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# Integrating large language models with industrial simulation for multi-level decision support: an innovation management perspective in Industry 5.0

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## Abstract

**Purpose** – This research addresses the accessibility challenge in industrial simulation by integrating Large Language Models (LLMs) with simulation tools to democratize decision-making processes across organizational hierarchies in Industry 5.0 environments.

**Design/methodology/approach** – The study develops and implements an AI-driven interface that connects LLMs with industrial simulation models, enabling natural language interaction with complex simulation data. The methodology includes a comprehensive framework for data processing, query interpretation and result visualization. A real case study in the energy technology sector validates the approach through practical application in a manufacturing facility producing turbine components.

**Findings** – The integration successfully transformed simulation-based decision-making by enabling non-expert users to access and interpret complex simulation data through natural language queries. The case study demonstrated improved operational efficiency through better resource allocation and reduced decision-making bottlenecks. The system's validation confirmed the accurate interpretation of user queries and precise analysis of simulation data, supporting more inclusive and informed decision-making processes across organizational levels.

**Originality/value** – This research presents a comprehensive interface for integrating LLMs with industrial simulation models, introducing a novel approach to democratizing simulation-driven insights from an innovation management perspective. The study contributes to organizational theory by demonstrating how natural language interfaces can bridge the technical knowledge gap between simulation experts and decision-makers, transforming traditional decision processes and advancing the human-centric decision management vision of Industry 5.0.

**Keywords** Simulation, LLMs, Industry 5.0, Generative AI, Data driven decision-making

**Paper type** Real Impact Article

## 1. Introduction

The digital transformation of manufacturing systems has fundamentally reshaped organizational decision-making processes in the era of Industry 5.0 (Omol, 2023).

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As organizations face increasingly complex operational environments, the need for effective decision support systems has become critical for maintaining competitive advantage and fostering open innovation practices (Huang *et al.*, 2023; Moghrabi *et al.*, 2023; Piccarozzi *et al.*, 2024). This transformation demands significant changes in organizational and managerial practices to successfully adopt and leverage new technologies, creating both challenges and opportunities for innovation management.

Modern manufacturing environments require decision-making capabilities that span multiple organizational levels, creating a fundamental tension between technical specialization and organizational accessibility (Flores-García *et al.*, 2019; Goncalves *et al.*, 2024). This tension manifests as a technological access gap between technical specialists and decision-makers, presenting a critical barrier to data-driven management in Industry 5.0 environments (Szukits, 2022; Wang *et al.*, 2024a). When decision-makers lack the specialized knowledge, tools and frameworks needed to effectively leverage advanced analytical capabilities, organizations struggle to translate technical insights into strategic action (Bousdekis *et al.*, 2021; Gökalp *et al.*, 2021). This accessibility challenge directly conflicts with Industry 5.0's emphasis on human-centric technological integration that enhances rather than restricts human capabilities across organizational levels (Ghobakhloo, 2020; Collins *et al.*, 2023).

Industrial simulation demonstrates significant potential for supporting multi-level organizational decision-making and innovation processes (Tiago *et al.*, 2020), enabling organizations to test scenarios without real-world risks and providing a foundation for more informed strategic decisions (Zhang *et al.*, 2019). Despite these advantages, simulation technologies face persistent accessibility barriers that limit their broader organizational impact (Goncalves *et al.*, 2024; Collins *et al.*, 2023). These barriers include substantial knowledge gaps between technical experts and decision-makers, difficulties in interpreting complex results for strategic decisions, time-intensive modeling processes and widespread lack of technical skills (Hill, 2022; Jahangirian *et al.*, 2015) that collectively restrict simulation's contribution to organizational innovation.

Dashboard systems attempt to transform complex data into actionable insights through visualization (Few, 2013; Wexler *et al.*, 2017), but nevertheless face their own usability challenges that restrict their effectiveness in supporting comprehensive decision-making (Hansen and Johnson, 2011; Almasi *et al.*, 2023). These challenges include cognitive overload from excessive information density and insufficient contextual information, hampering the proper interpretation of operational metrics across organizational levels. Moreover, a critical gap exists in the integration of artificial intelligence capabilities within current dashboard systems, limiting organizations' ability to process and interpret complex data effectively (Frazão *et al.*, 2021) across diverse stakeholder groups.

Against this backdrop, the emergence of Large Language Models (LLMs) presents a promising solution to these technological access challenges. Built on transformer architectures (Vaswani *et al.*, 2017), these models demonstrate remarkable capabilities in processing natural language and generating contextually relevant responses (Bandi *et al.*, 2023). Their ability to comprehend and process natural language makes them particularly valuable for bridging technical knowledge gaps and fostering knowledge transfer in organizational contexts (Yao *et al.*, 2024; Zhao *et al.*, 2023). In practical applications, LLMs show significant potential for transforming organizational processes, particularly in managerial work at strategic, functional and administrative levels (Korzynski *et al.*, 2023; Burger *et al.*, 2023). Furthermore, recent research reveals that innovation orientation and individual creativity positively influence the adoption of generative AI tools in innovation management (Cimino *et al.*, 2024a), indicating their potential for improving data-driven decision-making processes across diverse organizational contexts.

Building on these foundations, this paper, positioning itself within the innovation management literature on data-driven decision-making processes, addresses both the technical and organizational challenges in integrating LLMs with industrial simulation systems to

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revolutionize decision-making processes in Industry 5.0. Through our integrated approach, we focus on the democratization of complex analytical tools, exploring how technological integration can transform traditional expert-dependent decision processes into inclusive, collaborative frameworks that support innovation across organizational levels. To address the identified technological access gaps, our specific objectives are as follows:

(1) Develop an LLM-simulation interface that transforms organizational decision-making through inclusive, cross-level data access while ensuring analytical reliability.

(2) Create a system that democratizes technical simulation knowledge, bridging expertise gaps to foster human-centric innovation aligned with Industry 5.0 principles.

To present our research comprehensively, the remainder of this article is organized as follows: Section 2 presents a comprehensive literature review examining both the evolution of simulation models in industrial contexts and the transformative role of LLMs in management practices, establishing the theoretical foundation for our work. Section 3 outlines the methodological framework for integrating LLMs with industrial simulation, addressing the identified research gaps. Section 4 details the technical implementation of our integration framework, demonstrating the practical application of our conceptual approach. Section 5 presents an application through a case study from the energy technology sector, validating the effectiveness of our solution. Section 6 provides a discussion of findings, analyzing how the integration of LLMs with simulation systems contributes to organizational transformation and data-driven decision-making in manufacturing contexts. Section 7 discusses the theoretical and empirical implications of our approach, positioning our contributions within the broader innovation management landscape. Finally, Section 8 concludes by summarizing our contributions and addressing future research directions.

## 2. Literature review

This section examines the evolution of decision support systems in industry, focusing on simulation technologies, dashboard systems, and the emerging role of LLMs. The review analyzes how these technologies contribute to decision-making processes across organizational levels while highlighting current challenges and opportunities in their implementation and integration.

### *2.1 Decision process management in industry*

The evolution of manufacturing systems has transformed organizational decision-making processes, particularly with the emergence of Industry 4.0 and its progression toward Industry 5.0 (Ghobakhloo, 2020). This transformation affects multiple organizational levels, from strategic planning to operational execution, creating new challenges and opportunities for decision-makers (Huang *et al.*, 2023). The integration of digital technologies in manufacturing environments has redefined how organizations approach decision-making processes across their hierarchical structures (Moghrabi *et al.*, 2023).

Recent literature highlights a critical evolution in decision-making paradigms, where organizations must transition from siloed, expert-dependent processes toward more collaborative frameworks that integrate technical capabilities with human-centric values (Ghobakhloo, 2020; Korherr *et al.*, 2022). This shift aligns with Industry 5.0's core principles while addressing the documented challenges in decision support technologies. Manufacturing operations significantly influence decision-making at various organizational levels (Flores-García *et al.*, 2019). At the strategic level, organizations must balance technological innovation with organizational capabilities, while considering the broader implications of digital transformation (Omol, 2023). The tactical level focuses on implementing these strategies through structured decision-making processes that align with organizational objectives (Sinnaiah *et al.*, 2023). The operational dimension of decision-making has evolved

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considerably with technological advancement (Ahmed *et al.*, 2021). This evolution has led to integrated decision support systems that combine human expertise with technological capabilities (Romero *et al.*, 2016).

The knowledge gap between technical specialists and decision-makers presents a fundamental barrier to data-driven management in Industry 5.0 environments. This gap manifests primarily as technological access limitations, where decision-makers lack the specialized knowledge, tools and frameworks needed to effectively leverage advanced analytical capabilities (Szukits, 2022; Wang *et al.*, 2024a). Technological access encompasses both tangible dimensions – such as infrastructure availability, integration capabilities and appropriate analytical tools – and intangible dimensions including technical literacy, data interpretation skills and cross-functional communication frameworks (Bousdekis *et al.*, 2021; Gökalp *et al.*, 2021). These access barriers systematically restrict the flow of insights between technical and strategic organizational levels, creating bottlenecks in decision processes that significantly limit the potential of advanced analytics to drive organizational innovation (Moktadir *et al.*, 2019). Research has identified that addressing technological access challenges requires implementing systems that democratize access to complex technical data while maintaining analytical integrity – particularly through natural language interfaces, visual analytics tools and collaborative knowledge platforms that enable diverse stakeholders to participate in data-driven decision processes regardless of their underlying technical expertise (Roy Ghatak and Garza-Reyes, 2024; Babu *et al.*, 2024).

### *2.2 Decision support technologies*

The evolution of decision support technologies has led to various specialized systems, each presenting unique capabilities and challenges in supporting organizational decision-making processes. While these technologies offer significant potential, their effective implementation often faces barriers related to accessibility, integration and user expertise.

*2.2.1 Simulation models.* Industrial simulation has emerged as a cornerstone technology for supporting multi-level organizational decision-making. Ferreira *et al.* (2020) emphasize its role in developing planning and exploratory models that optimize decision-making in complex production systems. This technology enables organizations to test scenarios without real-world risks, providing a foundation for more informed strategic decisions (Zhang *et al.*, 2019).

The versatility of simulation in supporting decision-making is demonstrated across various applications. In production planning, Steinbacher *et al.* (2023), show its effectiveness in operational decision support, while Tiago *et al.* (2020) highlight its role in process optimization and predictive maintenance. Recent developments have enhanced simulation capabilities in internal supply chains, enabling real-time monitoring and optimization of production planning through what-if analyses (Cimino *et al.*, 2024b; Wocker *et al.*, 2023) demonstrate its application in inventory optimization and preventive maintenance, while Longo *et al.* (2023) show how simulation provides insights into potential disruptions and opportunities for improvement.

However, significant accessibility challenges persist in simulation systems. Goncalves *et al.* (2024) identify substantial barriers created by the lack of appropriate knowledge and expertise among non-expert users. These challenges manifest in two key dimensions: a substantial knowledge gap between technical experts and decision-makers, and difficulties in interpreting complex results for real-world strategic decisions (Collins *et al.*, 2023). Additional barriers include time-intensive model building processes, prohibitive software costs, and management skepticism towards new technologies (Hill, 2022).

*2.2.2 Dashboard systems.* Dashboard systems play an important role in organizational decision-making processes by transforming complex data into actionable insights. Few (2013) establishes fundamental principles for dashboard design that enable effective monitoring and decision-making, emphasizing the balance between information density and cognitive accessibility for management users. Wexler *et al.* (2017) expands these concepts by outlining

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critical factors for decision support, including clear objective definition and strategic information prioritization for different organizational levels. In organizational contexts, dashboards serve as vital tools for strategic decision-making. Maheshwari and Janssen (2014) present an eight-principle framework for organizational development support, focusing on how dashboards can facilitate decision-making across different management levels. Presthus and Canales (2015) further developed this approach by providing six guiding principles that enhance decision-making processes in complex organizational environments. The effectiveness of dashboards in supporting management decisions is demonstrated through various implementations. Kumar and Belwal (2017) explored how advanced visualization techniques can enhance strategic decision-making capabilities at the management level. Meanwhile, Simon *et al.* (2021) emphasize the importance of balancing technical and management requirements in dashboard design, ensuring that both operational efficiency and strategic oversight are effectively supported. A comprehensive review by Frazão *et al.* (2021) identifies a significant gap in current dashboard research: the limited integration of artificial intelligence in supporting management decision-making processes. This gap particularly affects the ability of organizations to process and interpret complex data effectively.

### *2.3 Large language models in industrial applications*

LLMs represent a transformative technology in industrial applications, demonstrating remarkable capabilities in processing natural language and generating contextually relevant responses (Bandi *et al.*, 2023). Their ability to comprehend and process natural language makes them particularly valuable for bridging technical knowledge gaps in organizational contexts (Yao *et al.*, 2024; Zhao *et al.*, 2023).

In management contexts, LLMs have shown significant potential for transforming organizational processes. Korzynski *et al.* (2023) demonstrate how generative AI tools create new possibilities for management theories, particularly influencing work at strategic, functional and administrative levels. Thomas *et al.* (2024) emphasize that these systems are not meant to replace humans but rather to help them achieve better results, potentially catalyzing innovation processes and enhancing decision-making capabilities.

Recent research has explored various applications of LLMs across industrial domains, as summarized in Table 1. These applications demonstrate the versatility of LLMs in supporting different aspects of industrial operations and their potential for enhancing decision support systems.

**Table 1.** Integration of LLMs in various industrial fields

| Reference | Field | LLM integration |
|---|---|---|
| Figliè *et al.* (2024) | Decision Support | Chatbot prototype using GPT-4 for simplifying decision-making in I5.0 applications |
| Wang *et al.* (2024c) | Robotics/Navigation | LLM-based vision and language cobot navigation for human-centric smart manufacturing |
| Xia *et al.* (2024) | Information Retrieval/ Code Generation | Error-assisted fine-tuning method for integrating manufacturing knowledge into LLMs |
| Lee and Su (2023) | Knowledge Management | Unified industrial large knowledge model (ILKM) framework for Industry 4.0 and smart manufacturing |
| Zhou *et al.* (2024) | Quality Control | CausalKGPT for quality defects reasoning in aerospace manufacturing |
| Fan *et al.* (2024) | Robotics/Tool Path Planning | LLM application for understanding human language commands and designing tool paths |
| Freire *et al.* (2024) | Knowledge Sharing | LLM-based system for efficient information retrieval and knowledge sharing among operators |

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*2.4 Research gaps and integration opportunities*

Current decision support technologies exhibit key gaps that hinder data-driven management in Industry 5.0 environments: technological access barriers that limit knowledge transfer between technical specialists and decision-makers (Szukits, 2022; Wang *et al.*, 2024a), accessibility challenges in simulation systems (Collins *et al.*, 2023), usability issues in dashboards (Hansen and Johnson, 2011; Almasi *et al.*, 2023), and limited AI integration (Frazão *et al.*, 2021). By addressing these interconnected challenges simultaneously, the integration of LLMs with simulation models and dashboard systems presents several significant opportunities for transformation:

(1) First, LLMs can provide natural language interfaces for simulation models, overcoming technological access barriers by democratizing complex technical information for diverse stakeholders (Thirunavukarasu *et al.*, 2023; Bousdekis *et al.*, 2021) while maintaining analytical integrity.

(2) Second, combined LLMs and dashboard visualizations enhance data interpretation across organizations, addressing both tangible and intangible dimensions of technological access by providing intuitive interfaces for data exploration (Wu *et al.*, 2023; Gökalp *et al.*, 2021) that bridge technical and strategic domains.

(3) Finally, integrated systems enable multi-level decision support throughout organizations, eliminating bottlenecks in decision processes caused by technological access limitations (Mbakwe *et al.*, 2023; Roy Ghatak and Garza-Reyes, 2024) and fostering collaborative innovation environments.

Consequently, this convergence of simulation, visualization and LLM technology offers potential to transform organizational decision-making by bridging the technological access gap identified in section 2.1, enhancing both accessibility and interpretation capabilities across operational, tactical, and strategic levels (Moktadir *et al.*, 2019; Babu *et al.*, 2024). This integrated approach directly addresses the democratization challenges identified in our theoretical framework. The technological access barriers in simulation systems create significant obstacles to effective knowledge transfer, manifesting in both technical language barriers and interface complexity that restricts non-expert usage (Collins *et al.*, 2023; Goncalves *et al.*, 2024; Jahangirian *et al.*, 2015; Szukits, 2022; Wang *et al.*, 2024a). Similarly, dashboard systems face persistent cognitive and usability challenges that limit their effectiveness in supporting comprehensive decision-making across organizational levels (Hansen and Johnson, 2011; Almasi *et al.*, 2023; Bousdekis *et al.*, 2021). The limited integration of artificial intelligence capabilities further reinforces traditional expertise barriers, restricting broad participation in analytical processes and conflicting with Industry 5.0's emphasis on human-centric technological integration (Frazão *et al.*, 2021; Moktadir *et al.*, 2019; Roy Ghatak and Garza-Reyes, 2024; Gökalp *et al.*, 2021).

By combining natural language interfaces with simulation models and dashboard systems, organizations can democratize access to complex analytical capabilities, enabling stakeholders across different expertise levels to engage directly with technical insights (Thirunavukarasu *et al.*, 2023; Wu *et al.*, 2023; Babu *et al.*, 2024). Building upon these identified gaps, this research addresses these gaps by developing an integrated approach that combines LLMs with industrial simulation capabilities, directly addressing the technological access barriers identified in the literature (Szukits, 2022; Wang *et al.*, 2024a; Moktadir *et al.*, 2019; Roy Ghatak and Garza-Reyes, 2024) to support more inclusive and collaborative decision-making processes across organizational levels. The following section presents our methodological framework for implementing this integration.

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## 3. Methodology

Building upon the research gaps identified in Section 2, this section presents a methodological framework that promotes inclusive and collaborative decision-making processes across organizational levels. As shown in Figure 1, the framework encompasses the Industrial System, Information Systems, Simulation Model and LLMs Interface, democratizing access to complex simulation data and analysis. Through this integrated approach, this sequence of steps transforms traditional simulation-based decision-making by enabling diverse stakeholders, regardless of their technical expertise, to participate in the analysis and decision process.

(1) Real data: At the beginning of the process, as a result of ongoing operations, the production system continuously generates real-time data. This data could include machine and process status, and operational data. Subsequently, the production system sends this raw, real-world data to the information systems for processing and storage.

(2) Simulation data: the information systems, acting as a central data repository and processing hub, take the real data from the production system and prepare it for use in simulation. This step ensures that diverse stakeholders work with consistent, reliable data, promoting informed collaboration across different organizational roles. The information systems then transmit this prepared data to the simulation model.

(3) Run scenarios: upon receiving the data, the simulation model initiates its simulation processes. It runs multiple simulation scenarios based on the current data and predefined parameters. These scenarios support collaborative decision-making by allowing different stakeholders to explore and evaluate various operational strategies.

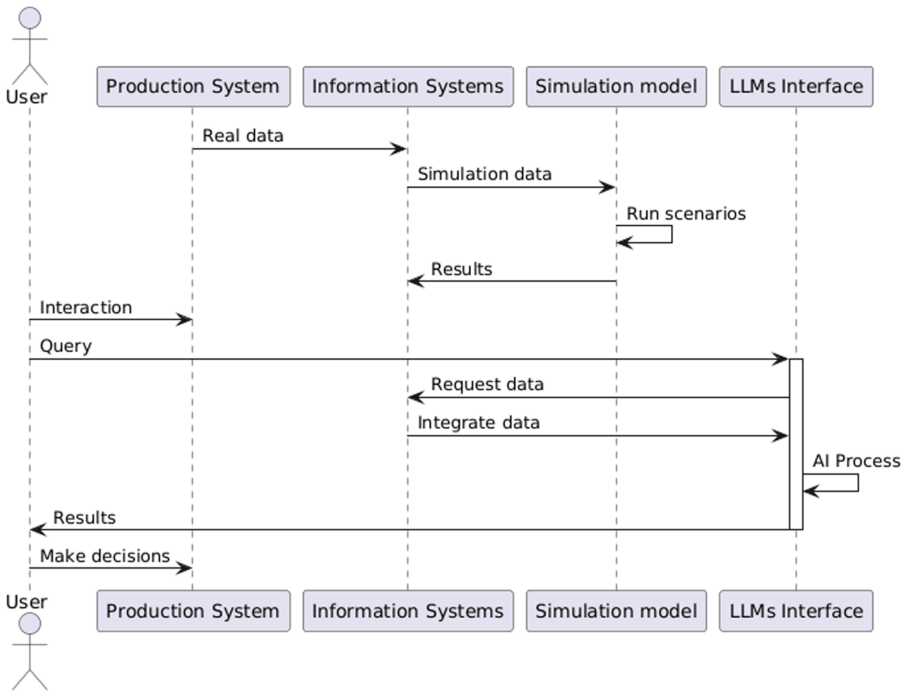


**Figure 1.** Integration of LLMs and Simulation Model. Source: Authors' own work

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(4) Results: after completing the simulation runs, the simulation model compiles the results of the various scenarios. It then sends these simulated results back to the information systems, making them available for broader organizational analysis.

(5) Interaction: the process begins with the user, who could be any stakeholder from operators to senior management (non-experts in simulation), interacting with the production system.

(6) Query: users can pose questions in natural language about any aspect of the production process, from efficiency metrics to strategic implications, without requiring technical expertise in simulation or data analysis.

(7) Requests data: to answer the user's question, the LLM system needs access to the simulation data output. It sends a request to the information systems for the relevant integrated data, translating user needs into specific data requirements regardless of their technical background.

(8) Integrate data: responding to the LLM system's request, the information systems retrieve and transmit the relevant simulation data, supporting the democratization of data access.

(9) AI Process: upon receiving data, the LLMs system processes the user's question and the available data to generate the appropriate analysis code. This automated translation from natural language to technical analysis eliminates traditional barriers to simulation insights, enabling inclusive participation in data-driven decision-making. The system generates visualizations and explanations that make complex analytical results accessible to all stakeholders. Further information about this step will be provided in the next section on the backend system description.

(10) Results: the LLM system presents its findings in an accessible format that supports collaborative decision-making. This presentation combines visual and textual elements to ensure that insights are comprehensible to stakeholders with varying levels of technical expertise.

(11) Make decisions: with democratized access to simulation insights, users across different organizational roles can make informed decisions about the production system. These decisions benefit from diverse perspectives and collaborative input, leading to more robust and inclusive operational improvements.

By breaking down traditional barriers to simulation analysis, this methodological framework enables broader participation in both operational and strategic decisions. The integration of LLMs with simulation capabilities creates an inclusive environment where diverse stakeholders can contribute to process optimization and innovation, aligning with Industry 5.0's vision of human-centric technological advancement. The next section details the technical implementation of this framework, demonstrating how our conceptual approach translates into practical application.

## 4. Simulation model and LLMs integration

Building upon the methodological framework presented in Section 3, this section details the technical implementation of integrating simulation models with LLMs, demonstrating how this solution enables organizational transformation in decision-making processes. The system combines industrial simulation with Generative AI capabilities, creating an innovative approach that enhances production data analysis while making complex simulation insights accessible to various stakeholders, from operational managers to strategic planners, supporting a more collaborative and data-driven organizational culture.

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*4.1 Simulation model*

The simulation component employs an innovative Automatic Simulation Model Generation (ASMG) methodology (Cimino *et al.*, 2025), representing a significant advancement in making simulation technology more accessible across organizational levels. This approach, implemented in Tecnomatix Plant Simulation software, transforms traditional simulation practices by enabling rapid model creation and modification without extensive technical expertise, supporting the democratization of simulation capabilities within organizations. The model utilizes an advanced approach based on object-oriented programming, combining modular and data-driven methodologies for flexibility and resilience (Cimino *et al.*, 2024c). This architecture supports organizational innovation by enabling rapid experimentation and scenario testing through various production scheduling rules. The system's innovation potential lies in its adaptability: users can modify input data to simulate various manufacturing scenarios without technical intervention, fostering a culture of data-driven experimentation. After simulation runs, outputs are processed through a structured data flow that integrates with the LLM system, transforming technical simulation data into accessible insights for decision-makers across all organizational levels.

*4.2 LLMs interface implementation*

The LLM interface implementation represents a comprehensive integration system designed to enhance organizational decision-making processes through accessible simulation analysis. The system architecture combines a sophisticated backend engine with an intuitive frontend interface, enabling users across different organizational levels to leverage complex simulation insights without requiring technical expertise.

*4.2.1 Backend system.* The backend system forms the core of our innovative approach to integrating LLMs with industrial simulation for enhanced decision-making in Industry 5.0 contexts. Building on the discussion of LLM capabilities in Section 2.3, this subsection provides a comprehensive overview of the system's architecture, focusing on how it processes user requests and generates actionable insights in a way that makes complex simulation data accessible to all organizational levels. As shown in Figure 2, the backend system encompasses several steps.

The process begins when a user submits a query through the interface (1), such as inquiries about production bottlenecks or potential order delays. The system then performs data preparation and management (2), organizing simulation outputs and historical data into a structured format suitable for AI analysis. During context building (3), the system creates a comprehensive framework that combines the user's query with relevant data context, similar to providing a human analyst with necessary background information. The AI-driven code generation phase (4) represents the system's core intelligence, where the Gemini AI model creates specific analysis instructions based on the user's requirements. The code execution phase (5) incorporates robust error management: if the initial analysis encounters issues, the system systematically logs the error, updates its approach, and attempts new solutions up to N times. This iterative process ensures reliable results even for complex queries. Upon successful execution, the system processes results and generates visualizations (6) that transform technical data into comprehensible insights. The system then generates natural language explanations (7) that translate technical findings into clear business insights. Throughout this process, the system incorporates continuous learning mechanisms (8), storing successful analysis patterns for future use. The cycle concludes with frontend integration (9), where results, visualizations and explanations are compiled into a format that supports informed decision-making across organizational levels.

*4.2.2 Frontend system.* The frontend interface, shown in Figure 3, provides an accessible entry point for stakeholders to interact with simulation data. The interface consists of several key components that facilitate collaborative decision-making across organizational levels:

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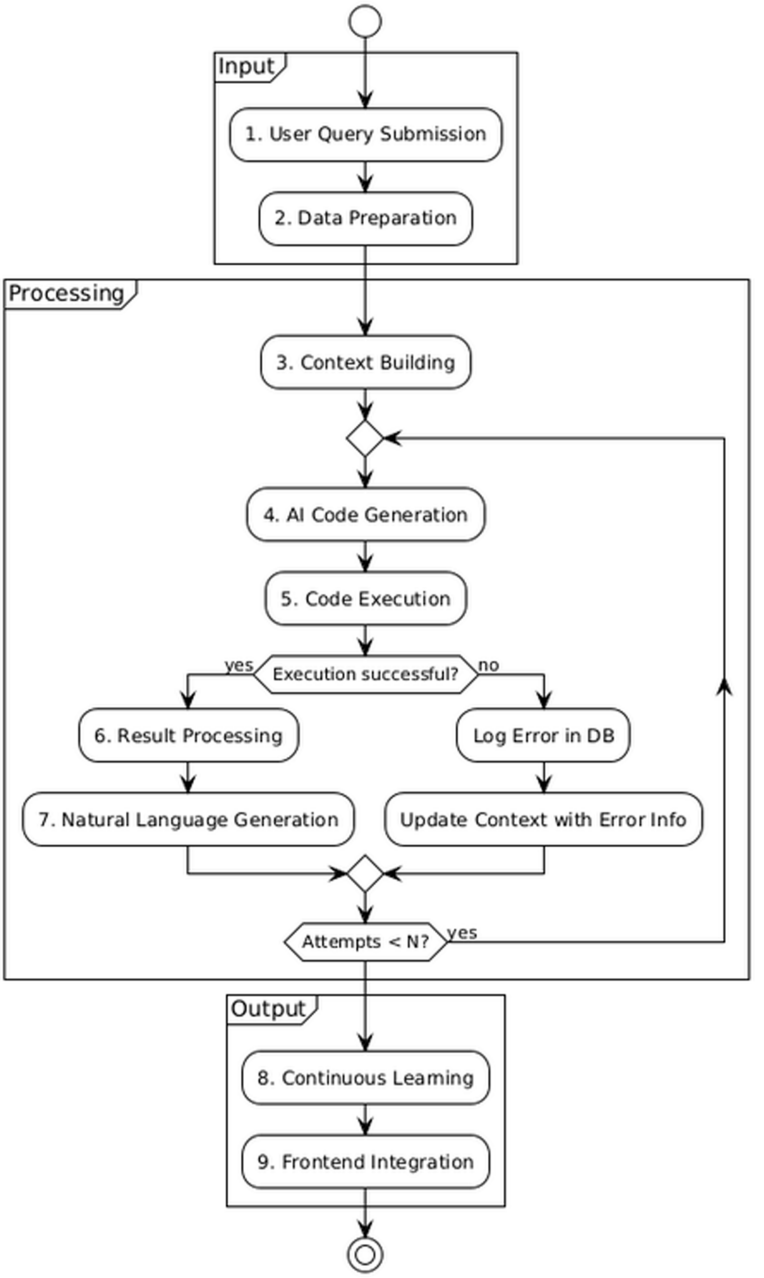


**Figure 2.** Backend system logic. Source: Authors' own work

(1) Query input: this prompt allows users to input their questions or analysis requests in natural language. This direct interface with the LLM system exemplifies the system's ability to interpret and process human language queries.

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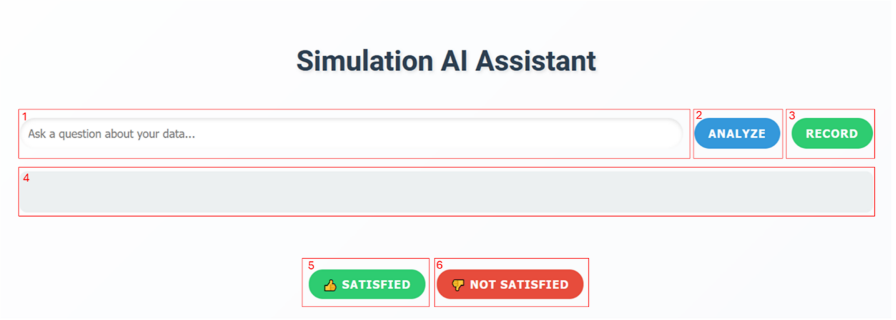


**Figure 3.** Simulation assistant interface. Source: Authors' own work

(2) Analysis initiation: the "Analyze" button triggers the backend processes, including the AI-guided code generation, safe code execution and data analysis phases described in the backend architecture.

(3) Voice input: this button enables speech to text functionality, allowing users to verbally input their queries. The system then translates this speech into text, showcasing the integration of advanced input methods and natural language processing.

(4) Results display: this area presents the system's response, including both graphical outputs and textual explanations.

(5) Positive feedback: this button allows users to provide positive feedback. When activated, it triggers the backend's continuous learning mechanism, storing the successful query response pair in a database for future reference and system improvement.

(6) Refinement request: if the users are not satisfied with the result, they can request a refinement. This activates the backend's iterative improvement process, generating a new result based on the feedback provided.

This integrated system transforms complex analytical processes into actionable insights through real-time communication between frontend and backend components. By democratizing access to simulation insights and providing multiple channels for interaction and feedback, the implementation supports effective data-driven decision-making across all organizational levels, bridging the gap between technical capabilities and strategic decision-making needs.

## 5. Application

Following the technical implementation detailed in Section 4, this section demonstrates the practical application of our approach for integrating LLMs with industrial simulation systems, validating the system architecture and methodological framework presented in Section 3. The framework emphasizes generality, flexibility and reusability across diverse manufacturing contexts. While our validation focused on the energy technology sector, the framework's industry-agnostic architecture enables its application across diverse manufacturing contexts where simulation technologies support operational decision-making processes. The natural language interface creates a generalizable approach to democratizing simulation insights regardless of the specific industrial domain, supporting broad applicability in various Industry 5.0 environments.

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*5.1 Case study*

To demonstrate how our integrated LLMs and industrial simulation system transforms decision-making processes, we present a comprehensive real case study of a manufacturing company in the energy technology sector. The manufacturing facility operates with 15 production resources across multiple shifts, maintaining continuous operations throughout the work week. The production system specializes in manufacturing three distinct turbine components for the energy technology market, managing an active production plan of 20 orders with specific technical requirements and delivery deadlines.

The firm faced three critical strategic challenges that highlighted the limitations of traditional simulation approaches. The first challenge centered on declining customer satisfaction, driven by consistently late order deliveries, which threatened the company's market position. The second challenge involved inefficient resource allocation patterns that created significant production bottlenecks, hampering operational efficiency. The third challenge stemmed from the inherent complexity of simulation tools, which limited the organization's ability to effectively evaluate different production strategies. These challenges were exacerbated by traditional approaches that necessitated extensive collaboration between simulation experts and operational managers, resulting in significant delays in the decision-making process.

In the following subsections, we detail how our system addressed these challenges. First, we present the simulation data outputs that form the foundation of our analysis. Then, we demonstrate a series of user interactions with the system through natural language queries, showing how non-expert users could investigate and resolve complex operational issues. These examples illustrate the system's ability to transform technical simulation data into actionable insights, though they represent only a small sample of the possible analyses the system can perform.

*5.1.1 Simulation data output.* The simulation model generates three primary data outputs that, through the LLM interface, become accessible strategic planning tools for non-expert users:

(1) Production Orders: a high-level overview of each order, including Order ID, product type, start and end dates, state, due date, flow time, and tardiness.

(2) Order Bill of Process: a detailed breakdown of all processes required for each order, including start and end dates, state, duration, resource allocation, and queue time.

(3) Production List: a comprehensive table recording all processes carried out (or to be carried out) on each resource, including product type, ID task, state, arrival, start and end due dates.

These outputs, traditionally challenging for non-expert users to interpret, become valuable strategic planning tools through the LLM integration, enabling informed decision-making across all organizational levels.

*5.1.2 User queries and LLM responses.* This section demonstrates how the LLM interface transformed the way non-expert users leverage simulation data for strategic decision-making. Through a series of natural language queries, we follow a user's investigation into the order delay problem, showcasing how the system enabled data-driven decision-making without requiring simulation expertise. Each query represents a step in strategic problem-solving that previously would have required technical expertise or simulation specialist support.

Query 1: "Orders late"

The investigation began with an analysis of order delays, demonstrating how non-technical users could immediately access strategic insights through simple natural language queries. The system responded with a clear visualization (Figure 4) showing projected late orders, providing immediate strategic visibility that would traditionally require significant data processing expertise.

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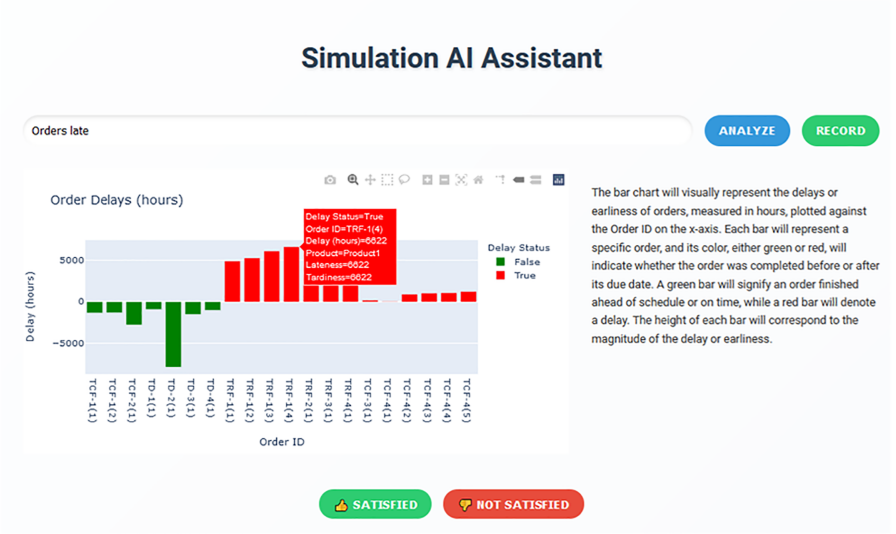


**Figure 4.** Orders lateness. Source: Authors' own work

This initial analysis provided valuable strategic insight further analysis can be required for deeper operational investigation, which the LLM interface made readily accessible to the user.

Query 2: "I wanna know the potential bottlenecks"

Building on the initial findings, the user interacted with natural language to investigate specific operational bottlenecks. The resulting visualization (Figure 5) revealed that OtherMachine 1 represented a major constraint on production flow, while other resources showed varying utilization levels. This insight, obtained without technical query formulation, enabled immediate strategic planning for resource optimization.

Query 3: "Queue level in 'othermachine 1'"

The third analysis focused then on understanding OtherMachine 1's specific workload patterns. Through another simple query, they obtained a detailed temporal analysis (Figure 6) showing workload fluctuations – information that traditionally would require extensive data processing and visualization expertise.

Query 4: "Gantt diagram of Milling and Othermachine 2 in 2025"

The investigation culminated in a strategic analysis of resource allocation possibilities. The user can easily requested and obtained a comparative view of two key resources (Figure 7), enabling the identification of load-balancing opportunities that would typically require extensive simulation expertise to uncover.

This analysis led to a comprehensive optimization strategy: redistributing workload between machines to improve overall system efficiency. The strategy emerged from the user's ability to easily access and interpret complex simulation data through natural language interaction.

### *5.2 Validation*

In the previous subsection has been demonstrated the system's ability to interpret user queries, analyze complex simulation data, and provide accurate, actionable insights for different

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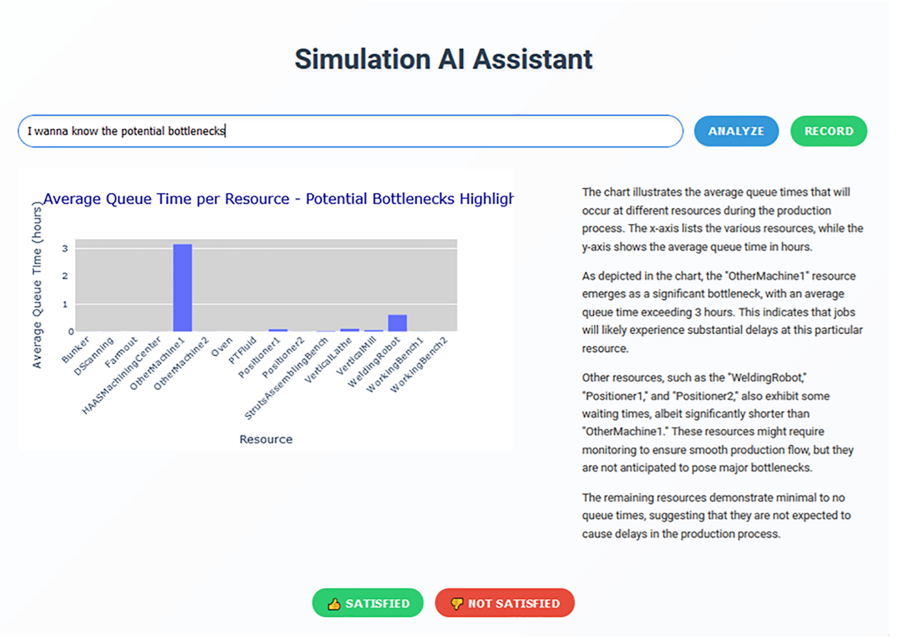


**Figure 5.** Resources average queue level. Source: Authors' own work

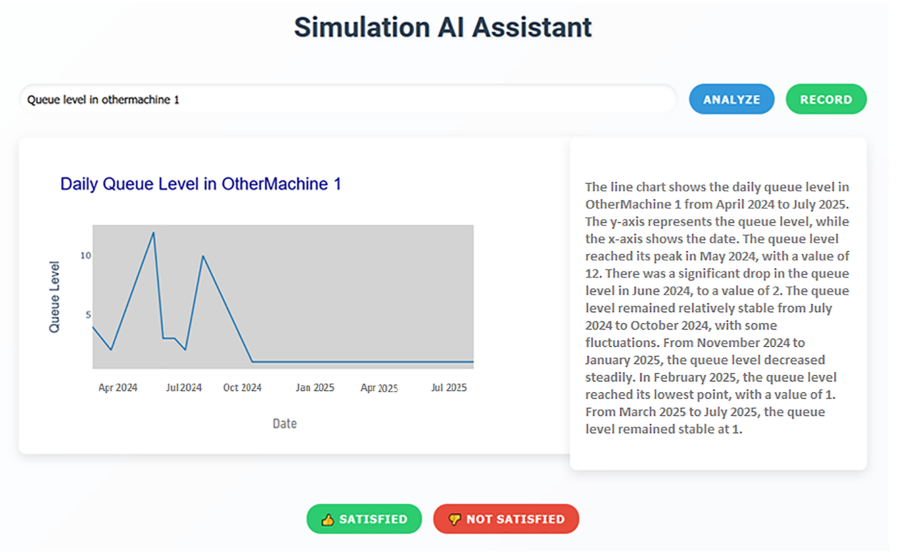


**Figure 6.** Othermachine 1 queue level. Source: Authors' own work

organization levels. To validate the effectiveness and accuracy of this integration, we examined two specific examples in detail by comparing LLMs model output and data input (simulation data output).

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**Figure 7.** Vertical Mill and Othermachine 2 processes during 2025. Source: Authors' own work

The first example (Figure 8) involved a query about orders completed more than four months late. The LLM processed the raw simulation data, which included order IDs, product types, start dates, completion dates, states and due dates (Figure 8). It accurately calculated the delay for each order, filtering those exceeding the four-month threshold. By cross-referencing the LLM's output with the raw data (highlighted in yellow box), we confirmed its accuracy in identifying seven delayed orders.

The second example involved a more specific query about the Turbine Rear Frame (TRF) product (Figure 9). The LLM generated a Gantt chart based on the provided simulation data, which included task IDs, start and end dates, queue times, durations and workstation assignments. It is important to note that the system correctly interpreted the TRF acronym and created a comprehensive visual representation of the project timeline. Validation of this output involved comparing the Gantt chart with the raw data (Figure 9), confirming that task durations, start and end dates and workstation assignments were accurately represented.

The implementation of the LLM-simulation integration in this case study offers insights into addressing the research objectives outlined earlier. The system's capacity to process natural language queries about order delays (Figure 4) provided decision makers without technical expertise immediate access to strategic performance indicators. The subsequent investigation into production bottlenecks (Figure 5) and specific resource utilization patterns (Figure 6) demonstrated how users could progressively deepen their analysis through conversational interaction, moving from identifying problems to exploring root causes. The culmination in comparative resource utilization analysis (Figure 7) illustrated how the interface empowered users to visualize scheduling across multiple resources, enabling identification of load-balancing opportunities without specialized technical skills. The validation of these capabilities, as evidenced in Figures 8 and 9, confirmed that the system maintained analytical accuracy while transforming complex simulation data into accessible visualizations and insights. This progressive analytical journey suggests that natural language interfaces may effectively bridge the technological access gap identified in Section 2, enabling

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(a)

(b)

| ID Order | Product Type | Start Date | End Date | Status | Due Date | Lateness |
|---|---|---|---|---|---|---|
| TCF-1(1) | Product2 | 14/01/2024 06:00 | 03/03/2024 11:00 | Completed | 2024-04-28 | -1333 |
| TCF-1(2) | Product2 | 14/01/2024 06:00 | 04/03/2024 19:00 | Completed | 2024-04-28 | -1301 |
| TCF-2(1) | Product2 | 11/02/2024 06:00 | 08/04/2024 09:00 | Completed | 2024-08-02 | -2775 |
| TD-1(1) | Product3 | 08/04/2024 06:00 | 03/06/2024 22:00 | Completed | 2024-07-12 | -914 |
| TD-2(1) | Product3 | 08/04/2024 06:00 | 23/06/2024 18:00 | Completed | 2025-05-17 | -7854 |
| TRF-1(1) | Product1 | 15/04/2024 06:00 | 20/07/2025 18:00 | Completed | 2024-12-29 | 4890 |
| TRF-1(2) | Product1 | 15/04/2024 06:00 | 05/08/2025 16:00 | Completed | 2024-12-29 | 5272 |
| TRF-1(3) | Product1 | 15/04/2024 06:00 | 09/09/2025 16:00 | Completed | 2024-12-29 | 6112 |
| TRF-1(4) | Product1 | 15/04/2024 06:00 | 30/09/2025 22:00 | Completed | 2024-12-29 | 6622 |
| TRF-2(1) | Product1 | 29/04/2024 06:00 | 14/01/2025 18:00 | Completed | 2024-08-30 | 3306 |
| TRF-3(1) | Product1 | 03/05/2024 06:00 | 07/11/2025 16:00 | Completed | 2025-05-06 | 4456 |
| TRF-4(1) | Product1 | 16/05/2024 06:00 | 24/03/2025 21:00 | Completed | 2024-10-04 | 4125 |
| TCF-3(1) | Product2 | 01/06/2024 06:00 | 26/08/2024 19:00 | Completed | 2024-08-19 | 187 |
| TCF-4(1) | Product2 | 27/06/2024 06:00 | 13/12/2024 15:00 | Completed | 2024-12-12 | 39 |
| TCF-4(2) | Product2 | 27/06/2024 06:00 | 18/01/2025 10:00 | Completed | 2024-12-12 | 898 |
| TCF-4(3) | Product2 | 27/06/2024 06:00 | 24/01/2025 12:00 | Completed | 2024-12-12 | 1044 |
| TCF-4(4) | Product2 | 27/06/2024 06:00 | 25/01/2025 20:00 | Completed | 2024-12-12 | 1076 |
| TCF-4(5) | Product2 | 27/06/2024 06:00 | 01/02/2025 11:00 | Completed | 2024-12-12 | 1235 |
| TD-3(1) | Product3 | 02/07/2024 06:00 | 24/09/2024 07:00 | Completed | 2024-11-26 | -1505 |
| TD-4(1) | Product3 | 30/07/2024 06:00 | 12/01/2025 18:00 | Completed | 2025-02-24 | -1014 |

**Figure 8.** LLM analysis of orders with over 4-month delays (a) compared to raw simulation data (b). Source: Authors' own work

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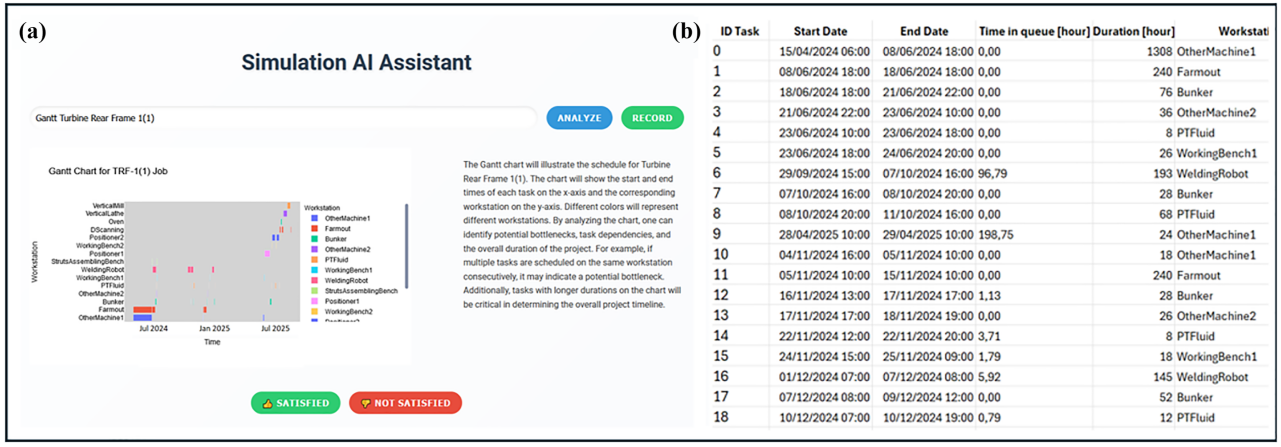


| ID Task | Start Date | End Date | Time in queue [hour] | Duration [hour] | Workstati |
|---|---|---|---|---|---|
| 0 | 15/04/2024 06:00 | 08/06/2024 18:00 | 0,00 | 1308 | OtherMachine1 |
| 1 | 08/06/2024 18:00 | 18/06/2024 18:00 | 0,00 | 240 | Farmout |
| 2 | 18/06/2024 18:00 | 21/06/2024 22:00 | 0,00 | 76 | Bunker |
| 3 | 21/06/2024 22:00 | 23/06/2024 10:00 | 0,00 | 36 | OtherMachine2 |
| 4 | 23/06/2024 10:00 | 23/06/2024 18:00 | 0,00 | 8 | PTFluid |
| 5 | 23/06/2024 18:00 | 24/06/2024 20:00 | 0,00 | 26 | WorkingBench1 |
| 6 | 29/09/2024 15:00 | 07/10/2024 16:00 | 96,79 | 193 | WeldingRobot |
| 7 | 07/10/2024 16:00 | 08/10/2024 20:00 | 0,00 | 28 | Bunker |
| 8 | 08/10/2024 20:00 | 11/10/2024 16:00 | 0,00 | 68 | PTFluid |
| 9 | 28/04/2025 10:00 | 29/04/2025 10:00 | 198,75 | 24 | OtherMachine1 |
| 10 | 04/11/2024 16:00 | 05/11/2024 10:00 | 0,00 | 18 | OtherMachine1 |
| 11 | 05/11/2024 10:00 | 15/11/2024 10:00 | 0,00 | 240 | Farmout |
| 12 | 16/11/2024 13:00 | 17/11/2024 17:00 | 1,13 | 28 | Bunker |
| 13 | 17/11/2024 17:00 | 18/11/2024 19:00 | 0,00 | 26 | OtherMachine2 |
| 14 | 22/11/2024 12:00 | 22/11/2024 20:00 | 3,71 | 8 | PTFluid |
| 15 | 24/11/2024 15:00 | 25/11/2024 09:00 | 1,79 | 18 | WorkingBench1 |
| 16 | 01/12/2024 07:00 | 07/12/2024 08:00 | 5,92 | 145 | WeldingRobot |
| 17 | 07/12/2024 08:00 | 09/12/2024 12:00 | 0,00 | 52 | Bunker |
| 18 | 10/12/2024 07:00 | 10/12/2024 19:00 | 0,79 | 12 | PTFluid |

**Figure 9.** Comparison of LLM-generated Gantt chart for Turbine Rear Frame (TRF) production (a) with corresponding simulation data (b). Source: Authors' own work



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diverse stakeholders to engage with simulation data through familiar communication patterns without sacrificing analytical integrity. These observations indicate potential for democratizing simulation capabilities in alignment with Industry 5.0's human-centric principles, potentially supporting more inclusive decision frameworks across organizational hierarchies.

## 6. Discussion

The implementation of LLM-simulation integration revealed significant insights into manufacturing simulation democratization and its influence on organizational decision processes. This section interprets these findings through the lens of our research objectives while examining their implications for transforming simulation-based decision support in Industry 5.0 environments. Our research aimed to develop a system that transforms decision-making by enabling cross-level access to simulation capabilities while maintaining analytical reliability. The findings demonstrate that natural language interfaces can effectively overcome the persistent accessibility barriers that have historically limited simulation adoption in manufacturing environments (Szukits, 2022; Wang *et al.*, 2024a). Traditional simulation technologies, despite their analytical power, have remained largely confined to technical specialists due to their complex interfaces and steep learning curves (Collins *et al.*, 2023; Goncalves *et al.*, 2024). The observed accuracy of simulation query interpretation suggests that LLM integration fundamentally transforms the user-simulation relationship, maintaining the full computational power and precision of underlying simulation models while eliminating technical barriers to their use (Huang *et al.*, 2023; Jahangirian *et al.*, 2015).

Building on this transformation of accessibility, our second research objective focused on creating a system that democratizes technical simulation knowledge to foster human-centric innovation aligned with Industry 5.0 principles. The findings reveal how LLM-enhanced simulation transforms traditional decision processes that have historically been constrained by simulation complexity (Hill, 2022). In conventional manufacturing environments, simulation insights typically follow a linear path where technical specialists develop models, run scenarios, interpret results and then translate findings for decision-makers, creating multiple opportunities for information loss. The observed ability of non-expert users to independently explore simulation scenarios suggests a fundamental reconfiguration of this process. When decision-makers engage directly with simulation models through natural language, the traditional knowledge transfer bottlenecks between technical and strategic domains disappear (Ghobakhloo, 2020), enabling decision-makers to explore variables, test scenarios, and evaluate outcomes based on their domain expertise without technical intermediaries (Flores-García *et al.*, 2019; Piccarozzi *et al.*, 2024).

This transformation extends beyond accessibility to create what might be termed "conversational simulation", an interactive, iterative approach to model exploration that more closely resembles human thinking patterns than conventional simulation workflows (Bousdekis *et al.*, 2021; Gökalp *et al.*, 2021). Traditional simulation approaches typically require pre-defined scenarios, structured parameters, and formal output analysis, while the LLM-enhanced approach enables progressive refinement of queries, allowing users to follow analytical threads as they emerge from initial findings. This conversational simulation pattern has significant implications for how organizations leverage simulation technology for innovation, supporting more organic knowledge development than traditional simulation approaches that rely on predetermined scenarios (Korzynski *et al.*, 2023). The observed pattern of progressive query refinement indicates that users engage with simulation models in fundamentally different ways when language barriers are removed (Tiago *et al.*, 2020; Sinnaiah *et al.*, 2023).

The research findings reveal three primary mechanisms through which LLM-enhanced simulation transforms manufacturing organizations. First, the democratization of simulation capabilities reduces decision latency by eliminating bottlenecks in the technical analysis

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process, enabling organizations to rapidly evaluate production alternatives without waiting for specialized modeling support (Omol, 2023). Second, natural language interfaces enhance simulation-based decision quality by enabling more diverse perspectives to engage with modeling insights, where operational managers can directly test their assumptions through simulation, resulting in decisions that benefit from both technical model validity and practical operational knowledge (Moktadir *et al.*, 2019). Third, accessible simulation supports more evidence-based decision cultures by making modeling capabilities available throughout organizational hierarchies (Babu *et al.*, 2024). These transformative effects align directly with Industry 5.0's vision of human-centric manufacturing environments by adapting complex simulation technology to human communication patterns rather than requiring humans to adapt to technical interfaces, exemplifying how advanced manufacturing technologies can enhance rather than replace human capabilities in decision processes. The findings demonstrate that integrating LLMs with industrial simulation systems fundamentally transforms these powerful analytical tools from specialized technical resources to accessible decision support mechanisms that operate across multiple organizational levels, creating significant opportunities for more inclusive, data-driven manufacturing innovation while maintaining the analytical precision that makes simulation technology valuable for complex production environments.

## 7. Theoretical and impact analysis

The integration of LLMs with industrial simulation models advances decision support in manufacturing by bridging knowledge gaps between technical specialists and decision-makers in Industry 5.0 contexts, as validated through our implementation. Our findings contribute to decision management theory through three mechanisms: First, natural language interfaces address technological access barriers (Szukits, 2022; Wang *et al.*, 2024a) and knowledge transfer challenges (Collins *et al.*, 2023); Second, the integration enhances AI capabilities within decision systems, resolving visualization limitations (Hansen and Johnson, 2011; Frazão *et al.*, 2021); Finally, the approach aligns with Industry 5.0's human-centric principles by facilitating broader participation in data-driven processes (Gökalp *et al.*, 2021). Table 2 synthesizes these transformative effects by contrasting traditional manufacturing simulation approaches with our LLM-enhanced system across key innovation dimensions.

The LLM interface democratizes technical knowledge by addressing both tangible barriers (infrastructure) and intangible barriers (technical literacy) (Bousdekis *et al.*, 2021; Roy Ghatak and Garza-Reyes, 2024). Through natural language processing, the system enables non-

**Table 2.** Manufacturing Innovation: Traditional vs. LLM-Enhanced Simulation

| Aspect | Traditional manufacturing simulation | LLM-enhanced system |
|---|---|---|
| Decision Support | Expert-driven technical analysis with limited accessibility | Natural language queries enabling multi-level decision-making |
| Knowledge Democratization | Restricted to simulation specialists | Organization-wide accessibility through conversational interface |
| Innovation Process | Limited by technical expertise requirements | Collaborative innovation through inclusive participation |
| Strategic Alignment | Disconnect between operational data and strategy | Direct integration of simulation insights with strategic planning |
| Workforce Development | Extensive technical training requirements | Rapid adoption through natural communication |
| Operational Agility | Delayed response due to expertise bottlenecks | Real-time insights supporting agile decision-making |

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technical stakeholders to engage with sophisticated analyses while maintaining analytical rigor (Babu *et al.*, 2024).

This integration transforms decision processes by creating intuitive interfaces for simulation data, advancing beyond practices where accessibility limitations restrict organizational impact (Jahangirian *et al.*, 2015; Hill, 2022). The approach enhances knowledge transfer between specialists and decision-makers (Thirunavukarasu *et al.*, 2023; Wu *et al.*, 2023). This transformation manifests through: innovation management advancement, economic value creation, organizational restructuring of decision hierarchies, and human-centric impact aligned with Industry 5.0's vision, while addressing policy and ethical considerations for AI-assisted decision-making.

### *7.1 Economic value creation*

The economic impact of the LLMs integration in the simulation model requires careful consideration of implementation costs and potential returns. Initial investments encompass several key components: simulation software licensing and maintenance fees, model development and customization costs following acquisition, LLM system development expenses, and ongoing API usage costs for LLM services. However, evidence from manufacturing implementations demonstrates substantial returns that offset these investments. Long-term financial benefits emerge through multiple channels, as demonstrated by successful simulation implementations in manufacturing. Michelin Company achieved significant cost reductions and efficiency improvements through simulation-based optimization of their production processes, while other manufacturers report substantial savings through improved resource allocation and reduced operational inefficiencies (MichelinCase Study, 2024). Studies of manufacturing simulation implementations consistently demonstrate ROI through reduced operational costs, improved capacity utilization, and enhanced production planning (Anylogic, 2023). The addition of LLM interfaces further amplifies these benefits by reducing training costs and democratizing access to simulation insights, enabling broader organizational participation in optimization efforts (Ghiani *et al.*, 2024). These advantages are particularly significant in complex manufacturing environments where traditional approaches to simulation often create expertise bottlenecks and limit the potential value realization from simulation investments.

### *7.2 Organizational transformation*

The synergy between LLMs and simulation models initiates profound organizational changes that support innovation management objectives in manufacturing environments, creating significant organizational impact across multiple dimensions. By enabling natural language interaction with complex simulation models, the system transforms traditional decision-making hierarchies into more collaborative structures (Gao *et al.*, 2024), with measurable impact on innovation outcomes and organizational effectiveness (Townsend and Romme, 2024; Corvello, 2025). This democratization of analytical capabilities creates new organizational learning dynamics, where insights flow freely across departmental boundaries, significantly impacting knowledge sharing and innovation diffusion. The case study demonstrates how this transformation's impact supports data-driven innovation culture while maintaining human centricity in decision processes. The organizational impact extends to structural adaptations that support inclusive innovation practices, fundamentally changing how organizations approach innovation management.

### *7.3 Human-centric impact*

Consistent with Industry 5.0's core principles, the incorporation of LLMs into simulation models enhances workforce engagement through human-centric technological integration (Madzik *et al.*, 2025). Through natural language accessibility, it reduces cognitive load in

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technical tasks while empowering workers across organizational levels to participate meaningfully in simulation-driven decision-making processes (Wu *et al.*, 2024), directly supporting Industry 5.0's vision of inclusive and sustainable workplaces. The human-centric benefits manifest through enhanced professional autonomy, as workers gain direct access to simulation insights leading to more informed and confident decision-making. This alignment with autonomy supportive leadership principles fosters an environment where employees can exercise greater control over their work processes and decisions, ultimately enhancing their engagement and well-being (Sarmah *et al.*, 2022). The integration of simulation tools within a human-centered organizational framework not only amplifies professional autonomy but also reinforces the humanistic values that prioritize positive workplace experiences and employee development (Townsend and Romme, 2024). Through this synergy of technological empowerment and human-centered organizational design, workers experience greater agency in their roles while benefiting from enhanced decision-making capabilities that support both individual growth and organizational success. The system promotes workplace well-being by democratizing access to technical knowledge, enabling workers to develop new competencies while maintaining focus on strategic thinking rather than technical manipulation. This democratization of simulation capabilities creates an inclusive environment where diverse perspectives contribute to organizational innovation, embodying Industry 5.0's emphasis on human-centricity and sustainable technological advancement.

### *7.4 Policy implications*

The convergence of LLMs and simulation models directly advances the European Commission's Industry 5.0 vision (EU_Industry, 2025), which emphasizes human-centricity, sustainability and resilience in manufacturing. The framework aligns with EU's approach to AI regulation (EU_AI, 2025), demonstrating how technological innovation can advance these principles while maintaining industrial competitiveness. Natural language interfaces exemplify the human-centric approach by making complex technical tools accessible to all workers (Wang *et al.*, 2024b). Policy support is warranted as the technology promotes workforce inclusivity through natural language interaction and supports human–machine collaboration, where technology enhances rather than replaces human capabilities. These alignments with Industry 5.0 objectives suggest policymakers should incentivize adoption through targeted funding, standards development and workforce initiatives. By supporting human-centric technological systems, policymakers can foster inclusive innovation while ensuring European manufacturing remains globally competitive.

### *7.5 Ethical framework*

Combining LLMs with simulation models requires careful consideration of ethical implications in AI-assisted decision-making, with particular attention to identifying and mitigating potential biases in AI systems (Resnik and Hosseini, 2024). Organizations must establish clear protocols for ensuring transparency and accountability in system operations, implementing robust validation procedures to verify AI-generated outputs and decisions (Kovari, 2024). When non-expert users interact with complex simulation data through natural language interfaces, it becomes crucial to maintain clear documentation of the decision-making process and establish verification mechanisms for AI-generated results. The ethical considerations encompass broader implications for organizational culture and research practices, requiring systematic approaches to bias detection and validation. Regular system audits, stakeholder engagement, and independent ethical reviews ensure responsible innovation that aligns with organizational values and Industry 5.0 principles. Our work emphasizes transparency in AI-assisted decision-making by integrating LLMs with simulation tools, enabling natural language interfaces for accessing complex data while ensuring

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accountability through validation protocols that allow stakeholders to evaluate and refine system-generated insights across organizational levels.

This LLM-simulation integration fulfills our dual research objectives by transforming organizational decision processes and democratizing technical knowledge. The integration delivers economic benefits, transforms organizational structures, enhances workforce engagement through human-centric design, aligns with Industry 5.0 policy objectives, and establishes ethical frameworks for responsible implementation – collectively forming a foundation for inclusive technological advancement in manufacturing.

## 8. Conclusion

This research advances both theoretical understanding and practical applications in innovation management within the Industry 5.0 paradigm through three primary contributions. First, our integration of LLMs with industrial simulation models represents a breakthrough in democratizing complex analytical tools, transforming traditionally expert-dependent simulation systems into accessible platforms through natural language interaction. This integration enables users across all organizational levels to directly query, analyze and interpret simulation results without specialized technical expertise, effectively breaking down long-standing barriers to simulation adoption. Second, our research demonstrates how this enhanced accessibility reshapes organizational dynamics, allowing decision-makers to move from passive consumers of simulation reports to active participants in the analysis process, fostering a culture of data-driven innovation through inclusive decision-making. Third, our work provides a practical framework that balances technological advancement with human-centric approaches in Industry 5.0 environments, showing how natural language interfaces can bridge the gap between technical complexity and strategic decision-making needs.

The current implementation has some limitations that need to be taken into consideration. The system's reliance on pre-processed data restricts real-time analysis capabilities, and output quality is fundamentally tied to the accuracy of initial simulation data. Complex technical queries may face interpretation challenges, impacting the precision of decision-making processes.

Future research opportunities emerge in three critical areas. The development of real-time data processing capabilities could significantly enhance the system's value for dynamic decision-making environments. Building upon these processing capabilities, the integration of more advanced AI capabilities, such as machine learning algorithms and enhanced LLM architectures, offers opportunities to improve query interpretation and response generation while maintaining human-centric decision support. Complementing these technological advancements, organizational research should explore how companies can optimally structure themselves to leverage such integrated systems, particularly focusing on how natural language interfaces can further democratize access to complex analytical tools.

As Industry 5.0 continues to evolve, the ability to transform complex technical systems into accessible decision support tools through LLM integration becomes increasingly crucial for sustainable competitive advantage. Our framework demonstrates how organizations can leverage natural language processing to make simulation capabilities accessible to all stakeholders, setting a foundation for more inclusive and effective technological integration in industrial settings.

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