A DIGITAL TWIN–BASED APPROACH FOR RISK MONITORING IN AUTOMOTIVE REPAIR WORKSHOPS

A. CANĂ - National University of Science and Technology POLITEHNICA Bucharest, Bucharest, Romania, alexandru.cana021985@gmail.com
M.G. BOBOCEA - National University of Science and Technology POLITEHNICA Bucharest, Bucharest, Romania
A.Ş. IACOB - National University of Science and Technology POLITEHNICA Bucharest, Bucharest, Romania
M. GHEORGHE - National University of Science and Technology POLITEHNICA Bucharest, Bucharest, Romania
C. BORDA, National University of Science and Technology POLITEHNICA Bucharest, Bucharest, Romania
D.F. NIȚOI - National University of Science and Technology POLITEHNICA Bucharest, Bucharest, Romania

Abstract: *In the context of the accelerated digitalization of industrial environments and the transition toward the Industry 4.0 paradigm, occupational risk management requires integrated approaches capable of overcoming the limitations of traditional, predominantly reactive methods. Automotive repair workshops represent complex socio-technical systems characterized by dynamic interactions between workers, vehicles, and equipment, where risks manifest spatially and temporally in ways that are difficult to anticipate using conventional approaches.*

This paper proposes an innovative framework based on the Digital Twin concept for real-time occupational risk assessment through the development of a Dynamic Risk Heat Map at the automotive workshop level. The model integrates a digital representation of the workspace, including safe zones and exclusion zones, the positions of workers and vehicles, and the operational status of equipment.

The main novelty lies in defining and implementing a mathematical risk quantification model based on spatial and operational parameters, enabling real-time computation of risk distribution R(x,y,t)R(x,y,t)R(x,y,t). The proposed methodology is based on discretizing the workspace into a grid of cells, where the risk level is determined through weighted aggregation of relevant factors such as proximity to hazard sources, activity density, and movement dynamics.

The results are visualized as a heat map highlighting low-, medium-, and high-risk zones, providing decision support for accident prevention and activity optimization. By integrating digital components, mathematical modeling, and spatial analysis, the study contributes to the development of a proactive risk management tool capable of transforming traditional risk assessment into a continuous, predictive, and adaptive process.

Keywords: accident prevention, assistance system, sensors, video cameras, occupational safety and health (OSH)

1.INTRODUCTION

Automotive repair workshops are complex working environments characterized by continuous interaction between workers, vehicles at various intervention stages, and technical equipment with varying levels of risk. Activities involve manual handling of heavy loads, the use of lifting equipment, exposure to hazardous substances, and operation in dynamic spaces where working conditions change frequently. In this context, occupational risks are not static but evolve continuously depending on worker positioning, equipment status, and the simultaneous execution of multiple technological processes.

Traditional occupational risk assessment methods, based on probability–severity relationships and periodic analyses, provide only a snapshot of risk levels. While essential for regulatory compliance and preventive planning, these methods show significant limitations in capturing the spatio-temporal dynamics of risks in highly variable work environments. In particular, they do not allow continuous risk monitoring or real-time identification of critical zones arising from simultaneous hazard interactions.

With the development of the Industry 4.0 concept, various solutions based on digital technologies—such as artificial intelligence, smart sensors, and video monitoring—have emerged to automatically detect hazardous situations and generate real-time alerts. However, most of these approaches focus on isolated hazard detection or specific risk types, without offering an integrated, continuous representation of risk distribution across the entire workspace. Consequently, tools capable of simultaneously correlating spatial, temporal, and operational risk dimensions remain scarce.

The identified scientific gap lies in the absence of an integrated model for real-time, dynamic occupational risk assessment that accounts for worker positioning, equipment status, and workshop spatial configuration. In particular, there is a lack of studies applying the Digital Twin concept to build a continuous risk heat map capable of reflecting instantaneous risk variations driven by workplace interactions.

Addressing this gap, the present paper proposes the development of a Digital Twin–based conceptual and methodological framework for digitally representing an automotive repair workshop and evaluating the real-time spatial distribution of occupational risks. The main contribution is the definition of a cell-level risk quantification model enabling the generation of a dynamic heat map that highlights variable-risk zones and supports preventive decision-making.

By integrating spatial modeling, operational data, and dynamic risk analysis, the proposed approach surpasses traditional methods and contributes to transforming risk assessment into a continuous, predictive, and adaptive process aligned with modern OSH paradigms.

2. STATE OF THE ART

The concept of the Digital Twin (DT) is defined in recent literature as a high-fidelity digital representation of a physical system, updated through bidirectional data streams, capable of supporting monitoring, simulation, diagnosis, and prediction [1]. In the field of occupational safety and health, DT is increasingly associated with a shift from reactive approaches—based on post-event findings—to proactive approaches centered on continuous monitoring, dynamic assessment, and real-time decision support [2].

A systematic review shows that digital twins are being used increasingly for safety analysis, risk assessment, and emergency management, while also highlighting that issues such as interoperability, the fidelity of "twinning," and data integration remain open challenges [3]. Early reviews dedicated to the relationship between Digital Twin and safety management were rather general in nature, focusing on publication trends, application areas, and the types of reported benefits [4]. One bibliometric and systematic study shows that the intersection between DT and safety management is still consolidating; it is dominated by applications oriented toward monitoring, simulation, and scenario analysis, rather than mature operational tools for fine-grained spatial risk assessment [5].

In the same direction, recently published multi-industry perspectives emphasize that safety-oriented DTs are useful for remote monitoring, risk assessment, predictive maintenance, and improving the efficiency of safety management, due to low latency and a high level of consistency between the physical system and its digital replica [6].

A distinct direction in the specialized literature is represented by the Human Digital Twin (HDT), where the emphasis shifts from equipment and process to the worker [7]. Park and colleagues have shown that DT applications oriented toward occupational safety and health are still an emerging domain, and that developing a robust human digital model requires the simultaneous integration of data acquisition technologies, virtual representation, and intelligent processing of information about workers [8]. Subsequently, Davila-Gonzalez and Martin expanded this perspective through an Industry 5.0 framework that includes not only the physical dimension but also the mental and emotional components of the worker, arguing that the current literature does not yet provide truly comprehensive solutions for human-centered industrial safety [9]. These contributions are important because they shift the focus from simple environmental surveillance toward an integrated understanding of workers' real-time state and behavior.

In parallel, research in industrial and manufacturing environments has begun linking DT to the new Industry 4.0 and Industry 5.0 paradigms, where it is used for process simulation, resilience assessment, and optimization of working conditions [10]. Recent literature shows that DTs can also support modeling of airflow circulation and contaminant concentrations in industrial spaces, indicating an extension of the concept beyond maintenance and productivity toward exposure control and the prevention of occupational risks [11]. This evolution confirms that DT is no longer viewed exclusively as a tool for operational performance, but as a digital infrastructure for integrated risk management.

At present, the most advanced DT applications for safety are found in sectors such as construction, critical infrastructures, and complex industrial systems [12]. In particular, the construction literature highlights the limitations of traditional safety management methods—characterized by data fragmentation, static standards, and delayed response—and shows that DT enables bidirectional interaction between the real and virtual environments, integration of heterogeneous data, and early identification of problems [13].

However, even these recent reviews underline that most studies describe application scenarios or DT architectures without a sufficiently clear deconstruction of the risk problem from a spatial and dynamic perspective. In other words, the literature has progressed considerably in monitoring and simulation, but less in the direction of continuous and localized quantification of risk.

In the automotive industry, the literature on digital twins is much more mature in areas such as product design, functional validation, predictive maintenance, cybersecurity, and vehicle monitoring across the life cycle than in the area of occupational safety in service workshops [14]. Recent documents and syntheses on digital twins in automotive primarily discuss use cases for automobiles, edge computing, predictive maintenance, or digital modeling of the vehicle—not the dynamic representation of occupational risk within the workshop space [15]. This orientation explains why, although there are numerous contributions regarding DT in automotive, the auto service facility as a socio-technical work environment remains insufficiently addressed from an occupational safety perspective.

Another important aspect is that the literature on risk assessment using DT emphasizes functions such as scenario simulation, fault prediction, condition monitoring, and support for emergency interventions, but more rarely the visualization of risk as a dynamic, real-time map [16]. There are examples of "heat maps" and dynamic risk maps in other domains, but these are generally applied to infrastructures, urban environments, construction, or energy systems—not auto workshops [17]. Consequently, there remains a clear research space for developing a framework that transforms operational, positional, and contextual data into a continuously updated Risk Heat Map, at the level of a zone or spatial cell.

Based on these observations, the research gap was identified: although the literature confirms the potential of the Digital Twin for monitoring, simulation, prediction, and safety management, studies dedicated to auto repair workshops are lacking that integrate into a single model: (i) the spatial configuration of the workshop, (ii) the position of workers and vehicles, (iii) the operational state of equipment, and (iv) the real-time computation of a spatially distributed risk indicator. The present study directly addresses the limitations identified in recent reviews and may constitute a relevant novelty both for the occupational safety literature and for industrial applications of the digital twin.

3. METHODOLOGY

The proposed methodology aims to develop a Digital Twin–based system capable of assessing and visualizing occupational risks in real time within an automotive repair workshop, by generating a dynamic Risk Heat Map. The approach is structured into several interdependent stages that reflect the data flow from the physical environment to decision support (fig.1).

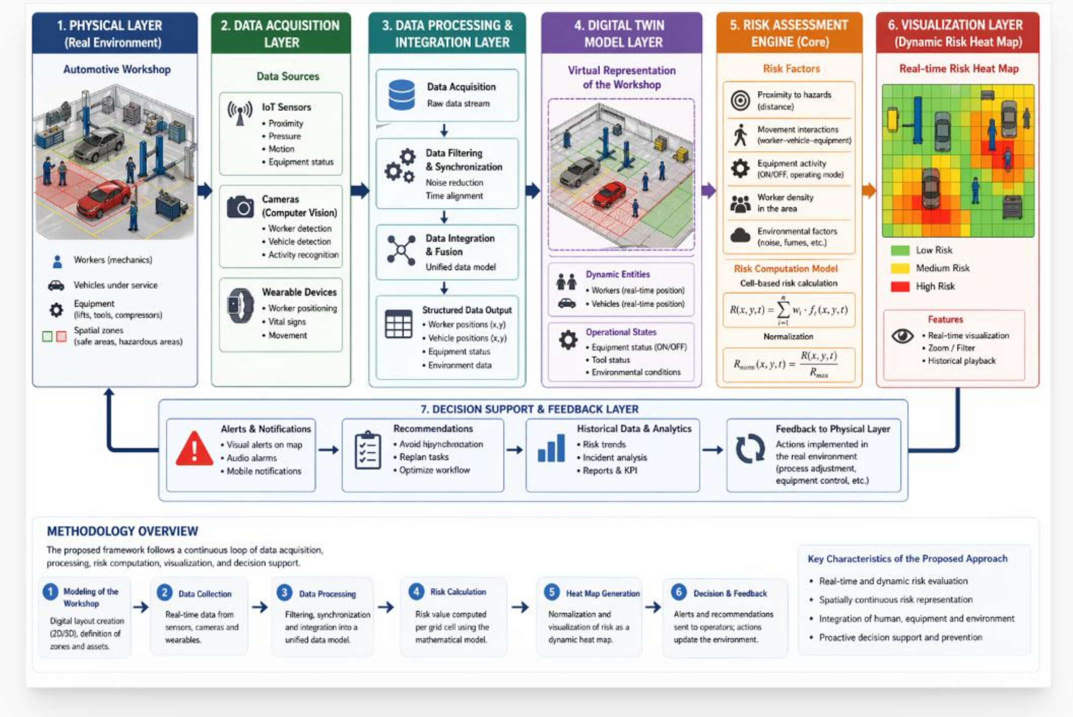


Figure 1. Methodological stages

3.1. Modeling the workspace (Digital Twin Initialization)

The first stage consists of building the digital model of the automotive workshop, which faithfully reproduces its physical structure. The space is modeled in 2D or 3D and includes the following elements:

- delineation of functional areas (work areas, circulation areas, exclusion zones);
- placement of fixed equipment (vehicle lifts, compressors, workbenches);
- definition of safe zones and high-risk zones.

For spatial analysis, the workshop is discretized into a grid of cells, each cell being defined by coordinates (x, y). This discretization enables local risk assessment.

Grid={(xi,yj)},i=1. .m, j=1..n

3.2. Data collection (Data Acquisition)

The data required to update the Digital Twin are collected **in real time** from multiple sources:

- IoT sensors (proximity, pressure, motion);
- computer vision systems (detection of workers and vehicles);
- wearable devices (workers' positions);
- equipment monitoring systems (ON/OFF state).

Collected data include: spatial positions (x, y); movement speeds and directions; equipment status; and environmental parameters *(optional*).

3.3. Data processing and integration

Raw data undergo filtering, time synchronization, and integration into a unified data model. The outcome is a coherent set of information describing the workshop state in real time:

D(t)={Positions,Equipment States,Movements,Context}

3.4. Updating the Digital Twin model

The digital model is continuously updated based on the processed data, reflecting:

- the current positions of workers;
- the positions of vehicles;
- the operational state of equipment;
- the spatial distribution of activities.

This synchronization ensures correspondence between the physical environment and its digital replica.

3.5. Risk assessment model

Risk is evaluated at the level of each grid cell using a mathematical model based on the aggregation of risk factors:

$$R(x, y, t) = \sum_{k=1}^{n} x_k * f_k(x, y, t) \qquad (1)$$

Where:

- $R(x, y, t)$ represents the risk level in cell (x, y)at time t;
- (f_k) are functions associated with risk factors;
- (w_k) are weighting coefficients.

The main factors considered include:

- distance to active equipment;
- proximity between workers and vehicles;

- worker density in a given area;
- movement dynamics (speed, direction);
- equipment operational status.

3.6. Risk normalization and classification

To ensure comparability and visualization, risk values are normalized:

$$R_{norm}(x,y,t) = \frac{R(x,y,t)}{R_{max}} \tag{2}$$

Based on normalized values, risk is classified into three levels:

- low risk (0 – 0.3);
- medium risk (0.3 – 0.7);
- high risk (0.7 – 1).

3.7. Generating the dynamic risk map (Risk Heat Map)

The assessment results are visually represented as a heat map, where each cell is colored according to its risk level:

- green – low risk;
- yellow – medium risk;
- red – high risk.

The map is updated in real time, reflecting instantaneous variations in risk depending on ongoing activities in the workshop.

4. RESULTS AND DISCUSSION

Applying the proposed methodology led to the development of a functional Digital Twin system capable of generating, in real time, a dynamic risk map (Dynamic Risk Heat Map) for a modeled automotive workshop. The results were obtained by simulating several relevant operational scenarios, using the previously defined mathematical risk assessment model.

4.1. Spatial distribution of risk

4.1.1 Dynamic heat map

The analysis of the spatial distribution of risk, carried out using the dynamic heat map, highlights the dynamic nature of occupational risks in automotive repair workshops. The results indicate that the risk distribution is directly influenced by three main factors: proximity to active equipment, interaction between workers and vehicles, and the density of activities performed in each area. These factors act simultaneously and interdependently, generating zones with variable risk that cannot be identified through classical assessment methods.

Regarding proximity to active equipment, it was observed that areas around vehicle lifts, compressors, and other operating equipment generate a risk gradient that decreases as distance increases. Around active lifts, risk reaches high values ($R > 0.7$) due to the combination of the potential for vehicle fall, the mechanical movements of the equipment, and the presence of workers within the operating zone. This radial distribution of risk confirms the hypothesis that distance from the hazard source is a critical factor in occupational risk assessment.

Another relevant aspect is the influence of worker–vehicle interaction. Areas where vehicle movement trajectories overlap with workers' positions show significant increases in risk level. In these areas, risk is not determined solely by the presence of a hazard factor, but by the high probability of interaction between moving entities. For example, when a vehicle moves inside the workshop, the cells located along its trajectory and in proximity to workers recorded risk values that increased rapidly from medium levels (0.4–0.6) to high levels (> 0.7). This dynamic emphasizes the importance of including motion parameters (speed, direction) in the risk assessment model.

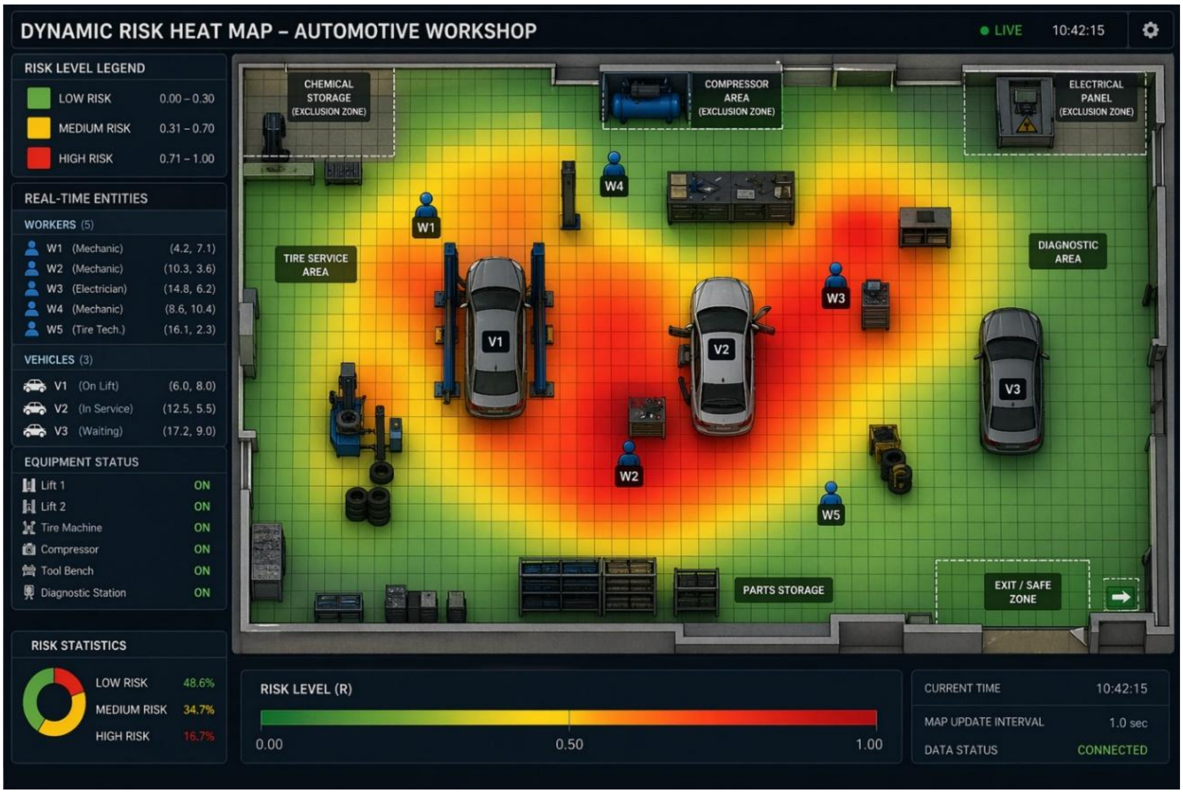
In addition, activity density in an area proved to be a determining factor in shaping the spatial distribution of risk. Areas where multiple workers simultaneously perform tasks—especially in confined spaces—generate risk accumulations due to the overlap of multiple potential hazard sources. In such situations, even in the absence of active equipment or moving vehicles, risk can reach medium or high levels because of crowding and the increased likelihood of incidents (collisions, improper tool handling, loss of balance).

The heat map enabled a clear identification of these distribution patterns, highlighting distinct zones according to risk level. Thus, critical zones, characterized by high-risk values (R > 0.7), were represented in red and were concentrated mainly: around active lifts; along vehicle movement paths; and in heavily used work areas.

Medium-risk zones (0.3 < R ≤ 0.7), shown in yellow, were associated with moderate activities or indirect proximity to risk sources. These zones often function as transition areas between safe and critical zones, being characterized by a latent potential for risk escalation depending on operational changes.

By contrast, low-risk zones (R ≤ 0.3), shown in green, were identified mainly in: unobstructed circulation routes; temporarily unused spaces; and administrative or storage areas.

An important aspect highlighted by the analysis is that the boundaries between these zones are not fixed but change over time depending on the dynamics of workshop activities. Thus, an area initially classified as low risk can quickly become a medium- or high-risk zone if an unforeseen activity occurs, such as introducing a vehicle or activating equipment.


DYNAMIC RISK HEAT MAP – AUTOMOTIVE WORKSHOP

● LIVE 10:42:15

RISK LEVEL LEGEND

🟩	LOW RISK	0.00 – 0.30
🟨	MEDIUM RISK	0.31 – 0.70
🟥	HIGH RISK	0.71 – 1.00

REAL-TIME ENTITIES

WORKERS (5)

W1	(Mechanic)	(4.2, 7.1)
W2	(Mechanic)	(10.3, 3.6)
W3	(Electrician)	(14.8, 6.2)
W4	(Mechanic)	(8.6, 10.4)
W5	(Tire Tech.)	(16.1, 2.3)

VEHICLES (3)

V1	(On Lift)	(6.0, 8.0)
V2	(In Service)	(12.5, 5.5)
V3	(Waiting)	(17.2, 9.0)

EQUIPMENT STATUS

Lift 1	ON
Lift 2	ON
Tire Machine	ON
Compressor	ON
Tool Bench	ON
Diagnostic Station	ON

RISK STATISTICS

LOW RISK	48.6%
MEDIUM RISK	34.7%
HIGH RISK	16.7%

CURRENT TIME	10:42:15
MAP UPDATE INTERVAL	1.0 sec
DATA STATUS	CONNECTED

Figure 2. Dynamic Heat Map for an Automotive Workshop

4.1.2 Three-dimensional risk map (3D Risk Surface Map)

The 3D Risk Surface Map offers an enhanced depiction of spatial risk distribution in the workshop by representing risk intensity on the Z axis over the X–Y workspace plane. Compared with a conventional 2D heat map, the 3D surface facilitates a more intuitive identification of critical areas through the detection of pronounced risk peaks and gradients.

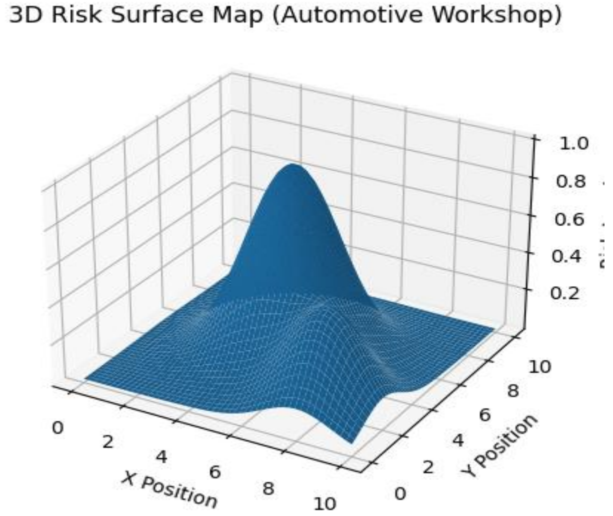


Figure 3. 3D risk surface representation of the automotive workshop, illustrating the spatial distribution of occupational risk levels based on proximity, interaction, and activity density factors.

It can be observed that there are distinct regions characterized by maximum risk values, corresponding to:

- intensively used work areas;
- proximity to active equipment;
- frequent interactions between workers and vehicles.

Low-risk zones are represented by flat surfaces, close to the minimum level, whereas critical zones form pronounced “peaks” on the surface. This distribution confirms the non-uniform and concentrated nature of risk in the analysed work environments.

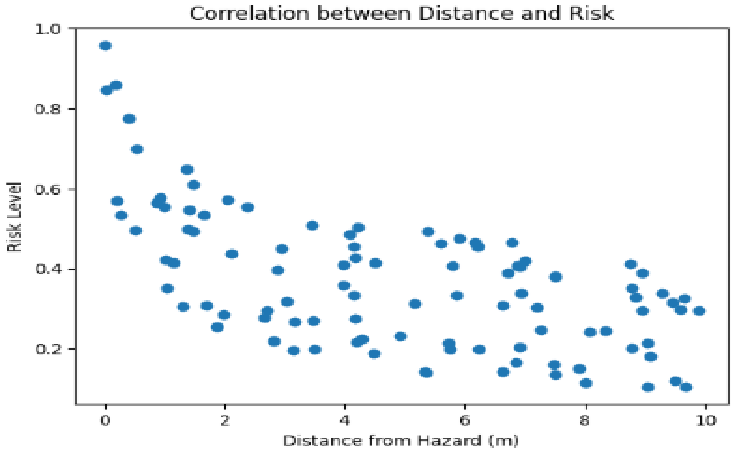


Figure 4. Correlation between distance from hazard sources and occupational risk level, showing an inverse relationship

Moreover, the spatial distribution of risk exhibits “cluster-like” characteristics, in which high-risk areas tend to group around operational nodes (vehicle lifts, workstations), generating compact risk regions. These clusters may have important implications for workplace layout, suggesting the need to redistribute equipment or reconfigure workflow routes in order to reduce congestion and hazardous interactions.

The scatter plot in Figure 4 depicts the relationship between distance to hazard sources and the corresponding risk level. The results show a clear inverse association, with higher risk values occurring at shorter distances from active equipment or hazardous zones. As distance increases, risk decreases markedly, confirming spatial proximity as a critical determinant within the proposed risk model. The dispersion of points further indicates variability attributable to additional contributing factors, including worker density and movement dynamics (e.g., speed and direction).

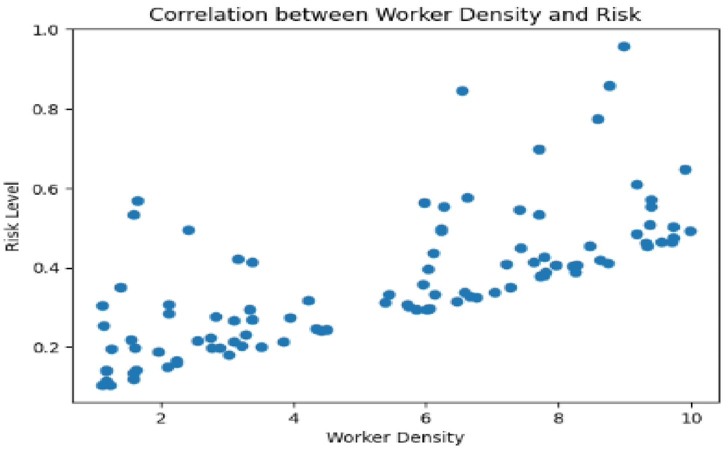


Figure 5. Correlation between worker density and occupational risk level, indicating a direct proportional relationship.

Figure 5 illustrates the correlation between worker density and risk level within the workshop environment. The results indicate a positive relationship, with risk increasing as the number of workers present in a given area rises. This trend underscores the role of congestion and interaction frequency as key contributors to occupational risk: areas with higher worker density exhibit a greater likelihood of unsafe interactions, which translates into elevated risk levels.

At the same time, the variability observed in the data suggests that density alone is not the sole determinant of risk. Rather, worker density acts in combination with other spatial and operational factors, such as proximity to active equipment, overlapping movement trajectories, task type, and the temporal dynamics of activities. Consequently, identical density levels may correspond to different risk outcomes depending on the local context and ongoing operations.

4.2. Temporal Dynamics of Risk

One of the most important results obtained in this study is the demonstration of the dynamic nature of occupational risk, analysed as a function of the temporal evolution of operational parameters within the workshop. Unlike traditional approaches, which treat risk as a static quantity or one assessed periodically, the proposed model enables continuous monitoring and real-time updating of risk distribution in response to changes in the working environment.

The results show that risk distribution is not constant but varies rapidly under the influence of dynamic factors such as worker movement, changes in equipment status, and the entry and exit of vehicles from the work area. These factors generate significant temporal fluctuations in risk level, which can occur over very short time intervals—sometimes on the order of fractions of a second.

With respect to worker movement, it was observed that their motion within the workshop space leads to continuous changes in risk distribution. Each change in a worker's position triggers a recalculation of the risk level in adjacent cells, depending on proximity to hazard sources and interactions with other entities. For example, the movement of a mechanic from a safe area toward an active work zone results in a progressive increase in risk along the trajectory, reflected in real time on the heat map. This evolution confirms that risk is directly dependent on human positioning and behaviour, being a dynamic and context-dependent quantity.

Another essential factor in the temporal dynamics of risk is the change in equipment status. The activation or deactivation of equipment produces significant variations in risk levels in surrounding areas. When a piece of equipment is activated (e.g., a vehicle lift or a compressor), risk in adjacent cells increases instantaneously due to the introduction of a new hazard source. Similarly, deactivating the equipment leads to an immediate reduction in risk, demonstrating the model's ability to reflect operational changes in real time.

The entry or removal of vehicles from the work area represents another critical element in risk dynamics. Vehicles—especially when in motion—constitute major sources of risk, influencing both local risk levels and their distribution over a wider surface. When a vehicle enters the workshop, the system instantly detects its presence and updates the risk distribution based on its position and trajectory. Areas located along the vehicle's path and in proximity to workers are characterized by rapid increases in risk, highlighting the dynamic and predictive character of the model.

A relevant example is the scenario in which a worker approaches a moving vehicle. In this case, the system recorded a rapid increase in risk level in adjacent cells due to the overlap of two critical factors: proximity and relative motion. The risk level increased from medium values ($R \approx 0.4$–0.5) to high values ($R > 0.7$) within a very short time interval. This change was detected and visualized in under one second, confirming the system's high performance in terms of real-time updating.

The analysis of temporal risk dynamics also highlighted the existence of specific evolution patterns, such as:

- abrupt risk increases when a critical interaction occurs;
- gradual variations during slow worker movement;
- periodic fluctuations in areas with repetitive activity.

These patterns suggest that risk not only varies over time, but can also exhibit predictable behaviours, which may be leveraged to anticipate hazardous situations.

Another important aspect is the low latency of the system, enabling rapid updates of the risk map. The system response time, estimated at below one second, is sufficiently small to allow proactive interventions before hazardous situations lead to accidents. This represents a major advantage over traditional monitoring systems, which rely on delayed reactions.

Furthermore, the temporal dynamics of risk emphasize the importance of correlating the spatial and temporal dimensions. Risk cannot be analysed only as a function of location; rather, it must be interpreted as a function dependent on time, position, and interactions:

$$R = R(x, y, t) \tag{3}$$

This formulation underlines the multidimensional character of risk and the need for models capable of integrating these dimensions coherently.

5. CONCLUSIONS

This study has demonstrated that integrating the Digital Twin concept into the field of occupational safety and health (OSH) provides an innovative and effective framework for monitoring and managing occupational risks in complex work environments, such as automotive repair workshops. Through the proposed approach, risk assessment is transformed from a static, periodic, and predominantly reactive process into a continuous, dynamic, and predictive process, aligned with the requirements of the Industry 4.0 paradigm.

A first essential outcome of the study is the development of an integrated model that correlates the spatial, temporal, and operational dimensions of risk. By discretizing the workspace into cells and defining the risk function R(x,y,t)R(x,y,t)R(x,y,t), a granular representation of risk distribution was obtained, capable of reflecting in real time the variations generated by interactions among workers, vehicles, and equipment. This approach overcomes the limitations of traditional methods, which cannot capture the dynamics of work environments characterized by high variability.

The results highlight that occupational risk in automotive workshops is strongly dependent on proximity to hazard sources, activity density, and movement dynamics. The analysis confirmed clear relationships between these factors and risk level: an inverse relationship between distance to active equipment and risk, and a direct relationship between worker density and risk level. In addition, interactions between moving entities (worker–vehicle) generate rapid increases in risk, emphasizing the importance of incorporating dynamic parameters into risk assessment models.

A major contribution of this research is the development and implementation of a dynamic Risk Heat Map, enabling intuitive, real-time visualization of risk distribution. This representation facilitates the identification of critical zones, transition zones, and safe zones, providing decision support for rapid and effective interventions. Extending the analysis through a three-dimensional risk representation highlighted the non-uniform and clustered nature of risk, suggesting the need to reorganize the workspace and operational flows in order to reduce exposure to hazards.

Another important result is the demonstration of the dynamic character of occupational risk. The study shows that risk evolves continuously in response to changes in the work environment, and the proposed system is able to detect and update these variations in real time, with low latency (under one second). This performance enables a shift from reaction to prevention by allowing hazardous situations to be anticipated before they materialize into accidents.

From an applied perspective, the developed system can support multiple functionalities relevant to OSH management: generating real-time alerts, automatically identifying high-risk zones, optimizing workspace organization, and improving operational workflows. Thus, the Digital Twin becomes not only a monitoring tool, but an integrated decision-support platform.

Nevertheless, the study also has certain limitations. The proposed model is based on a selected set of risk factors, and extending it to include additional variables (ergonomic factors, chemical exposures, or psychosocial factors) could improve assessment accuracy. Practical implementation also depends on the availability of technological infrastructure (sensors, vision systems, processing capacity), as well as on integrating data from heterogeneous sources.

Future research directions include developing AI-based predictive models capable of anticipating short-term risk evolution, integrating the Human Digital Twin concept for a more faithful representation of worker behavior, and validating the system under real working conditions. In addition, extending the application to other types of industrial environments could confirm the generalizability of the proposed methodology.

In conclusion, this research demonstrates that using a Digital Twin to monitor occupational risks is a promising direction for modernizing OSH systems, contributing to the creation of safer, more efficient work environments adapted to the requirements of the digital era.

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