robotic system configuration was selected, which was then documented in an extensive 100,000-word engineering specification covering structural design, functional integration, and system-level justifications. This comprehensive output, covering every aspect of the design, ensures the system can be implemented with minimal design omissions or integration errors. The proposed methodology enhances early-stage robotic design by systematically generating, evaluating, and documenting configurations, reducing risks in later development stages.*

Keywords: *Explorative AI, Conceptual Design, Autonomous Robotics, Modular System Engineering, Smart Urban Services.*

1. INTRODUCTION

As autonomous robotic systems become more common in urban settings, optimizing the design process is crucial. This involves selecting and integrating components while addressing mobility, energy efficiency, scalability, and regulatory compliance. Early-stage decisions greatly influence system feasibility and long-term performance [1].

Traditional design relies on iterative prototyping, which is costly, slow, and limits the number of tested alternatives, risking suboptimal configurations. Computational approaches enable broader exploration before physical implementation, but most optimize predefined structures rather than dynamically generating and refining architectures [2].

This study presents an Explorative AI model for systematically generating and evaluating modular robotic configurations. Unlike conventional AI-assisted design tools [3], it explores a vast solution space rather than relying on fixed templates. Using multi-objective optimization, it refines designs based on predefined constraints, ensuring subsystem compatibility and functional flexibility. The model applies to various robotic design challenges, demonstrated through an urban service robot case study.

To guide the investigation, the following research questions are addressed:

1. How can an Explorative AI model improve the conceptual design of autonomous robotic systems by systematically evaluating significant design alternatives?
2. What criteria and constraints must be integrated into an AI-driven design process to ensure the feasibility of a modular robotic platform for urban applications?
3. How does the AI-generated design compare with traditional iterative design approaches regarding early-stage error reduction and optimization efficiency?

The study also incorporates security as a critical design constraint, ensuring that all generated configurations comply with safety regulations for autonomous systems. Security considerations extend beyond simple operational reliability, encompassing aspects such as cybersecurity, fail-safe mechanisms, and environmental adaptability.

The study highlights how AI-driven design enhances early-stage development by identifying viable configurations before prototyping, reducing risks, and improving system integration. The following sections detail the model's methodology, present a selected robotic configuration, and analyze feasibility and limitations.

Artificial intelligence (AI) integration in robotic design has evolved from assisting in specific tasks such as motion planning and control to playing a central role in conceptual design and system architecture generation. Various AI-based methodologies have been explored in this domain, each with distinct advantages and limitations.

1.1 AI-Based Optimization in Robotic System Design

Traditional robotic design relies on heuristics, expert judgment, and iterative prototyping, limiting efficiency in complex, multi-functional systems [4]. AI-driven optimization, including genetic algorithms (GA) [5], particle swarm optimization (PSO) [6], and evolutionary strategies (ES) [7], automates design space exploration by iteratively refining candidates based on objectives such as power efficiency, mobility, and structural robustness [9]. However, these methods operate within predefined solution spaces, limiting their ability to generate novel configurations beyond initial assumptions [10]. As a result, they primarily optimize existing designs rather than create entirely new architectures, restricting their use in early-stage conceptual design.

1.2 Generative AI and Large Language Models in Conceptual Design

With the advancement of transformer-based large language models (LLMs), AI has gained the ability to assist in creative and conceptual tasks, including design synthesis and ideation for complex engineering systems [11]. Models such as GPT-4, BERT, and T5 have demonstrated the ability to extract design patterns from large datasets and generate textual descriptions of conceptual systems [12].

In robotic design, LLMs have automatically generated component specifications, suggested system configurations, and justified design choices [13]. Despite these capabilities, LLMs lack intrinsic engineering validation mechanisms and must be combined with structured optimization techniques to ensure feasibility [14].

Their strength lies in generating diverse, text-based design proposals, but they do not inherently evaluate mechanical constraints, material properties, or dynamic interactions within a robotic system [15].

1.3 Explorative AI for Conceptual Design of Complex Systems

Unlike traditional AI optimization and LLM-driven ideation, Explorative AI integrates structured clustering, rule-based reasoning, and generative synthesis to analyze large solution spaces dynamically [16]. This approach simultaneously generates and evaluates multiple system architectures, identifying viable configurations beyond predefined templates.

The proposed Explorative AI model in this study represents an advancement in conceptual design methodology by combining:

1. Clustering-based feature organization – using KMeans [17] to structure high-dimensional design spaces and identify latent relationships between components.
2. Multi-objective constraint optimization – evaluating trade-offs between power efficiency, modularity, regulatory compliance, and operational adaptability in an iterative selection process.
3. Generative knowledge synthesis – utilizing LLM-driven reasoning to formulate detailed functional descriptions of components based on structured engineering principles (e.g., SAVE and TRIZ methodologies) [18].

This hybrid AI framework improves early-stage robotic design by identifying optimal configurations before physical prototyping, reducing late-stage modifications and integration conflicts. While AI-driven techniques are widely applied in architecture and mechanical engineering, they primarily optimize predefined structures rather than generate new system configurations. In architecture, AI assists with spatial planning, energy-efficient building design, and structural optimization through generative adversarial networks (GANs) [19] and reinforcement learning [20], ensuring regulatory compliance [21]. Similarly, mechanical engineering employs AI-based topology optimization and evolutionary algorithms to refine mechanical components for material efficiency, aerodynamics, and structural integrity [22]. Unlike these approaches, the Explorative AI model systematically generates and evaluates robotic architectures, enhancing modularity and adaptability across various autonomous robotic systems [23].

1.4 Limitations of Existing AI Models in Robotic Design

Although AI has demonstrated significant potential in robotic system design, existing models face limitations that hinder their broader application in conceptual development:

- Rule-based expert systems require extensive domain knowledge encoding and cannot autonomously generate novel designs beyond predefined templates.
- Evolutionary algorithms do not inherently consider design feasibility in dynamic environments.
- LLMs generate text-based design descriptions but lack intrinsic physical validation without integration with structured engineering models [24].

By addressing these limitations, Explorative AI bridges the gap between computational optimization and creative synthesis, enabling scalable, early-stage robotic system development.

1.5 Research Gap and Contribution

The reviewed AI methodologies demonstrate the increasing role of computational models in robotic system conceptualization. Still, they either lack structured feasibility validation (generative AI) or operate within restrictive optimization frameworks (traditional AI) [25]. This study advances the field by introducing a generalizable Explorative AI model capable of:

- Systematically generating novel robotic architectures while integrating functional constraints.
- Optimizing early-stage design decisions using structured clustering and multi-objective evaluation.
- Enhancing modular robotic design flexibility through AI-driven iterative synthesis.

This framework provides a scalable method for ensuring early-stage design quality in multi-functional robotic platforms while avoiding late-stage modifications and inefficiencies. A case study demonstrates the proposed model's effectiveness, showcasing its ability to produce validated robotic configurations tailored to specific urban service applications.

2. METHODOLOGY

This section introduces the structured pipeline, a key component of our methodology. This pipeline is instrumental in generating and evaluating modular robotic platform configurations. It incorporates feature clustering, multi-objective constraint optimization, and generative synthesis, thereby ensuring an efficient and optimized early-stage design process.

2.1 Data Processing and Feature Clustering

The input dataset consists of modular robotic design features categorized based on importance and functionality. Each feature is defined by:

- A feasibility or priority score indicating its suitability for integration.
- A cluster classification (e.g., "Basic," "Nice-to-Have").
- A textual description detailing its functionality.

The KMeans clustering algorithm structures the design space by grouping features based on functional dependencies, importance, and feasibility constraints. This ensures that critical components are prioritized while additional modules are classified for advanced configurations.

2.2 Multi-Objective Optimization of System Configurations

Following feature clustering, a multi-objective optimization framework evaluates possible system configurations. Four key constraints guide the optimization process:

1. Energy efficiency – The power system can support all selected modules.
2. Subsystem compatibility – Avoiding conflicts between navigation, communication, and operational modules.
3. Scalability – Ensuring the robotic platform remains adaptable for future modifications.

4. Regulatory compliance – Filtering out configurations that do not meet industry and deployment regulations.
5. Security constraints – Ensuring compliance with cybersecurity, fail-safe mechanisms, and environmental adaptability.

Each candidate configuration is scored using a weighted objective function, enabling the system to eliminate infeasible options and prioritize optimal designs systematically.

The methodology that is used in this work is presented in Figure 1 - Methodology Flowchart.

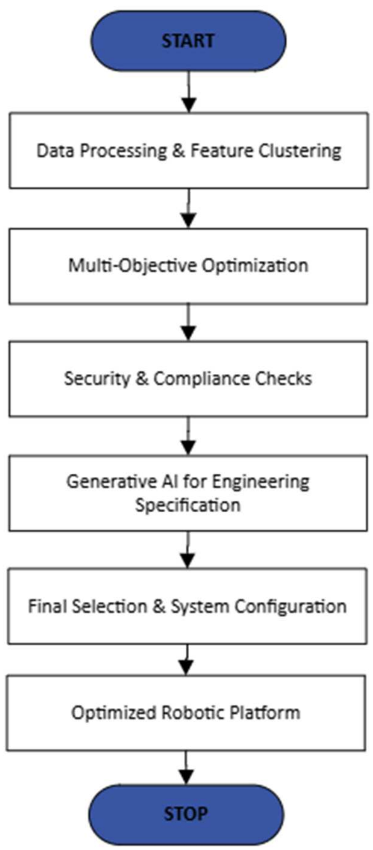

Fig. 1. Methodology Flowchart.

2.3 Generative Synthesis for Engineering Specification

After optimization, Generative AI is employed to generate comprehensive engineering documentation. A language model (LLM), guided by SAVE and TRIZ principles, ensures that each final design includes:

- Component functionality – Explanation of how each module contributes to the system.
- Operational scenarios – How the robotic platform behaves in different environments.
- Integration constraints – Identification of potential issues and solutions for system assembly.

An example of generating the Base Platform Module is given to understand the application of this method.

The use of TRIZ principles, such as Principle 40 (Composite Materials), which suggested a hybrid construction of aluminum and reinforced carbon fiber, and Principle 1 (Segmentation), which motivated the development of a modular interlocking system, played a significant role in the design process. In contrast, Principle 31 (Porous Materials) used a honeycomb internal structure to reduce weight without sacrificing strength.

After the initial concepts were developed, SAVE principles enhanced and confirmed the designs: a. Modular design for easier manufacturing and assembly to guarantee production efficiency; b. Flexibility for different robotic setups to support varying operational requirements; c. Cost-benefit evaluations verifying the advantages of composite materials regarding durability and energy efficiency.

By integrating TRIZ-inspired innovations with SAVE's practical assessments, Explorative AI developed a lightweight, robust, and versatile Base Platform Module that balances technical performance with economic viability. This process extends beyond conceptual design, generating detailed engineering specifications (~100,000 words) that provide engineers with implementation-ready guidance.

2.4 Selection and Final System Configuration

The model generated over 1400 viable configurations, from which the final system architecture was selected based on the following:

1. Cluster-wide optimization performance – Highest-ranked solutions were prioritized.
2. Expert evaluation of subsystem integration feasibility system – Ensuring a balanced and coherent system.
3. Detailed generative synthesis – Ensuring completeness of engineering documentation.

The final robotic platform design represents an optimized, fully documented system that minimizes late-stage modifications and integration challenges. This structured AI-driven methodology enhances early-stage robotic development, reduces costs, and accelerates deployment while ensuring adaptability to evolving operational needs.

3. RESULTS AND DISCUSSION

This section presents the outcomes of the Explorative AI-driven conceptual design, demonstrating its ability to generate a fully functional robotic platform while overcoming the limitations of traditional AI-assisted methods. The discussion systematically addresses the research questions from the Introduction, comparing this model with conventional approaches.

3.1 From Design Space Exploration to Final Robot Selection

The implementation of the Explorative AI model integrates machine learning algorithms, optimization techniques, and generative AI models, leveraging Python-based frameworks for computational efficiency. The core clustering and optimization processes rely on:

a. Scikit-learn's KMeans algorithm to structure high-dimensional design spaces and identify latent relationships between system components.
b. Custom constraint-solving algorithms – for multi-objective optimization, balancing power efficiency, subsystem compatibility, scalability, and regulatory compliance.
c. Generative synthesis using Large Language Models (LLMs) – to produce comprehensive engineering specifications.

Multi-objective optimization is executed through tailored constraint-solving algorithms, ensuring balanced performance across multiple design parameters. The integration of LLMs, such as OpenAI's GPT-based systems, enables generative synthesis, structuring domain-specific prompts to evaluate configurations using TRIZ and SAVE principles. TRIZ contradictions and inventive principles assess potential design improvements, while SAVE principles align optimization strategies with structured innovation methodologies.

The final implementation phase integrates automated evaluation pipelines with expert validation loops, ensuring that generated designs are computationally optimized and practically feasible for real-world deployment.

The Explorative AI model analyzed millions of potential configurations, filtering them through a multi-objective optimization framework. This resulted in over 1,400 feasible robotic system architectures, from which an optimal configuration was selected based on three key criteria:

1. System feasibility – Ensuring all selected modules met power, weight, and structural compatibility constraints.
2. Performance metrics—We Prioritized modules that scored highest in mobility, navigation accuracy, operational efficiency, and safety.
3. Scalability and modularity – Selecting components that allow for future upgrades without requiring fundamental design changes.

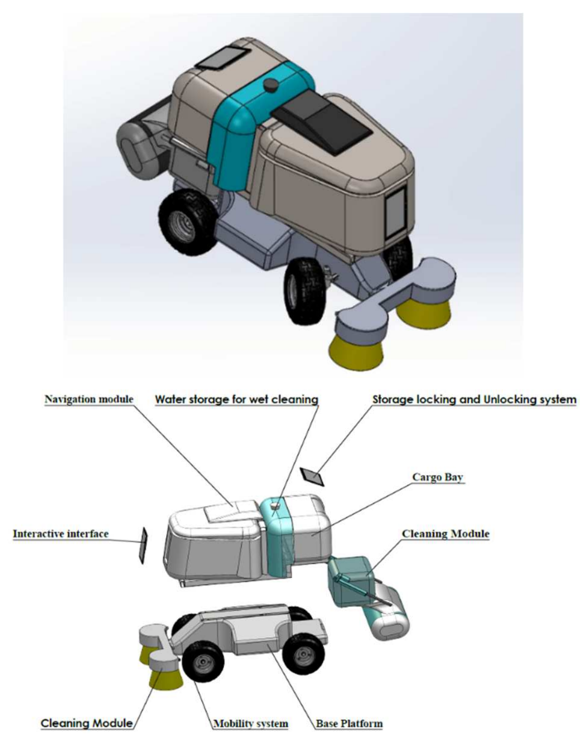

Fig. 2. Conceptual design of the robotic platform.

The final robotic platform integrates a balanced set of hardware and software modules into 50 modules, ensuring robust urban operations. Figure 2 shows only the system's significant modules.

The final robotic platform integrates three levels of features:

1. Basic features – Essential for autonomous operation (navigation, power management, safety modules).
2. Advanced features – Enhancing real-world adaptability (surface cleaning, pedestrian detection, IoT connectivity).

Nice-to-Have features – Optimizing usability (gesture recognition, cloud monitoring, branding customization).

Each of the 50 modules was evaluated based on feasibility (F), ease of implementation (E), and manufacturability (M), ensuring a balanced final selection. The final system integrates features such as dynamic route planning, pedestrian avoidance, high-capacity batteries, energy harvesting modules, biometric access control, anti-theft tracking, and a modular attachment system for future expansions. Each module was described in 16,000–20,000 words by the AI system, detailing structural specifications, functional requirements, integration constraints, material selection, manufacturing processes, operational scenarios, maintenance guidelines, and industry compliance. This level of detail ensures a fully implementation-ready blueprint, reducing integration conflicts and late-stage modifications.

3.2 Addressing Research Question 1

How can an Explorative AI model improve the conceptual design of autonomous robotic systems by systematically evaluating ample design alternatives?

Existing AI-based optimization methods are limited by predefined architectures, meaning they can only refine pre-existing designs rather than generate new robotic system architectures. The Explorative AI model, in contrast, actively explored novel configurations, ensuring that:

- No viable design alternatives were overlooked due to human bias or constraints in manual testing.
- Latent relationships between subsystems (e.g., navigation modules requiring more substantial computational power for real-time adjustments) were automatically identified.
- The entire robotic architecture was optimized holistically, not just individual components.

For instance, while traditional modular designs emphasize individual mobility systems, the AI-generated platform synchronizes navigation, obstacle avoidance, and pedestrian interaction, ensuring greater adaptability in urban environments.

3.3 Addressing Research Question 2

What criteria and constraints must be integrated into an AI-driven design process to ensure the feasibility of a modular robotic platform for urban applications?

The feasibility of a robotic platform depends on both technical and operational constraints. The Explorative AI model incorporated four key evaluation metrics, as shown in Table 1.

As a result, the final robot met all operational requirements before prototyping, eliminating the need for costly late-stage revisions.

Table 1

Comparative analysis of approaches.

Constraint	**AI Integration**	**Traditional Limitations**
Energy Efficiency	Evaluated based on battery autonomy vs. module consumption.	Often optimized after selecting the design.
Subsystem Compatibility	Ensured no conflicts between navigation, power, and payload modules.	Manually verified, increasing the risk of overlooked conflicts.
Scalability	Selected modular components that allow future upgrades.	Fixed architectures, requiring redesign for modifications.
Regulatory Compliance	Filtered out non-compliant configurations before final selection.	Addressed post-design, leading to potential legal issues.

3.4 Addressing Research Question 3

How does the AI-generated design compare with traditional iterative design approaches regarding early-stage error reduction and optimization efficiency?

A comparative analysis evaluated the Explorative AI model against a traditional iterative design approach. The evaluation focused on design space coverage, feasibility validation, and the risk of late-stage design errors.

The AI-driven process significantly reduced design errors, ensuring all critical elements were optimized before prototyping. By contrast, manual iteration often led to late-stage failures, requiring additional development time and increased costs.

Table 2

Comparison of AI-Driven vs. Traditional Design Approaches.

Evaluation Criterion	Explorative AI Model	Traditional Approach
Design Space Coverage	Explored millions of configurations, resulting in 1400+ viable options.	Limited to manually tested configurations (~10-50 options).
Feasibility Validation	Integrated power, compatibility, scalability, and compliance before design selection.	Checked post-design, leading to frequent rework.
Optimization Time	Completed design generation in hours.	Required weeks to months for manual iterations.
Error Prevention	Eliminated conflicts between subsystems early.	Often resulted in late-stage design failures.

3.5 Economic and Practical Impact

Last-mile delivery accounts for over 50% of total logistics costs [26][27], with urban deliveries projected to grow by 78% by 2030 [28]. Traditional delivery methods, relying on trucks alone, face challenges like congestion, inefficiencies, and high operational costs. The industry is shifting toward hybrid models, integrating trucks with autonomous delivery robots, which can reduce last-mile delivery costs by up to 68% [29].

To boost this efficiency further, our work integrates Explorative AI, a cutting-edge approach to designing and optimizing last-mile delivery robots. Unlike traditional design methods, which require engineers to test and refine prototypes manually, Explorative AI generates and evaluates thousands of potential designs autonomously. This means it can find the most cost-effective, lightweight, and energy-efficient configurations, saving significant costs in a fraction of the time.

The benefits of using Explorative AI in last-mile robot development are clear:

AI's role in reducing costs is significant. Automating the design process slashes development expenses and material waste, making production more affordable. AI-driven exploration is not just about finding designs but also about finding the best ones. These optimal designs, tailored for real-world conditions, ensure the efficiency and durability of the robots, giving you a sense of security in their performance. Explorative AI's unique ability to continuously refine robots based on real-world data is a game-changer. It ensures that the robots perform well and excel in different urban settings, giving you a strong sense of confidence in their adaptability.

By integrating Explorative AI, last-mile delivery becomes scalable, efficient, and economically viable, shaping the future of logistics automation.

3.6 Broader Implications and Future Directions

The findings demonstrate that Explorative AI is a design tool and an end-to-end system architecture generator. Its potential applications extend beyond this robotic platform, including intelligent city automation (e.g., optimized service robots for urban environments), industrial robotics (e.g., automated assembly systems with high modularity), and healthcare & assistive robotics (e.g., AI-driven robotic caregivers with adaptable architectures).

Despite its advantages, the current model does not yet incorporate real-time deployment feedback. Future improvements will focus on:

- Integrating real-world operational data to refine designs dynamically.

- Extending the AI's capability to assess economic feasibility alongside technical constraints.
- Enhancing human-AI collaboration to balance automated optimization with domain expertise.

4. CONCLUSION

This study introduced an Explorative AI-driven methodology for conceptualizing a multi-functional autonomous robotic platform, demonstrating its effectiveness in systemically generating, evaluating, and optimizing modular configurations. The model analyzed millions of possible configurations, identified over 1400 feasible designs, and selected a final optimized robotic system, documented with a 100,000-word engineering specification to guide real-world implementation.

The results demonstrate that Explorative AI outperforms traditional iterative design methods, often constrained by limited manual testing and late-stage feasibility validation. Unlike conventional approaches that refine predefined architectures, this model enables comprehensive design space exploration, ensuring no viable configurations are overlooked. Before prototyping, the automated multi-objective optimization process integrates power efficiency, subsystem compatibility, scalability, and regulatory compliance. The outcome is a fully defined implementation-ready robotic platform that minimizes development risks and late-stage design errors.

This study presents a new AI-driven conceptual design methodology combining clustering, multi-objective optimization, and generative synthesis to systematically generate and refine robotic system architectures. Empirical validation was achieved by developing a fully functional robotic platform, demonstrating how this methodology facilitates the creation of a functionally optimized, modular, and scalable system for innovative urban services. The study also provides a structured comparison with traditional design approaches, highlighting the efficiency, accuracy, and comprehensiveness of AI-assisted conceptualization in contrast to conventional iterative methods.

While the Explorative AI model successfully produced an optimal robotic system, certain limitations remain. Real-world performance validation is required, and future work should involve physical prototyping and testing to assess real-time behavior and adaptability in dynamic urban environments. Economic feasibility constraints need further integration, as the current model optimizes technical feasibility but does not fully incorporate cost-effectiveness and manufacturability metrics. Expanding the AI model's adaptability by enhancing real-time learning capabilities would allow it to adjust system configurations based on operational data dynamically.

This research demonstrates the potential of Explorative AI as a transformative tool in robotic system design, bridging the gap between automated conceptualization and practical implementation. By eliminating design inefficiencies, reducing late-stage modifications, and ensuring high modularity, the methodology sets a new standard for AI-driven engineering innovation. Future advancements will re-fine its applicability across robotics, automation, and innovative infrastructure domains, positioning it as a key enabler for next-generation autonomous systems. The economic impact analysis shows that AI-driven design optimization can significantly reduce development costs and time-to-market, making autonomous robotic platforms more accessible for various urban applications.

The integration of security constraints throughout the design process ensures that the resulting robotic platform not only meets functional requirements but also complies with cybersecurity standards, fail-safe mechanisms, and environmental adaptability needs. This comprehensive approach to robotic system design represents a significant step forward in addressing the growing demand for efficient, adaptable, and secure autonomous solutions in urban environments.

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Inteligență artificială exploratorie pentru proiectarea conceptuală și ingineria specificațiilor unei platforme robotice autonome multifuncționale pentru servicii urbane inteligente

Proiectarea sistemelor robotice autonome implică selectarea și integrarea componentelor, asigurând în același timp fezabilitatea acestora în raport cu constrângerile funcționale și de mediu. Acest studiu introduce o metodologie exploratorie bazată pe inteligență artificială pentru generarea și rafinarea configurațiilor platformelor robotice modulare. Modelul de inteligență artificială a analizat milioane de configurații de design, identificând peste 1400 de variante fezabile pe baza constrângerilor de mobilitate, consumului de energie, compatibilității subsistemelor, scalabilității operaționale și conformității reglementare. Un proces de optimizare multi-obiectiv a rafinat aceste variante, asigurând compatibilitatea între subsisteme și minimizând conflictele de integrare. Dintre acestea, a fost selectată o configurație optimizată finală a sistemului robotic, care a fost apoi documentată într-o specificație inginerească detaliată de 100.000 de cuvinte, acoperind designul structural, integrarea funcțională și justificările la nivel de sistem. Acest rezultat cuprinzător garantează că sistemul poate fi implementat cu omisiuni minime de design sau erori de integrare. Metodologia propusă îmbunătățește procesul de proiectare timpurie a sistemelor robotice prin generarea, evaluarea și documentarea sistematică a configurațiilor, reducând riscurile în etapele ulterioare de dezvoltare.

Cuvinte cheie: *AI explorativă, design conceptual, robotică autonomă, inginerie de sistem modular, servicii rbane inteligente.*

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