

Providing a Model for Intelligent Monitoring of Maintenance in the Railway Industry

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ABSTRACT

The aim of this study was to present a model for intelligent monitoring of maintenance in the railway industry. Therefore, in terms of purpose, it is an applied research, as in addition to its informative and scientific aspects, it also has practical implications for various companies and organizations, particularly in the railway industry. Considering the aim and nature of the study, the research method is qualitative. Moreover, since this research seeks to design a model, it is exploratory in nature. The results indicated that the intelligent monitoring model for maintenance in the railway industry consists of: data and repair management (data management and interactive dashboards, resource management and repair optimization, scalability and integration of systems and sensors), system and maintenance management (sensor management and system maintenance, data analysis and anomaly detection, alert systems and data monitoring), monitoring and integration (data management and system integration, performance monitoring and system optimization, prediction and preventive maintenance), optimization and customization (improving user experience and customization, collecting and analyzing user feedback, system optimization), security and maintenance (maintenance management and production optimization, data analysis and machine learning, data security and regulatory compliance), and usability and human resources (security and user design, monitoring and maintenance, human resource training and development).

Keywords: Intelligent monitoring, maintenance, railway industry

1. Introduction

Maintenance is a critical component of operational efficiency, asset longevity, and organizational sustainability, particularly in infrastructure-intensive and production-oriented industries. Over the past few decades, the concept of maintenance has evolved from reactive repair

approaches to integrated, predictive, and optimization-driven strategies, enabling organizations to enhance performance while reducing operational costs (Eze et al., 2024; Jeze et al., 2024). In infrastructure systems such as water supply, railway networks, and manufacturing plants, maintenance is not merely a technical necessity but a strategic enabler for safety, environmental stewardship, and

customer satisfaction (Jambadu, Pilo, et al., 2024; Sarfaraz et al., 2023). In this context, intelligent monitoring and advanced maintenance frameworks are gaining prominence as they combine technological capabilities with systematic decision-making, thereby addressing both technical and managerial challenges (Salahi et al., 2023; Sharifzadegan et al., 2023).

Total Productive Maintenance (TPM) remains one of the most influential paradigms in modern maintenance management, focusing on maximizing equipment effectiveness through proactive involvement of employees across all levels (Wolska, 2023; Yang & Yang, 2023). By integrating TPM principles with Lean Manufacturing techniques, organizations can improve reliability, reduce waste, and increase operational responsiveness (Risonarta & Wardhani, 2023; Saenagri, 2023). The application of these principles has been documented across diverse sectors, from pharmaceuticals (Saenagri, 2023) to automotive manufacturing (Farihi, 2023) and other high-precision industries (Firdaus et al., 2023). In each of these cases, the combination of systematic maintenance schedules, real-time monitoring, and continuous improvement processes has proven effective in reducing unplanned downtime and enhancing quality outputs.

In large-scale infrastructure systems, particularly those involving complex and geographically dispersed assets, the integration of intelligent monitoring with maintenance strategies is paramount. Recent research emphasizes that predictive maintenance—leveraging sensor networks, big data analytics, and machine learning—offers significant advantages in anticipating failures before they occur (Kaewunruen, 2023; Meddaoui, 2023). Predictive models can detect patterns invisible to manual inspections, enabling proactive intervention and resource allocation (Cacereño et al., 2023; Kaya & Ulutagay, 2023). This approach is especially relevant in high-risk environments such as railway infrastructure, where operational disruptions have cascading impacts on safety, service reliability, and economic performance (Kaewunruen, 2023).

The optimization of maintenance strategies is not solely a matter of technological advancement but also of organizational adaptation. For example, the successful implementation of condition-based maintenance (CBM) depends on aligning technical capabilities with management structures, resource availability, and employee competencies (Kaya & Ulutagay, 2023; Lestari, 2023). Studies have shown that integrating fuzzy inference systems and multi-objective optimization techniques with CBM frameworks can enhance

decision-making under uncertainty, balancing cost-efficiency with reliability (Cacereño et al., 2023; Sharifzadegan et al., 2023). Similarly, hybrid optimization models, such as those combining simulation-based design with maintenance planning, offer comprehensive tools for maximizing operational value (Cacereño et al., 2023).

The human factor remains a decisive element in the effectiveness of maintenance systems. Employee participation in TPM initiatives fosters a bottom-up approach that strengthens ownership, accountability, and knowledge sharing (Lestari, 2023; Yang & Yang, 2023). In welfare service centers and other public service contexts, the role of maintenance extends beyond technical reliability to encompass care and accessibility, especially at the intersections of analog and digital systems (Kaun & Liminga, 2023). This aligns with broader organizational development principles, where training, development, and empowerment of human resources are fundamental to sustaining long-term maintenance performance (Fan et al., 2023; Lestari, 2023).

Moreover, balanced scorecard frameworks have been applied to assess maintenance performance comprehensively, integrating financial, operational, learning, and customer perspectives (Hraiga et al., 2023). Such frameworks facilitate the translation of maintenance objectives into measurable indicators, which can be linked to corporate strategies and regulatory compliance (Heidari, 2023; Sarfaraz et al., 2023). In highly regulated industries, this is critical for ensuring safety, environmental protection, and adherence to legal requirements (Eze et al., 2024; Jeze et al., 2024).

Maintenance also plays a significant role in sustainable development. For example, studies on the upkeep of traditional building materials, such as mud houses, highlight the importance of context-specific methods that align with environmental and cultural sustainability goals (Eze et al., 2024; Jeze et al., 2024). Similarly, in manufacturing contexts, sustainable maintenance practices—such as energy-efficient scheduling, lifecycle optimization, and waste minimization—contribute directly to reducing the ecological footprint (Kaewunruen, 2023; Meddaoui, 2023). These approaches underscore the dual role of maintenance as both an operational and environmental strategy.

In water infrastructure systems, the politics of maintenance intersect with issues of technology transfer, labor relations, and institutional capacity (Jambadu, Monstadt, et al., 2024; Jambadu, Pilo, et al., 2024). Hybrid labor arrangements in maintenance activities, combining

formal employment with community participation, have been shown to enhance service resilience in resource-constrained settings (Jambadu, Monstadt, et al., 2024; Sarfaraz et al., 2023). However, these arrangements require careful governance to ensure quality, accountability, and equitable resource allocation.

Recent advances in railway infrastructure maintenance have demonstrated the potential of integrating reinforcement learning techniques with sustainability objectives (Kaewunruen, 2023). By modeling the trade-offs between operational efficiency, carbon emission reduction, and cost minimization, such innovations align maintenance with broader environmental and social priorities. This is consistent with the growing emphasis on “maintenance for sustainability,” which reframes maintenance not only as a cost center but also as a strategic investment (Kaewunruen, 2023; Meddaoui, 2023).

The integration of production planning with maintenance scheduling is another area of increasing importance. Mathematical models have been proposed to coordinate production and preventive maintenance under uncertainty, considering constraints such as resource availability and facility disruptions (Salahi et al., 2023; Sharifzadegan et al., 2023). These models aim to optimize system throughput while minimizing downtime, thereby increasing overall competitiveness (Risonarta & Wardhani, 2023; Saenagri, 2023). In this respect, advanced scheduling approaches are crucial for industries where operational interruptions carry high financial or reputational costs.

From a methodological perspective, multi-objective optimization and simulation-based approaches have proven effective in simultaneously addressing multiple performance criteria in maintenance systems (Cacereño et al., 2023; Kaya & Ulutagay, 2023). This is particularly relevant in contexts where trade-offs exist between cost, availability, and reliability. Predictive and prescriptive analytics—when embedded in maintenance decision-making—enable organizations to prioritize interventions dynamically, based on real-time data and evolving operational conditions (Meddaoui, 2023; Sarfaraz et al., 2023).

In sum, the body of literature illustrates that effective maintenance systems require an integrated approach, combining advanced analytical tools, robust human resource strategies, and sustainable operational practices. Whether applied to traditional housing (Eze et al., 2024; Jeze et al., 2024), manufacturing plants (Risonarta & Wardhani, 2023; Saenagri, 2023), railway infrastructure (Kaewunruen, 2023; Meddaoui, 2023), or welfare service facilities (Kaun &

Liminga, 2023), maintenance is most successful when it is embedded in a broader organizational and societal context. The convergence of predictive technologies, participatory management, and sustainability-driven design offers a promising pathway for future maintenance innovation (Fan et al., 2023; Wolska, 2023).

The present study contributes to this evolving field by developing and validating an intelligent monitoring model for maintenance in the railway industry. Building upon existing frameworks in predictive maintenance, total productive maintenance, and integrated planning, the proposed model seeks to bridge technological capabilities with practical management solutions. It incorporates sensor-based data acquisition, real-time anomaly detection, and performance optimization, supported by human resource development and systemic integration. In doing so, the study addresses the dual challenge of enhancing operational reliability and aligning maintenance practices with contemporary sustainability and efficiency objectives

2. Methods and Materials

Considering the aim and nature of the study, this research was qualitative in method and was conducted through interviews with subject-matter experts. The research approach was based on grounded theory. The qualitative section of the study included interviews with experts; therefore, the statistical population consisted of individuals familiar with the research topic (university professors in the fields of industry and artificial intelligence, as well as senior managers of maintenance in the railway industry). In this section, theoretical sampling was employed. In theoretical sampling, events rather than individuals are sampled; if individuals are approached, the main objective is to explore the events. Although there is no specific rule for sample size in qualitative strategies, it has been suggested that for homogeneous groups, 6 to 8 units are appropriate, and for heterogeneous groups, 12 to 20 units are recommended. The interviews continued until theoretical saturation was achieved. In this study, saturation was reached after interviewing 12 experts (university professors in the fields of industry and artificial intelligence, and senior managers of maintenance in the railway industry).

Sampling was conducted within the framework of qualitative methodology and on a purposive basis. Two purposive sampling methods were employed: purposive sampling and snowball sampling. In qualitative research, purposive sampling is generally used to obtain the most

comprehensive information; thus, the researcher selected participants who were “information-rich,” meaning that, based on the principles of qualitative research, samples were chosen that could provide a strong representation of the phenomenon under study. The qualitative section of the study was grounded in grounded theory methodology and was conducted using MAXQDA software.

3. Findings and Results

Table 1 presents the initial themes, secondary themes, and main categories derived from the interviews.

Table 1

Open Coding, Axial Coding, and Selective Coding

Selective Coding	Axial Coding	Open Coding
Data and repair management	Data management and interactive dashboards	Designing interactive dashboards for real-time data insights; Ensuring user-friendly and accessible visualizations; Integration with data sources; Enabling users to customize views and reports according to their needs; Ensuring fast loading of visualizations and efficient management of large datasets; Mobile compatibility
Data and repair management	Resource management and repair optimization	Linking repairs with inventory; Accurate validation of repairs; Maintaining up-to-date inventory of available resources (tools, parts, personnel); Assigning tasks based on the skill sets of available personnel; Even workload distribution among maintenance teams; Cost-effective resource allocation; Ensuring resource availability when needed to prevent delays; Forecasting future resource needs based on maintenance schedules; Training personnel to perform different types of maintenance tasks; Coordination with external vendors for specialized resources
Data and repair management	System and sensor scalability and integration	Scalable architecture; Using load balancing techniques to manage traffic and workload; Employing distributed storage systems to handle large data volumes; Implementing parallel processing to enhance efficiency and processing speed; Adding more servers to increase system capacity; Upgrading existing hardware to expand capacity
System and maintenance management	Sensor management and system maintenance	Selecting suitable sensor types for various train components and track sections; Determining optimal sensor placement for maximum data accuracy; Developing installation protocols to ensure sensor stability and reliability; Integrating sensors with existing train and track infrastructure; Calibration methods to maintain sensor accuracy over time; Power solutions for sensors, including battery options and energy harvesting; Setting up wireless communication for real-time data transmission; Environmental protection measures for sensors against weather and physical damage; Regular maintenance programs for inspecting and replacing sensors; Complying with industry standards and regulations for sensor use
System and maintenance management	Data analysis and anomaly detection	Regular testing of alarm systems to ensure reliability and effectiveness; Developing a centralized data repository for storing various data types; Implementing data normalization techniques to ensure consistency; Using data transformation tools to convert data into usable formats; Creating data pipelines for automated data flow; Integrating data from IoT devices, legacy systems, and external sources; Real-time data synchronization across platforms and devices; Cleaning and organizing data for analysis readiness
System and maintenance management	Data analysis and anomaly detection	Using statistical methods to identify trends and deviations; Time series analysis; Clustering techniques; Anomaly detection algorithms; Using charts for visual identification of patterns and anomalies; Setting up systems to detect anomalies as they occur; Comparing current data with historical data for anomaly detection; Adapting pattern detection techniques to industry-specific needs; Implementing systems that learn from detected anomalies to improve detection accuracy
System and maintenance management	Alert systems and data monitoring	Providing alerts as soon as events occur; Configurable alert settings; Multi-channel notifications; Classifying alerts by importance to help users prioritize responses; Allowing users to acknowledge receipt of alerts; Automatic escalation of alerts if unresolved within a specified time frame; Keeping records of past alerts for review and analysis; User-friendly interface; Integration with other systems
Monitoring and integration	Data management and system integration	Seamless data exchange between systems; Data governance policies to manage access and usage; Systems for monitoring data flows and integration performance; Scalability solutions to handle increasing data volumes; Using standard protocols for data exchange; APIs; Ensuring data compatibility and consistency across systems; Selecting and managing appropriate communication protocols; Using common data formats to facilitate information exchange; Hardware compatibility; Ensuring compatibility between different software versions; Managing system changes to maintain interoperability; Providing training and documentation for users and developers; Conducting tests to compare system performance with industry standards; Seamless integration with existing maintenance workflows

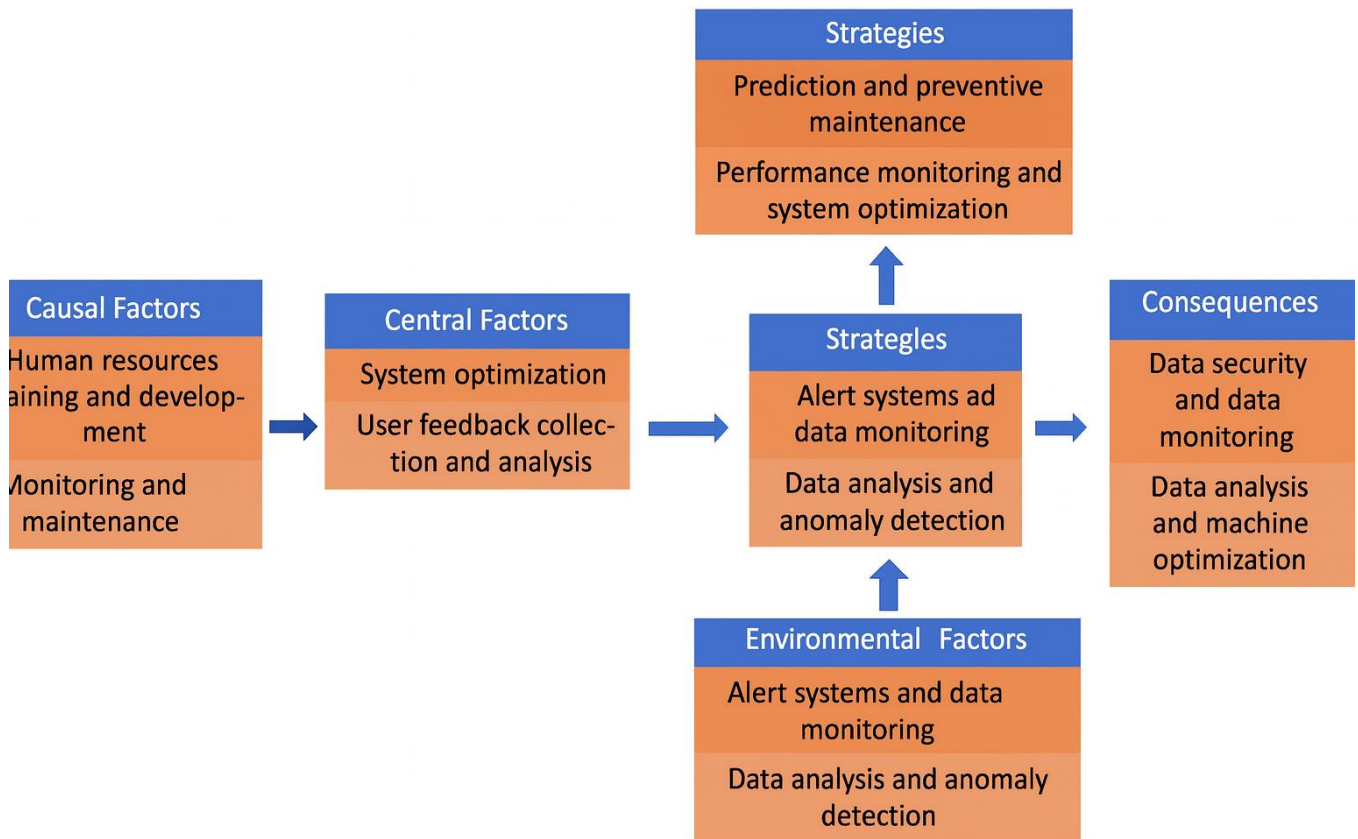
Monitoring and integration	Performance monitoring and system optimization	Linking repair data with system performance; Tracking system response times to user inputs; Measuring frequency and types of system errors; Monitoring memory and network performance for efficiency; Logging incidents and system downtime duration; Collecting user feedback specifically on system performance; Regularly evaluating system security measures and protocols; Assessing system capacity to manage user and data growth; Setting alerts to notify managers of performance issues; Conducting regular tests to ensure proper operational collaboration
Monitoring and integration	Prediction and preventive maintenance	Gathering relevant data from sensors and historical records; Identifying key indicators that predict equipment failure; Implementing real-time equipment monitoring systems; Anomaly detection; Estimating time to failure or failure probability; Creating alerts for maintenance actions based on predictions; Updating models with new data to improve accuracy
Optimization and customization	User experience enhancement and customization	Allowing customization and prioritization of information on the main user interface; Providing options to change system colors, fonts, and overall appearance; Enabling users to create shortcuts for frequently used actions; Allowing users to manage personal information and preferences; Giving users control over how and when alerts are received; Providing support for multiple languages and regional settings
Optimization and customization	User feedback collection and analysis	Regular distribution of surveys to gather user opinions and suggestions; Implementing easily accessible feedback forms within the system; Conducting user interviews for deeper insights; Observing user interactions to identify pain points; Organizing focus groups; Engaging users in beta testing; User-centered design; Monitoring online platforms for reviews and ratings
Optimization and customization	System optimization	Tracking social media mentions; Analyzing system usage data to identify recurring problems; Reviewing customer support reports; Gathering user feedback on system performance; Implementing agile methods; Continuous integration and deployment; Developing and maintaining a roadmap for future features; System technology upgrades; Continuous performance optimization; Regular security upgrades
Security and maintenance	Maintenance management and production optimization	Determining maintenance task urgency based on equipment importance; Considering personnel and tool availability; Planning maintenance to minimize downtime; Using predictive analytics; Balancing costs and operational efficiency; Ensuring compliance with industry standards; Adjusting schedules for unexpected changes; Coordinating maintenance with production; Using task feedback to improve future scheduling; Using scheduling software
Security and maintenance	Data analysis and machine learning / Data security and regulatory compliance	Training staff on best practices for data quality; Selecting suitable machine learning algorithms; Creating input variables; Training models with labeled datasets; Classifying failures; Tuning model parameters; Combining models for accuracy; Integrating models into production systems; Updating models with new data; Ensuring model interpretability; Implementing data validation rules; Data cleansing; Setting accuracy metrics; Conducting audits; Using ML for anomaly detection; Feedback loops for quality improvement; Data lineage tracking; Metadata management; Encryption for data protection; Access control; Strong authentication; Secure key management; Activity monitoring; Security training; Firewalls and intrusion detection; Backup and recovery; Compliance assurance; Regular security testing
Usability and human resources	Security and user design	Focusing on user needs and behaviors; Simple and consistent navigation; Logical information architecture; Visual cues for importance; Consistency across system sections; Immediate feedback to users; Accessible design; Familiar icons and labels; Cross-device compatibility
Usability and human resources	Monitoring and maintenance	Verifying correct repairs; Task checklists; Offline system use; Monitoring key fleet components; Monitoring fuel tanks; Monitoring traction systems; Monitoring doors; Locomotive fire alarm health; Early failure detection with AI; Passenger car safety equipment monitoring; Intelligent HVAC monitoring; Intelligent turnout monitoring; Intelligent track monitoring; Intelligent signaling monitoring
Usability and human resources	Human resource training and development	Fire extinguishing training for operators; Crisis management training; Full regulatory familiarity; Excessive checklist items; Irrelevant checklist items; Frequent inspectors; Redundant checks; Proper inspector training; Untimely failure reporting; Lack of inventory-repair coordination

Based on the final categorization, it is observed that the final categories and axes include 186 open codes, 18 axial codes, and 6 selective codes. These codes consist of data and repair management (data management and interactive dashboards, resource management and repair optimization, system and sensor scalability and integration), system and maintenance management (sensor management and system maintenance, data analysis and anomaly detection, alert systems and data monitoring), monitoring and integration (data management and system integration, performance monitoring and system optimization, prediction and

preventive maintenance), optimization and customization (user experience enhancement and customization, user feedback collection and analysis, system optimization), security and maintenance (maintenance management and production optimization, data analysis and machine learning, data security and regulatory compliance), and usability and human resources (security and user design, monitoring and maintenance, human resource training and development). Subsequently, these factors were placed within the paradigm model.

Figure 1

Intelligent Monitoring Model for Maintenance in the Railway Industry



4. Discussion and Conclusion

The results of this study led to the development of an intelligent monitoring model for maintenance in the railway industry that integrates six selective codes—data and repair management, system and maintenance management, monitoring and integration, optimization and customization, security and maintenance, and usability and human resources—supported by 18 axial codes and 186 open codes. This comprehensive model reflects a convergence between technical, managerial, and human resource considerations, indicating that high-performing railway maintenance systems must be grounded in both advanced technological tools and structured organizational processes. The categorization of factors into causal, contextual, intervening, central, and consequence dimensions further reinforces the relevance of systems thinking in maintenance design, where interdependencies between hardware, software, and human expertise must be acknowledged (Salahi et al., 2023; Sharifzadegan et al., 2023).

A key finding is that data management and interactive dashboards form the backbone of the model, enabling real-time decision-making through accessible, visualized, and user-customizable interfaces. This aligns with prior studies emphasizing the role of data-driven decision-making in optimizing maintenance schedules and reducing downtime (Cacereño et al., 2023). By integrating data pipelines, normalization techniques, and real-time synchronization, the model ensures that information from IoT sensors, historical records, and legacy systems is not only aggregated but also actionable. Such integration resonates with frameworks proposed in water supply infrastructure management, where centralized data repositories and analytical platforms have enhanced responsiveness and efficiency (Jambadu, Pilo, et al., 2024; Sarfaraz et al., 2023).

The resource management and repair optimization dimension addresses allocation efficiency, ensuring that tools, spare parts, and personnel are deployed cost-effectively without compromising availability. This finding is consistent with the principles of Total Productive Maintenance (TPM), which seek to balance preventive strategies with operational demands to minimize unplanned

stoppages (Wolska, 2023; Yang & Yang, 2023). The study's emphasis on scalability and system integration further validates the relevance of adaptive architectures capable of expanding in response to increased data volumes or operational complexity (Kaya & Ulutagay, 2023).

System and maintenance management emerged as a pivotal area, incorporating sensor management, anomaly detection, and alert systems. The empirical evidence suggests that optimal sensor deployment—both in type selection and placement—combined with predictive algorithms significantly enhances the early detection of equipment failures. These results support prior work demonstrating that predictive maintenance strategies, when paired with machine learning models, can accurately forecast failures and guide timely interventions (Kaewunruen, 2023; Meddaoui, 2023). Furthermore, the inclusion of alert systems with configurable thresholds and multi-channel notifications ensures that maintenance teams can prioritize and escalate issues appropriately, mirroring similar advancements in manufacturing and automotive contexts (Farihi, 2023; Risonarta & Wardhani, 2023).

The monitoring and integration category of the model—covering performance monitoring, system optimization, and preventive maintenance—highlights the necessity of linking repair data with performance metrics. The capacity to analyze these linkages in real time supports continuous improvement and is consistent with balanced scorecard approaches to maintenance performance evaluation (Hraiga et al., 2023). Predictive and preventive elements in this category draw on statistical modeling, clustering, and anomaly detection to identify emerging issues before they affect operations, a strategy shown to significantly improve reliability in both transport and manufacturing industries (Fan et al., 2023; Saenagri, 2023).

Optimization and customization elements in the model reveal the importance of tailoring interfaces, workflows, and system settings to user needs. This finding aligns with the literature on user-centered design in welfare and public service contexts, where customization not only improves usability but also fosters greater stakeholder engagement (Kaun & Liminga, 2023; Lestari, 2023). The feedback collection and analysis components of this category ensure that user experience remains a driver of system evolution, reflecting agile development principles in maintenance software design (Firdaus et al., 2023).

Security and maintenance capabilities—including production optimization, machine learning integration, and data security—were found to be integral for safeguarding

system integrity. The model's focus on encryption, access controls, and compliance with regulations reflects established best practices for protecting operational and customer data in critical infrastructure sectors (Eze et al., 2024; Jeze et al., 2024). By incorporating machine learning into maintenance optimization, the model aligns with trends in lean maintenance and predictive analytics, where continuous model updates and explainable AI improve both transparency and accuracy (Heidari, 2023).

Finally, the usability and human resources dimension emphasizes human resource training, monitoring, and user security design. This component acknowledges that even the most technologically advanced maintenance systems rely on well-trained personnel for effective execution. The focus on training in crisis management, safety protocols, and equipment operation is supported by studies demonstrating that empowered employees are more capable of maintaining asset reliability and responding effectively to unexpected issues (Jambadu, Monstadt, et al., 2024; Sharifzadegan et al., 2023). Moreover, the design principles embedded in this dimension—simplicity, accessibility, and feedback—mirror usability standards that have been shown to increase adoption and reduce errors in digital maintenance tools (Fan et al., 2023).

In synthesis, the results validate that a holistic, multi-dimensional model—combining data integration, predictive analytics, human resource development, and security—can significantly enhance railway maintenance systems. This conclusion is consistent with cross-sectoral findings in manufacturing, public infrastructure, and service delivery, where integrated approaches yield superior outcomes in terms of cost, reliability, and sustainability (Kaewunruen, 2023; Salahi et al., 2023). The study thus contributes to both theoretical and practical discourses on maintenance by providing a replicable framework adaptable to other high-reliability sectors.

Despite the comprehensiveness of the proposed model, several limitations must be acknowledged. First, the study was conducted within the specific context of the railway industry, which may limit its generalizability to sectors with different operational dynamics, regulatory frameworks, or technological infrastructures. Second, the reliance on expert interviews and qualitative coding—while valuable for depth and context—may introduce subjective biases in the interpretation of findings. The thematic saturation achieved with 12 experts, though consistent with qualitative research standards, might not capture the full diversity of perspectives in larger or more varied operational environments.

Additionally, the model has not yet undergone large-scale empirical testing in live operational contexts, meaning that its predictive accuracy, integration feasibility, and cost-effectiveness remain to be validated through longitudinal and quantitative assessments. Technological dependencies, such as the availability of high-quality sensor data and reliable connectivity, also pose potential challenges for implementation in regions with limited infrastructure.

Future research could expand the empirical testing of the intelligent monitoring model across multiple railway systems in diverse geographical and operational contexts to assess scalability and adaptability. Comparative studies between railway and other critical infrastructure sectors—such as power grids, aviation, and maritime transport—could further validate the model’s applicability and reveal sector-specific modifications. Incorporating hybrid research designs that blend qualitative insights with quantitative performance metrics would strengthen the robustness of findings. Another promising direction would be to integrate emerging technologies such as edge computing, digital twins, and blockchain into the monitoring framework, thereby enhancing real-time decision-making, security, and traceability. Investigating the socio-technical dynamics of implementation—particularly how organizational culture, change management strategies, and workforce readiness affect adoption—would also provide valuable practical insights.

For practitioners, the model offers a structured blueprint for enhancing maintenance performance in railway operations. Implementation should begin with a thorough audit of existing data infrastructure, sensor capabilities, and workforce competencies to identify gaps relative to the model’s requirements. Building a phased rollout plan—starting with data integration and predictive analytics, followed by customization and security layers—can help manage resource demands and minimize disruption. Regular training programs for operational staff, combined with iterative feedback loops from system users, will ensure continuous refinement and alignment with evolving needs. Collaboration between technical teams, operational managers, and regulatory bodies is essential for ensuring that the system remains compliant, secure, and effective in delivering both operational and sustainability goals.

Authors’ Contributions

Authors contributed equally to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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Ethics Considerations

In this research, ethical standards including obtaining informed consent, ensuring privacy and confidentiality were considered.

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