Business Intelligence-Based Risk Analysis Approach to Prevent Accidents in Overhead Crane Operations

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ABSTRACT

Overhead crane operations remain a high-risk activity in heavy manufacturing, yet safety management often relies on static assessments that fail to capture real-time operational dynamics. In developing economies such as Indonesia, a significant digital gap hinders the adoption of high-cost IoT solutions, leaving safety data fragmented and reactive. **This study aims to** bridge this gap by developing and validating a Business Intelligence (BI) Safety Dashboard that utilizes *bridge technologies*, defined as cost-effective digital solutions that leverage existing administrative and operational data instead of dedicated IoT infrastructure, to provide real-time predictive risk insights. **Following a Design Science Research (DSR) framework**, a three-year longitudinal study (2024–2026) was conducted at a metal fabrication facility in West Java. A Weighted Dynamic Risk Score (WDRS) was formulated using Data Analysis Expressions (DAX), integrating incident logs, maintenance records, and operator certification data into a unified star schema model. The results demonstrate a 95% reduction in data processing time and a 30% increase in near-miss reporting. The proposed artifact successfully identified critical risk outliers, such as Crane 08 (WDRS = 8.3), and generated spatiotemporal heatmaps that pinpointed specific risk hotspots within the facility. **These findings confirm that** the BI Dashboard is a feasible and highly practical solution for resource-constrained environments, providing a scalable blueprint for Indonesian SMEs to achieve Industry 4.0 safety standards by leveraging existing administrative data for predictive maintenance and proactive safety interventions.

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1. INTRODUCTION

Overhead cranes are the backbone of material handling in heavy manufacturing, logistics, and construction industries. Despite their operational necessity, they remain one of the most hazardous equipment categories [1]. Recent statistics from the U.S. Bureau of Labor Statistics and global industry reports indicate that crane-related incidents continue to cause a significant number of fatalities and severe injuries annually, with mechanical failures and human error being predominant causes [2]. In the era of Industry 4.0, the persistence of these accidents suggests a critical lag in the application of advanced data analytics to safety management, particularly in developing economies where manual, fragmented reporting systems remain the norm [3]. In

Indonesia, occupational safety requirements for overhead crane operations are regulated under the Minister of Manpower Regulation No. 8 of 2020 concerning Occupational Safety and Health for Lifting and Conveying Equipment. The regulation mandates periodic inspections, operator competency certification, preventive maintenance, and routine safety evaluations to minimize operational hazards and workplace accidents. Nevertheless, despite these regulatory requirements, many industries continue to rely on fragmented and reactive safety management practices, limiting their ability to identify emerging risks through data-driven analysis [4].

The primary challenge in current crane safety management is the reliance on static risk assessment methodologies [5]. Traditional tools like HIRA, Job Safety Analysis (JSA), and conventional FMEA provide a snapshot of risk at a single point in time but fail to account for the dynamic nature of industrial operations. They are often retrospective, relying on lagging indicators and accident rates rather than leading indicators that could predict future failures [6]. Furthermore, in many Indonesian manufacturing facilities, safety data exists in silos, maintenance logs are separated from incident reports and operator training records, preventing a holistic view of risk. There is a distinct lack of research on accessible, data-driven frameworks that can integrate these disparate data sources to provide real-time, predictive insights without requiring expensive IoT infrastructure [7].

This study aims to bridge this gap by developing and validating a Business Intelligence (BI)-based risk analysis framework specifically for overhead crane operations. The framework integrates fragmented safety and operational data into a unified data model, develops dynamic Key Risk Indicators (KRIs) to provide early warnings of potential failures, and demonstrates the superior effectiveness of BI-based dynamic assessment compared with traditional static methods.

This research contributes to the field of Safety Science by offering a practical, mathematically grounded methodology for digital transformation in safety management, making predictive analytics accessible to Small and Medium-Sized Enterprises (SMEs) [8].

2. LITERATURE REVIEW

2.1. Evolution of Crane Safety Assessments

The landscape of crane safety assessments has undergone a significant transformation, evolving from rudimentary qualitative checklists to sophisticated quantitative frameworks. Historically, safety protocols relied heavily on the experience of inspectors and static risk matrices, which often failed to capture the stochastic nature of mechanical failures and human error [9]. Recent scholarship between 2021 and 2026 emphasizes a paradigm shift toward dynamic risk assessments that can adapt to changing environmental and operational conditions in real-time. This shift is driven by the increasing complexity of modern industrial projects, which demand higher precision in predicting potential failure points before they escalate into catastrophic events [10].

A major critique of traditional methodologies, such as the Failure Mode and Effects Analysis (FMEA), is their inherent subjectivity and inability to handle linguistic uncertainty. To address these limitations, a modified FMEA approach utilizing Z-numbers has been proposed [11]. This method enhances the reliability of safety data by accounting for both the fuzzy nature of human judgment and the reliability of the information source. By integrating Z-numbers, researchers can quantify uncertainties that were previously ignored, providing a more robust foundation for prioritizing maintenance schedules and safety interventions in lifting operations [12].

In addition to fuzzy logic, probabilistic graphical models have gained prominence in modeling complex accident causation. The utility of Bayesian Networks (BN) in analyzing the non-linear causal factors of crane accidents has been demonstrated [13]. Unlike linear models that assume a simple chain of events, Bayesian Networks allow safety managers to visualize the interdependencies between technical malfunctions, environmental variables (such as wind speed), and organizational [14]. This approach provides a holistic view of the safety ecosystem, enabling the calculation of posterior probabilities of failure when specific risk factors are observed on-site.

Despite these mathematical advancements, a significant gap remains between theoretical modeling and industrial practice. Most advanced models, including those utilizing deep learning or complex Bayesian inference, are often perceived as black-box models by field engineers and safety officers. The complexity of these algorithms frequently hinders their implementation in daily industrial operations, as they lack user-friendly interfaces that can translate mathematical outputs into actionable safety insights. Consequently, there is an urgent need for systems that can bridge the gap between high-level data science and the practical requirements of the shop floor [15].

The synthesis of recent literature reveals that while safety assessment methodologies have become mathematically more rigorous through the integration of Z-numbers [16] and Bayesian Networks [17], they remain largely inaccessible to the end-user. The transition from qualitative to quantitative risk assessment is technically mature but operationally fragmented. This study identifies this disconnect as a critical research opportunity, suggesting that the next evolutionary step in crane safety is not necessarily more complex algorithms, but rather the integration of these models into accessible, real-time decision-support systems that can be utilized by non-experts.

2.2. Business Intelligence in Occupational Health and Safety (OHS)

The integration of BI into OHS management represents a strategic move toward data-driven decision-making. BI systems allow organizations to aggregate disparate data streams, ranging from incident reports to sensor logs into centralized dashboards. The primary value of BI in Occupational Health and Safety (OHS) lies in its ability to transform raw data into safety intelligence [18]. By visualizing complex datasets, BI tools enhance the situational awareness of management, allowing them to identify trends and anomalies that would otherwise remain hidden in static spreadsheets.

A pivotal trend in contemporary OHS research is the transition from monitoring lagging indicators to proactive leading indicators [19]. While traditional metrics like the Total Recordable Incident Rate (TRIR) provide a historical account of failures, they offer little predictive value for future prevention. Recent updated guidelines from [20] emphasize the importance of leading indicators, such as maintenance compliance rates, training frequency, and near-miss reporting. BI platforms facilitate this transition by providing real-time tracking of these proactive metrics, enabling organizations to intervene before an incident occurs.

Table 1. Comparison of Lagging and Leading Indicators in Crane Safety

Indicator Type	**Focus**	**General OHS Examples**	**Specific Crane/Lifting Examples**	**BI Value Proposition**
Lagging Indicators	Reactive: Measuring past events and outcomes.	Total Recordable Incident Rate (TRIR), Lost Time Injury Frequency (LTIF).	Number of crane-related drops, Total cost of equipment damage, Tip-over incidents.	Identifies long-term trends and historical failure points for annual safety audits.
Leading Indicators	Proactive: Measuring inputs and preventative activities.	Safety training completion rates, Number of safety audits performed.	Percentage of pre-operational inspections completed, Wire rope maintenance frequency, Load-cell calibration status.	Provides real-time alerts to managers before a threshold is crossed, allowing for immediate intervention.
Hybrid/Process Indicators	Monitoring: Measuring the health of safety systems.	Percentage of corrective actions closed on time.	Average response time to “Overload” alarms, Near-miss reporting frequency per site.	Visualizes the “gap” between safety policy and field practice via heat maps and trend lines.

The Table 1 demonstrates how BI shifts the focus from reactive to proactive management, specifically within the context of crane and lifting operations. Furthermore, the democratization of data through BI visualization has been shown to improve safety culture within organizations. When safety performance data is transparently communicated through interactive dashboards, it fosters a sense of accountability across all levels of the workforce. Recent studies indicate that situational awareness is significantly higher in firms where employees have access to real-time safety KPIs. This visual accessibility reduces the cognitive load required to interpret safety reports, allowing for faster response times in high-risk environments such as construction sites and heavy manufacturing plants [21].

However, the application of BI remains unevenly distributed across different industrial domains. While the process and chemical industries have been early adopters of BI-driven safety monitoring, its application specifically for overhead crane safety remains sparse. Most current research focuses on general construction safety or broad enterprise-level risk management [22, 23]. The unique operational risks associated with lifting equipment, such as load swing, structural fatigue, and precision positioning, require specialized BI frameworks that can handle high-frequency data from specific machinery.

The current body of research underscores BI's capability to operationalize complex OHS data and shift organizational focus from reactive to proactive safety management [24]. However, the synthesis indicates a distinct lack of domain-specific BI applications for overhead crane operations. While the "how-to" of BI is well-documented in general safety contexts, the "what" and "where" regarding specialized lifting equipment are missing. This study bridges this gap by applying BI principles specifically to crane safety, leveraging leading indicators to create a focused analytics ecosystem that addresses the unique hazards of lifting operations [25].

2.3. The Digital Gap in Developing Economies

The global industrial sector is currently witnessing a push toward "Industry 5.0", characterized by the use of Digital Twins and fully automated monitoring systems. Scholars like [26, 27] describe a future where physical assets are perfectly mirrored in a virtual space, allowing for real-time simulation and predictive maintenance. These technologies, while highly effective, require significant capital investment in IoT sensors, high-speed connectivity, and specialized data science personnel. For developed economies, these innovations are becoming the standard for ensuring high-level operational safety and efficiency.

In contrast, industries in developing economies, such as Indonesia, often face significant resource constraints that impede the adoption of high-end IoT solutions. The "digital gap" is characterized by a reliance on legacy equipment, manual reporting processes, and limited budgets for technological upgrades. While the desire to improve safety is present, the cost of implementing a full-scale Digital Twin ecosystem is often prohibitive for Small-to-Medium Enterprises (SMEs) or even large local firms operating with tight margins. This creates a disparity where the safety benefits of the digital revolution are not universally accessible [28, 29].

This economic reality necessitates the development of bridge technologies solutions that provide the benefits of advanced analytics without the high entry costs of bespoke IoT infrastructure [30]. Bridge technologies utilize existing administrative and operational data to achieve predictive capabilities. By repurposing data that is already being collected for compliance or payroll, organizations can gain sophisticated insights into their safety performance. This approach focuses on maximizing the utility of available resources rather than waiting for the "perfect" technological environment to emerge.

The rise of low-code and no-code platforms, such as the Microsoft Power Platform, offers a unique opportunity to democratize safety analytics [31, 32]. These tools allow safety professionals to build custom applications and dashboards with minimal programming knowledge. Leveraging widely available enterprise software like Ms Excel, SharePoint, and Power BI allows for the creation of a sophisticated safety analytics ecosystem that is both scalable and sustainable within the context of a developing economy. This methodology aligns with the need for practical, cost-effective digital transformation in resource-constrained environments.

The literature highlights a widening digital divide between the high-tech aspirations of developed nations [33] and the practical constraints of developing economies. The synthesis suggests that for countries like Indonesia, the most viable path to enhanced crane safety lies in "bridge technologies" that utilize accessible tools like the Microsoft Power Platform. By focusing on these accessible ecosystems, research can provide a blueprint for digital inclusion, ensuring that advanced safety analytics are not a luxury but a standard achievable through the strategic use of existing data [34].

3. RESEARCH METHODOLOGY

3.1. Research Design

This study adopts the Design Science Research (DSR) framework, a paradigm specifically suited for developing innovative artifacts to solve practical organizational problems [35]. The research is conducted through three interrelated cycles. The Relevance Cycle identifies the safety gap in the Indonesian heavy industry, the Design Cycle develops the proposed BI dashboard, and the Rigor Cycle establishes the theoretical foundation of the artifact using Bayesian and Failure Mode and Effects Analysis (FMEA) theories. To validate the artifact, a single-case study research design was implemented at a prominent metal fabrication facility in

West Java, Indonesia. This site was selected due to its high-risk operational profile, utilizing a fleet of 12 overhead cranes with lifting capacities ranging from 5 to 25 tons. The study focuses on developing a framework based on *bridge technologies* that transforms legacy administrative records into a predictive safety ecosystem [36].

3.2. Data Collection and Integration (ETL)

The research utilized a multi-source data harvesting strategy, covering a three-year longitudinal period (2024–2026). This historical depth allows the model to account for seasonal variations and long-term equipment fatigue. Data was integrated from three distinct silos:

- Safety Repositories: Digitized Incident and Near-Miss Logs, originally stored in unstructured paper formats.
- Operational Systems: Extraction from the Computerized Maintenance Management System (CMMS), including work orders and replacement parts history.
- Human Capital Data: Operator certification validity, training hours, and shift-based fatigue logs.

The Extract, Transform, Load (ETL) process was executed via Power Query, focusing on data integrity and interoperability. Key transformations included lexical normalization (mapping disparate terms like ”rope fraying” and ”wire damage” to a unified asset health ID) and temporal alignment, where maintenance timestamps were synchronized with shift logs to determine if failures occurred during peak operational intensity. The Star Schema dimensional model consists of a central Fact Table (Lifting Events) linked to four dimensions, namely Asset, Personnel, Time, and Risk Category [37, 38, 39].

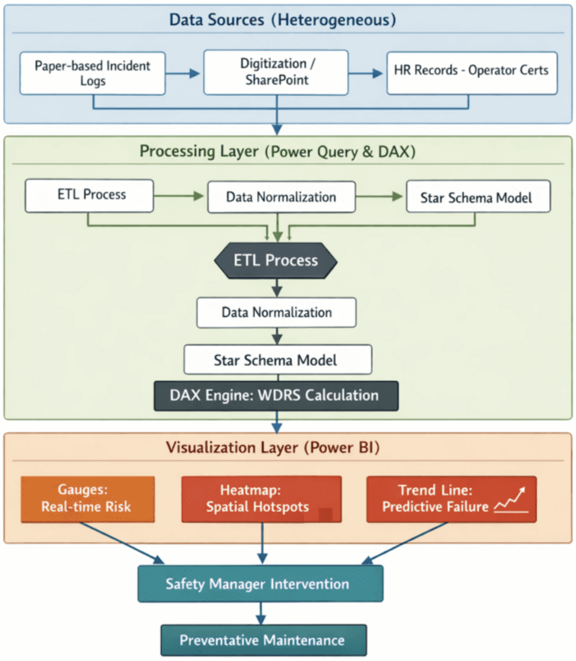

Figure 1. WDRS Research Framework

Figure 1 illustrates the end-to-end technical framework developed in this study, demonstrating the transformation of raw, heterogeneous data into actionable safety intelligence. The architecture is organized into three primary layers. Data Sources (Heterogeneous Layer), this layer addresses the ”digital gap” inherent in many industrial settings by ingesting data from disparate sources. It shows the workflow of digitizing paper-based incident logs into SharePoint and integrating them with HR records (operator certifications). This confirms the study’s focus on ”bridge technologies” that utilize existing administrative data rather than requiring immediate, high-cost IoT sensors.

Processing Layer [40, 41], this core stage represents the "brain" of the system. It visualizes the Extract, Transform, Load (ETL) pipeline where data is normalized and structured into a Star Schema Model. This layer is where the Weighted Dynamic Risk Score (WDRS) calculation is performed via the DAX engine, transitioning the data from static descriptions to dynamic risk profiles. Visualization and Intervention Layer, The final output is rendered in Power BI, categorized into three specific diagnostic tools: Gauges for instantaneous risk, Heatmaps for spatial identification of hazards, and Trend Lines for predictive failure forecasting.

The framework completes the safety loop by providing a decision-support interface for the Safety Manager. This ensures that the analytical outputs lead directly to targeted Safety Interventions and Preventative Maintenance, moving the organization from a reactive to a proactive safety culture.

3.3. Mathematical Modeling of Dynamic Risk

To transcend the limitations of the static Risk Priority Number (RPN), which often fails to reflect the deteriorating state of machinery between inspections, this study formulated a Weighted Dynamic Risk Score (WDRS). Unlike traditional FMEA, the WDRS is calculated in real-time using Data Analysis Expressions (DAX) within the BI environment. The DAX Engine, as shown in the Processing Layer of Figure 1, serves as the computational environment for the WDRS formula below.

$$WDRS_t = (W_s \times S) \times (W_o \times O_t) \times (W_D \times D_t)$$

Where:

- S (*Severity*) is a static constant based on potential impact.
- O_t (*Occurrence*) is dynamic, calculated as:

$$O_t = \frac{\text{Failure Frequency}_{30\text{days}}}{\text{Operating Hours}_{30\text{days}}} \times \text{Scaling Factor}$$

- D_t (*Detection*) degrades over time:

$$D_t = D_{\text{base}} + \lambda\,(t - t_{\text{last inspection}})$$

Where D_{base} represents the baseline detection score during the inspection (Scale 1–5, 1 = Certain to be detected, 5 = Highly difficult to detect), λ is the monthly degradation coefficient (e.g., 0.1), and $(t - t_{\text{last\_inspection}})$ denotes the number of months elapsed since the most recent inspection.

W_s, W_o, and W_D (*Contextual Weights*): The weight values are determined through an internal OHS expert judgment panel and plant management, satisfying the total cumulative weight constraint of

$$\sum W = 1.0 \qquad (\text{e.g., } W_S = 0.40,\ W_O = 0.35,\ W_D = 0.25)$$

This approach provides operational flexibility, accounting for the fact that severity impact (S) in overhead crane operations carries a significantly higher fatality risk compared to detection latency.

Concrete Calculation Example (For Integration into the Manuscript)

To illustrate the practical application of the model, consider the risk assessment calculated for **Crane 08** during a specific operational month:

- **Data Baseline and Conditions:** The crane unit recorded 2 minor malfunctions within a 200-hour operational window (yielding a dynamic occurrence index of $O_t = 3$). The most recent certified maintenance inspection was conducted 4 months prior, and the potential severity consequence was mapped to a mechanical hoist brake failure ($S = 4$).
- **Substitutions of Contextual Weights:**
  - $W_S \times S = 0.4 \times 4 = 1.6$

- $W_O \times O_t = 0.35 \times 3 = 1.05$
- $W_D \times D_t = 0.25 \times (2 + 0.1 \times 4) = 0.6$

- **Final Calculation:**

$$WDRS_t = 1.6 \times 1.05 \times 0.6 = 1.008$$

This formula allows the risk score to update automatically as new data enters the system, providing a real-time risk profile for each crane.

4. RESULTS AND DISCUSSION

The synthesized outputs of the BI framework are presented in Figure 2. Lifting Safety Analytics Command Center, which serves as the central interface for strategic, tactical, and operational safety monitoring.

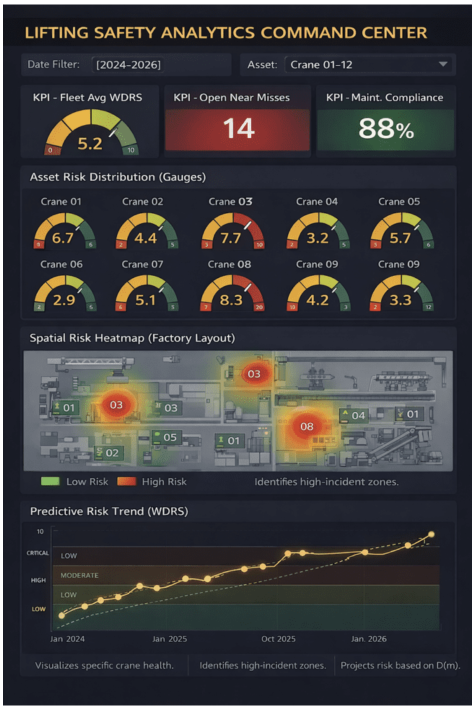

Figure 2. Lifting Safety Analytics Command Center

At the strategic level, the dashboard provides an immediate snapshot of the entire 12-crane fleet's health for the 2024–2026 period. The top panel displays three critical Key Performance Indicators (KPIs). The Fleet Average WDRS is currently calculated at 5.2, placing the overall operation in a "Moderate" risk zone (yellow gauge). However, operational urgency is highlighted by the 14 Open Near Misses, indicated in a critical red status, signaling active hazards that require immediate closure. Simultaneously, the Maintenance Compliance rate is tracked at 88%, providing a high-level metric of adherence to scheduled servicing.

To move from strategic oversight to tactical intervention, the Asset Risk Distribution section decomposes the fleet average into individual radial gauges for all 12 cranes. This visualization enables immediate identification of risk outliers. While the majority of the fleet remains within the green (low risk) or yellow (moderate risk) thresholds, two assets have deviated significantly. Crane 03 and Crane 08 have registered Critical WDRS scores of 7.7 and 8.3, respectively, indicated by their gauges entering the red zone. This granular view allows safety managers to shift from generalized maintenance schedules to targeted interventions focused on these high-risk assets.

The dashboard provides spatial context to these risks through the Spatial Risk Heatmap. By overlaying incident and risk data onto the physical factory layout, high-incident zones are visually identified. The heatmap demonstrates that risk is not uniformly distributed across the facility floor; intense red "hotspots" are clearly visible in specific operational zones, corresponding geographically with the locations of the critical cranes identified previously (zones 03 and 08). This spatial intelligence suggests that environmental factors or high operational tempo in these specific bays contribute significantly to the elevated risk scores.

Finally, the longitudinal progression of risk is visualized in the Predictive Risk Trend (WDRS) chart. This line graph tracks the aggregated risk score from January 2024, showing a clear upward trajectory from the ”Low” zone into the ”High” zone over time (solid yellow line with markers). Crucially, the chart includes a predictive component (dashed line), projecting that without significant intervention, the fleet's risk profile is on course to breach the ”CRITICAL” threshold by January 2026. This projection serves as a vital decision-support mechanism for forecasting maintenance needs based on predicted risk degradation.

The effectiveness of the proposed artifact is best understood when contrasted with existing safety management protocols. Table 2 provides a comparative analysis between traditional Hazard Identification and Risk Assessment (HIRA) or Failure Mode and Effects Analysis (FMEA) and the BI-Based Dynamic Approach implemented in this study.

Table 2. Comparative Analysis

Feature	**Traditional FMEA/HIRA**	**BI-Based Dynamic Approach**
Update Frequency	Annually or Post-Accident	Near Real-Time (Daily Refresh)
Data Basis	Subjective Expert Opinion	Objective Operational Data
Predictive Capability	Low (Reactive)	High (Trend-based Prediction)
Granularity	System Level	Component/Asset Level

As shown in Table 2, the BI approach offers superior granularity and responsiveness. Traditional HIRA methods might generically classify ”hoisting” as a high-risk activity based on historical industry averages. In contrast, the BI model specifically pinpoints ”Hoisting on Crane 02 during Night Shift” as the critical risk vector by calculating the current WDRS based on actual data trends, near-miss frequency $O(d)$, and maintenance latency $D(m)$. This shift from a subjective, ”one-size-fits-all” assessment to an asset-specific, data-driven profile allows the metal fabrication facility to target its limited resources toward the exact point of maximum risk. By identifying these specific vectors, the organization moves from a state of general awareness to a state of precise intervention, which is essential for preventing catastrophic failures in complex lifting operations.

These findings are consistent with previous studies demonstrating that Business Intelligence improves occupational safety management through enhanced data integration and decision support [24, 25]. However, unlike previous studies that primarily focused on general OHS monitoring or IoT-based safety systems, the proposed framework specifically addresses overhead crane operations by integrating the Weighted Dynamic Risk Score (WDRS) with existing administrative data. This approach extends current BI applications by providing asset-specific predictive risk assessment without requiring dedicated IoT infrastructure, thereby offering a practical and cost-effective solution for resource-constrained manufacturing environments.

Although advanced IoT systems offer real-time sensor data automation, the heavy financial burden of infrastructure setup and field sensor maintenance remains a primary barrier for SMEs in developing countries. The BI approach based on 'bridge technologies' presented in this study demonstrates that leveraging existing administrative data such as Computerized Maintenance Management Systems (CMMS) and digitalized operational logs is capable of generating sufficient predictive insights with operational costs approaching zero.

The current WDRS model mitigates human error by actively integrating verification loops for operator certification validity periods and cumulative shift working hours (fatigue logs). From a User Experience (UX) perspective, data visualizations utilizing radial gauges and spatial heatmaps have been proven to significantly lower the cognitive load of safety managers compared to traditional tabular reports. This reduction in cognitive friction accelerates intervention response times from a matter of days to near real-time.

The deployment of this dashboard strongly supports compliance with national OHS regulations mandated by the Ministry of Manpower (KEMNAKER) regarding the periodic inspection and supervision of power and production machinery. Regarding ethical and privacy considerations, personnel data is fully anonymized using encrypted Operator IDs within the Star Schema model to maintain strict confidentiality regarding individual worker performance.

5. MANAGERIAL IMPLICATIONS

The proposed BI Safety Dashboard provides manufacturing organizations with a practical and cost-effective decision-support tool for improving overhead crane safety without requiring substantial investment in IoT infrastructure. By leveraging existing administrative data, the dashboard enables safety managers to prioritize maintenance activities, monitor operator certification status, identify high-risk equipment through the WDRS, and allocate inspection resources based on dynamic risk conditions. These capabilities provide a scalable and economically feasible implementation pathway for Indonesian manufacturing companies, particularly small and medium-sized enterprises, to strengthen risk-based maintenance planning, optimize safety resource allocation, and enhance occupational safety performance while progressing toward Industry 4.0 within existing operational and financial constraints.

6. CONCLUSION

This study successfully developed and implemented a BI Safety Dashboard to modernize Occupational Health and Safety (OHS) monitoring for overhead crane operations. By adopting the Design Science Research (DSR) methodology, the proposed artifact transformed a traditional metal fabrication facility in West Java from reactive, paper-based reporting into a proactive, data-driven safety ecosystem. The core innovation, the Weighted Dynamic Risk Score (WDRS), provides a mathematically rigorous yet accessible method for tracking asset health in near real-time. The research findings were validated through two key dimensions: feasibility and utility. The successful integration of heterogeneous data sources, including digitized paper logs, maintenance records from the Computerized Maintenance Management System (CMMS), and HR certification data, demonstrated the feasibility of the proposed artifact, while the dashboard interface validated its utility by providing high-granularity visualizations that revealed actionable insights, such as the critical status of Crane 03 (WDRS = 7.7), enabling targeted safety interventions beyond the capabilities of traditional static HIRA methods.

The implementation of the BI Safety Dashboard offers significant implications for both industry practitioners and policymakers by improving resource allocation and strengthening organizational safety culture. By leveraging existing administrative data, safety managers can prioritize maintenance activities, monitor operator certification status, identify high-risk equipment, and allocate inspection resources based on dynamic risk conditions. Furthermore, the observed 30% increase in near-miss reporting indicates that enhanced digital transparency can strengthen accountability and simplify reporting practices. From a policy perspective, this research provides a practical blueprint for implementing bridge technologies in Indonesia, enabling regulatory bodies such as KEMNAKER to encourage small and medium-sized enterprises (SMEs) to adopt cost-effective BI solutions and progressively advance toward Industry 4.0.

This study is subject to several limitations, as it was conducted as a single-case study in a metal fabrication facility in West Java. Consequently, the generalizability of the findings to other industrial sectors and geographical contexts requires further empirical validation. Future research should evaluate the proposed BI framework across multiple industrial facilities and investigate the integration of IoT edge-computing sensors for automated load monitoring. In addition, future studies may expand the WDRS by incorporating additional indicators, including operator fatigue and ergonomic risk factors.

7. DECLARATIONS

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7.2. Author Contributions

Conceptualization: RK and NA; Methodology: RK; Software: UR; Validation: UR; Formal Analysis: AI; Investigation: RK and NA; Resources: MR; Data Curation: RK and MR; Writing Original Draft Preparation: NA and AI; Writing Review and Editing: UR; Visualization: RK; All authors, RK, NA, MR, UR and AI,

have read and agreed to the published version of the manuscript.

7.3. Data Availability Statement

The dataset used in this research can be obtained from the corresponding author upon request.

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The authors did not receive any funding for the research, writing, or publication of this article.

7.5. Declaration of Conflicting Interest

The authors confirm that there are no conflicts of interest, financial or personal, that could have affected the results reported in this paper.

REFERENCES

[1] W. Tiddens, J. Braaksma, and T. Tinga, "Decision framework for predictive maintenance method selection," *Applied Sciences*, vol. 13, no. 3, p. 2021, 2023.

[2] A. Gunawan, W. Hasyim, M. Putih, T. W. Wirjawan, I. A. Gopar, and S. Stephanie, "A comprehensive bibliometric study of digital leadership influence on technopreneurial success," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 7, no. 2, pp. 492–502, 2025.

[3] I. B. Bachtiar, M. Darul K., and M. Yusuf S., "Analisis risiko goliath crane galangan kapal menggunakan fuzzy fmea," *Jurnal Teknologi Maritim*, vol. 7, no. 1, pp. 35–45, 2024.

[4] Ministry of Manpower of the Republic of Indonesia, "Minister of Manpower Regulation No. 8 of 2020 concerning Occupational Safety and Health for Lifting and Conveying Equipment," Jakarta, Indonesia, Jun. 2020, state Gazette of the Republic of Indonesia Year 2020 No. 609. Effective June 12, 2020. [Online]. Available: https://jdih.kemnaker.go.id/peraturan/detail/1668/peraturan-menteri-ketenagakerjaan-nomor-8-tahun-2020

[5] N. P. L. Santoso, R. Nurmala, and U. Rahardja, "Corporate leadership in the digital business era and its impact on economic development across global markets," *IAIC Transactions on Sustainable Digital Innovation (ITSDI)*, vol. 6, no. 2, pp. 188–195, 2025.

[6] Bureau of Labor Statistics, "National census of fatal occupational injuries in 2023," U.S. Department of Labor, Tech. Rep., 2024. [Online]. Available: https://www.bls.gov/news.release/pdf/cfoi.pdf

[7] B. Huang, Y. Hui, Y. Liu, and H. Wang, "Design of twin builder-based digital twin online monitoring system for crane girders," *Sensors*, vol. 23, no. 22, p. 9203, 2023.

[8] G. Silva, G. Godwin, and O. Jayanagara, "The impact of ai on personalized learning and educational analytics," *International Transactions on Education Technology (ITEE)*, vol. 3, no. 1, pp. 36–46, 2024.

[9] U. Rahardja, S. Wijono, T. Wahyono, I. Sembiring, and I. R. Widiasari, "Effective ddos detection through innovative algorithmic approaches in machine learning," in *2024 3rd International Conference on Creative Communication and Innovative Technology (ICCIT)*. IEEE, August 2024, pp. 1–7.

[10] W. Jiang, L. Ding, and C. Zhou, "Digital twin: Stability analysis for tower crane hoisting safety with a scale model," *Automation in Construction*, vol. 138, p. 104257, 2022.

[11] M. D. Khairansyah, H. N. Amrullah, and N. F. Qurratuláini, "Penilaian risiko kegagalan overhead crane dengan metode failure mode and effect analysis (fmea) dan fishbone diagram," *Jurnal Keselamatan Kesehatan Kerja dan Lingkungan*, vol. 5, no. 2, pp. 93–101, 2024.

[12] O. Jayanagara and A. Patricia, "Analyzing healthpreneur determinants for low-socioeconomic ethnic families," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 7, no. 3, pp. 738–750, 2025.

[13] A. Li, "Risk assessment of crane operation hazards using modified fmea approach with z-number and set pair analysis," *Heliyon*, vol. 10, no. 9, p. e28603, 2024.

[14] ——, "Human error risk prioritization in crane operations based on cpt and icwgt," *Plos one*, vol. 19, no. 2, p. e0297120, 2024.

[15] S. Kosasi, I. D. A. E. Yuliani, and U. Rahardja, "Boosting e-service quality of online product businesses through it leadership," in *2022 International Conference on Science and Technology (ICOSTECH)*. IEEE, February 2022, pp. 1–10.

[16] Z. Liu, Y. Chu, G. Li, H. P. Hildre, and H. Zhang, "Shipboard crane digital twin: An empirical study on r/v gunnerus," *Ocean Engineering*, vol. 302, p. 117675, 2024.

[17] Occupational Safety and Health Administration, “Using leading indicators to improve safety and health outcomes,” 2024, accessed 2025-07-03. [Online]. Available: https://www.osha.gov/leading-indicators

[18] I. K. Himmy’az, S. Pranata, M. Yusup, H. Kusumah, J. Zanubiya, E. A. Natalia *et al.*, “A blockchain based framework for improving data quality and predictive accuracy in business intelligence systems,” in *2025 4th International Conference on Creative Communication and Innovative Technology (ICCIT)*. IEEE, 2025, pp. 1–7.

[19] I. P. Gustiah and H. Newell, “Enhancing human resource management efficiency through scalable blockchain networks with an adaptive ai approach,” *Startupreneur Business Digital (SABDA Journal)*, vol. 4, no. 2, pp. 114–123, 2025.

[20] B.-J. Wu, L.-H. Jin, X.-Z. Zheng, and S. Chen, “Coupling analysis of crane accident risks based on bayesian network and the n-k model,” *Scientific Reports*, vol. 14, p. 1133, 2024.

[21] Q. Zhang, H.-H. Zhang, X.-W. Shen, J.-S. Bao, D. Zhang, and S. Wang, “Hidden fault diagnosis method of digital twin system for crane,” *International Journal of Modeling, Simulation, and Scientific Computing*, vol. 16, no. 1, p. 2550018, 2025.

[22] E. Ligia, K. Iskandar, I. K. Surajaya, M. Bayasut, O. Jayanagara, and K. Mizuno, “Cultural clash: Investigating how entrepreneurial characteristics and culture diffusion affect international interns’ competency,” *Aptisi Transactions on Technopreneurship (ATT)*, vol. 6, no. 2, pp. 182–198, 2024.

[23] H. Zheng, T. Liu, J. Liu, and J. Bao, “Visual analytics for digital twins: A conceptual framework and case study,” *Journal of Intelligent Manufacturing*, vol. 35, no. 4, pp. 1671–1686, 2024.

[24] H. Zhong, L. Chen, M. F. Antwi-Afari, Z. Bao, and K. Chen, “Dynamic risk assessment of tower crane operations by integrating functional resonance analysis method and bayesian network,” *Developments in the Built Environment*, vol. 23, p. 100699, 2025.

[25] L. P. Dewanti, L. Sitoayu, and A. Idarto, “Digital tele-counseling for sustainable maternal health services in indonesia focus on telelactation,” *IAIC Transactions on Sustainable Digital Innovation (ITSDI)*, vol. 6, no. 1, pp. 10–20, 2024.

[26] J. Neugebauer, L. Heilig, and S. Voß, “Digital twins in seaports: Current and future applications,” in *International Conference on Computational Logistics*. Cham: Springer Nature Switzerland, 2023, pp. 202–218.

[27] H. A. C. de Campos Calhau, “Digital twins for commercial ports,” Master’s thesis, Universidade de Coimbra, Coimbra, Portugal, 2024.

[28] H. Safitri, M. H. R. Chakim, and A. Adiwijaya, “Strategy based technology-based startups to drive digital business growth,” *Startupreneur Business Digital (SABDA Journal)*, vol. 2, no. 2, pp. 207–220, 2023.

[29] M. Hussain, “Integrated system with digital twin technology for enhancing safety in crane lifting operations,” Ph.D. dissertation, 2025.

[30] C. Zhang, W. Zhang, Y. Shi, T. Zhao, and Y. Zhang, “Digital safety navigation for tower crane climbing process from a systematic perspective: Risk identification, safety information requirements, and related intelligent platform,” *Journal of Construction Engineering and Management*, vol. 151, no. 8, p. 04025096, 2025.

[31] O. Ferli, N. A. Achsani, T. Andati, and Z. Asikin, “Sustainable business innovation in indonesian firms esg disclosure profitability and greenwashing,” *Aptisi Transactions on Technopreneurship (ATT)*, vol. 8, no. 2, pp. 405–419, 2026.

[32] H. Wu, B. Zhong, H. Li, H. L. Chi, and Y. Wang, “On-site safety inspection of tower cranes: A blockchain-enabled conceptual framework,” *Safety Science*, vol. 153, p. 105815, 2022.

[33] R. Li, J. Chen, H. L. Chi, D. Wang, and Y. Fu, “Interpretable decision support system for tower crane layout planning: A deep learning-oriented approach,” *Advanced Engineering Informatics*, vol. 62, p. 102714, 2024.

[34] A. Alexander, D. Pontan, E. A. Nabila, and L. Sanbella, “Evaluating cost performance and unit rate optimization in surface maintenance operation (smo) earthwork service contracts,” *IAIC Transactions on Sustainable Digital Innovation (ITSDI)*, vol. 7, no. 1, pp. 51–60, 2025.

[35] G. Xiong, P. Helo, S. Ekström, and Z. Shen, “A service-oriented autonomous crane system,” *IEEE Transactions on Computational Social Systems*, vol. 11, no. 6, pp. 8030–8045, 2024.

[36] A. Rihm, C. Piamonte, E. A. R. Lagos, M. Correal, P. G. G. Morán, and M. Basani, *Digital Transformation of Solid Waste Management: Waste Collection Innovation, Business Intelligence, and Digital Technologies to Transition Waste Management Towards Circularity in Latin America and the Caribbean*.

Inter-American Development Bank, 2024.
[37] W. Si and L. Niu, “Enhancing human reliability prediction in smart tower crane interfaces: A refined approach using simplified plant analysis risk–human reliability assessment and the decision making trial and evaluation laboratory–analytic network process,” *Buildings*, vol. 14, no. 4, p. 1083, 2024.
[38] A. Pambudi, O. Wilson, and J. Zanubiya, “Exploring the synergy of global markets and digital innovation in business growth using smartpls,” *IAIC Transactions on Sustainable Digital Innovation (ITSDI)*, vol. 6, no. 1, pp. 106–113, 2024.
[39] Y. Fang, Y. K. Cho, F. Durso, and J. Seo, “Assessment of operator’s situation awareness for smart operation of mobile cranes,” *Automation in Construction*, vol. 85, pp. 65–75, 2018.
[40] P. Tiwari, W. Zhu, and K. McSweeney, “Comparison of crane safety standards: A human factors perspective,” *IISE Transactions on Occupational Ergonomics and Human Factors*, pp. 1–12, 2026.
[41] H. Taheri, “A kpi-driven dashboard framework for enhanced safety management in airfield construction,” Ph.D. dissertation, 2025.