

Analysing Spatio-Temporal Worker Movement Patterns: Implications for Safety and Productivity in Smart Factories

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Abstract: Understanding the spatio-temporal dynamics of worker movements within complex factory environments, such as shipbuilding facilities, is crucial for proactively assessing safety and enhancing operations through potential process adjustments and factory layout optimizations. While existing literature offers methods to study worker movements, the detailed elicitation of movement patterns remains limited. This research proposes an analytical framework for studying spatio-temporal worker movements using Ultra-Wideband (UWB) tracking data. The framework classifies worker movements into two categories: dwell and transit, serving as the foundation for uncovering movement patterns. The study reports the movement patterns derived from data collected on six workers performing an assembly task and offers actionable recommendations to improve workplace safety and productivity.

Keywords: Worker safety, Facility planning and materials handling, Industry 4.0, Risk Management

1. INTRODUCTION

Safety, productivity, and sustainability are three critical pillars of efficient manufacturing operations. Despite significant technological advancements, worker safety remains a major concern, particularly in processes that are not fully streamlined or automated. The manufacturing sector, second only to the construction industry, experiences a high rate of work-related fatalities (Kang et al., 2022). According to Kang et al., the highest fatality rate in 2020 was attributed to collisions and being struck by objects (31.7%), surpassing other categories such as entanglement in machinery, fire or explosions, crushing incidents, and falls or collapses. This statistic underscores the prevalence of collisions in factory environments and the pressing need for efficient safety support systems.

Developing effective safety support systems for manufacturing facilities is inherently complex due to the interactions and involvement of multiple elements, including workers, equipment, processes, material handling units, and environmental factors. Among these, modelling workers' behavioural movements presents a significant challenge due to their unpredictability (Kasarapu et al., 2024). To design robust safety systems, a detailed study of worker movements in real-world operational environments is essential. Spatio-temporal trajectories of factory workers can offer valuable insights into their movement behaviours.

Advances in real-time location tracking technologies, such as Ultra-Wideband (UWB), Radio Frequency Identification (RFID), Global Positioning System (GPS), and vision-based sensing systems, have made tracking workers' movements feasible. However, deriving meaningful behavioural insights from tracking data remains a significant challenge.

This research analyses spatio-temporal worker movements to evaluate their implications for safety and productivity in a smart factory and proposes potential improvement strategies. An analytical framework was developed by classifying dwell and transit movement points. The structure of the paper is as follows: Section 2 reviews existing approaches to trajectory analysis and safety implications. Section 3 outlines the research objectives, methodologies, and parameters studied. Section 4 details the tricycle assembly case study. Section 5 presents the results derived from the movement dataset of an assembly task. Section 6 concludes with a discussion and suggestions for future work.

2. LITERATURE ON TRAJECTORY ANALYSIS AND SAFETY

This section is divided into two parts, focusing on trajectory analysis and safety implications.

2.1 Trajectory analysis

Trajectory segmentation and semantic enrichment are foundational tasks for extracting meaningful insights from workers' movement data. Various parameters such as distance, speed, location, heading angle, location diameter, curvature, sinuosity, shape-fitting criteria, and time have been employed to segment trajectories (Buchin et al., 2013; Yan et al., 2011). These segmented trajectories are then used to classify object states. Commonly identified states include "moves" and "stopovers," which can be further refined into substates and specific activities (Arslan et al., 2017). Depending on domain requirements, different combinatorial properties are applied to segment trajectories and classify object states.

Sankararaman et al. (2013) used dynamic time warping and sequence alignment techniques to distinguish similar and dissimilar trajectory segments. Lee et al. (2007) introduced the

TRACCLUS algorithm, which employs DBSCAN and the minimum description length principle to cluster 2D trajectories and identify common sub-trajectories. Despite these advancements, challenges persist in accurately classifying trajectories while ensuring efficient runtime across varying domains. Trajectory parameters and segmentation criteria often need to be tailored to specific datasets and domain contexts.

Beyond segmentation, context awareness and semantic mapping are critical for understanding movement behaviours. Automated annotation approaches using ontological modelling have been proposed (Nogueira et al., 2017). Orellana and Renso (2010) developed an interaction-based taxonomy for pedestrian movements, categorizing behaviours into encounter, approaching, guiding-following, visiting, route choosing, attraction, flocking, aggregation, and trail formation. Dodge et al. (2008) provided a taxonomy of movement patterns, classifying them into generic (spatial, spatio-temporal, temporal) and behavioural patterns. These patterns are characterized by primitive parameters, primary and secondary derivatives such as position, instance, distance, direction, speed, duration, curvature, and acceleration.

While these taxonomies and frameworks are valuable for semantic annotations, their application in new and dynamic environments remains challenging due to unknown contexts and situational variability. Most studies have focused on trajectories in domains such as animal movements, shopper behaviours in supermarkets, and commuting patterns. However, their application to manufacturing environments remains limited, highlighting a gap in research tailored to factory settings.

2.2 Movement-based safety analysis

The literature has explored various aspects of movement-based hazard detection, including collision risks, at-risk behaviours, near-misses, hazardous areas, and hazard exposure. This section reviews studies related to pattern extraction for safety analysis. Hamdi et al. (2022) introduced the concept of spatial-temporal risk patterns, defined as risk transition features within trajectories. These features include risk cluster patterns and frequently occurring risk patterns. Arslan et al. (2017) utilized Haversine distance to identify points of intersection and closest points between trajectories in specific locations, enabling safety monitoring at construction sites. Similarly, Duan et al. (2023) applied complex network theory to analyse construction worker traffic patterns. Their study identified key risk areas and risk transition patterns through network measures, such as complexity, tightness, network entropy, and repeated transitions. However, their analysis excluded critical parameters like travel speed, altitude, approach distance, and direction relative to hazard sources.

Arslan et al. (2019) employed a Hidden Markov Model (HMM) to detect unsafe movements based on steps, rotations, and turns in worker trajectories. More recently, Aslan et al. (2024) proposed an optimization algorithm to generate alternative facility layouts by utilizing worker localization data, aiming to minimize travel time and congestion in labour-intensive manufacturing systems. Li et al. (2017) highlighted

a significant gap in the literature related to the omission of safety information embedded in dynamic group trajectories. Most existing studies focus on interactions between workers and hazards, neglecting detailed analyses of workers' behavioural patterns based on their movements. Future research should address this gap by characterizing individual worker behaviours and relationships between workers. Additionally, it is critical to account for the evolving and temporary nature of risk zones, moving beyond the traditional focus on fixed danger areas.

3. RESEARCH AIM AND METHODOLOGY

This research aims to analyze spatio-temporal worker movements to understand their implications for safety and productivity in a smart factory, while also proposing potential improvement strategies. The analytical framework is developed by classifying dwell and transit movement points. Table 1 provides a summary of the methodologies employed for these analyses. The details associated with each approach are explained in the Result section.

Table 1. Analytical framework for spatio-temporal worker movements

Objective	Approach	Parameters
Characterize worker movement behaviour	Classify dwell and transit points using a speed threshold and minimum duration	Number of dwell-to-transit occurrences, and dwell-to-transit duration ratio
Study workspace utilization and collaboration	Cluster dwell points using the DBSCAN algorithm	Spatial extent of dwell cluster zones and overlap between zones
Examine task coordination through interactions	Analyse worker proximity, frequent interaction zones, and common trajectories using DBSCAN clustering of transit points	Euclidean distance and movement patterns derived from transit clusters
Identify safety risk zones	Characterize transit clusters	Distance travelled and speed

4. CASE STUDY

This study utilizes a UWB dataset from an assembly process of a tricycle conducted by six workers (Delamare et al., 2020) to demonstrate the proposed framework. The assembly involves six key stations, each responsible for specific tasks (Figure 1). The workflow begins with the lower frame assembly (Rig 1), which is passed to Rig 2 for axle assembly. Rig 3 handles the assembly of the saddle and pedal board. Both Rig 2 and Rig 3 then transfer their assemblies to Rig 4, where the rear wheels and axle unit are integrated before being forwarded to Rig 6. Meanwhile, Rig 5 assembles the front wheel and axle unit, which is also sent to Rig 6. Finally, Rig 6 completes the tricycle assembly. Notably, Rig 4 serves as a

critical hub, managing two input transfers and one output transfer.

The UWB data collected from the six workers is used to evaluate the safety and productivity of each task and worker. The UWB tags capture position data at 100 ms intervals. To facilitate analysis, the position data is averaged over each second, yielding one position measurement per second. This averaging process also smooths the data. Any missing data points are replaced with the worker's last known position to maintain continuity and avoid abrupt position changes. The dataset spans 2 hours and 40 minutes of movement data for the six workers, providing comprehensive insights into the assembly process.

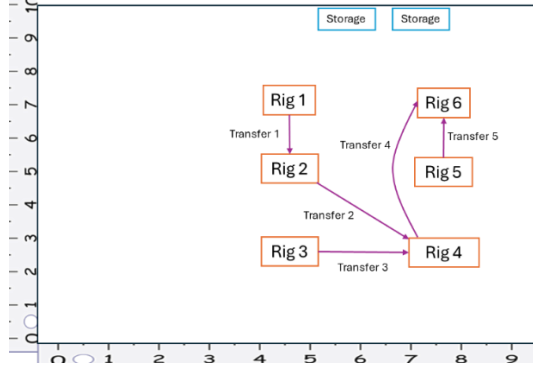


Figure 1. Assembly rig structure and flow of sub-assemblies. Rig 1: Lower Frame; Rig 2: Axle; Rig 3: Saddle and Pedalboard; Rig 4: Rear-wheel axle unit; Rig 5: Front-wheel axle unit; Rig 6: Final assembly. The layout dimensions are in meters.

5. RESULTS

5.1 Dwell and transit classification

The movement patterns of each worker were analysed and classified as "dwell" based on a speed threshold of less than 500 m/hr sustained for at least 8 continuous seconds. The speed threshold and minimum duration for classifying dwell and transit points have been chosen based on observing and validating the simulated motion video generated from the movement data. Table 2 provides the percentage of time each worker spent in "dwell" versus "transit" modes. On average, workers spent approximately 60% of their time in transit, with Worker 6 exhibiting a significantly higher transit percentage compared to others. To analyse dwell-to-transit movement patterns, Figure 2 illustrates the relationship between the dwell-to-transit event ratio and the cumulative dwell-to-transit duration. In this chart, a slope of zero indicates rapid transitions with minimal dwell periods, whereas a slope of 90° suggests extended dwell periods relative to transit. This slope classification provides a useful tool for identifying significant dwell and transit events, enabling a deeper understanding of worker movement behaviour. Key observations from Figure 2 include:

- High Transit Workers: Workers 1, 3, and 4 exhibit relatively low dwell-to-transit ratios and cumulative dwell-to-transit duration ratios. These patterns indicate limited variation between dwell and transit states, with these workers spending a significant portion of their time in transit compared to dwell.
- High State-Change Worker: Worker 5 has the highest number of dwell-to-transit events and a notably

higher cumulative dwell-to-transit duration ratio, reaching 890. This indicates frequent alternation between dwell and transit states, with dwell periods exceeding transit durations.

- Unexpected Dwell Worker: Worker 6, despite having the lowest overall dwell duration, displayed significant dwell periods early in the workflow. These periods caused a dramatic increase in the cumulative dwell-to-transit duration ratio, rising from 150 to 650 with relatively few dwell-to-transit events. This behaviour may be attributed to idle time, as Rig 6 requires completion of prior tasks at other stations before proceeding.

These observations highlight distinct movement patterns and behaviours among workers, reflecting variations in their dwell and transit dynamics. High transit workers focus more on movement-intensive tasks (could be for material transfer), while workers with higher dwell-to-transit ratios, such as Worker 5, may be engaged in tasks requiring frequent pauses or state changes. Worker 6's early dwell behaviour suggests potential inefficiencies linked to workflow dependencies.

Understanding these patterns is critical for linking movement characteristics to safety and productivity outcomes. The findings will guide targeted assessments in subsequent sections, addressing potential improvements in workflow efficiency and worker safety. This analysis underscores the importance of examining dwell and transit events to optimize task allocation and minimize idle times.

Table 2. Worker duration percentage between dwell and transit

	Worker 1	Worker 2	Worker 3	Worker 4	Worker 5	Worker 6
Dwell (%)	40.4	42.6	45.0	35.1	40.2	22.9
Transit (%)	59.6	57.4	55.0	64.9	59.8	77.1

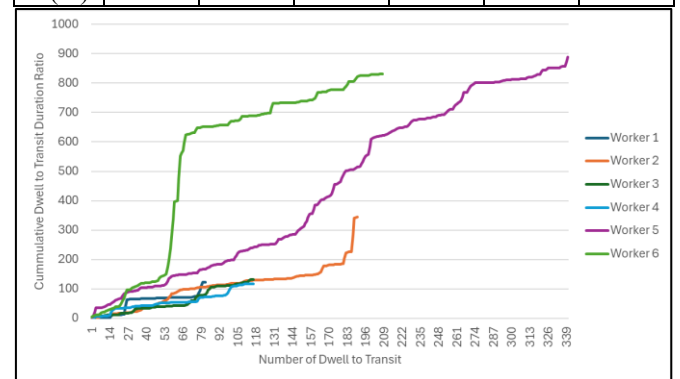


Figure 2. Plot between the "number of dwell-to-transit" to "cumulative dwell-to-transit duration ratio" for all six workers.

5.2 Dwell regions

Figure 3 illustrates the dwell points for all six workers, clustered using the DBSCAN approach (parameters: eps = 0.4, minimum samples = 3). The clustering analysis reveals the spatial distribution of dwell zones, offering insights into workspace utilization and collaboration. Key observations include:

- Workbench design requirements: The current workbench dimensions appear inadequate, as all workers require additional space in their dwell zones.

Rig 5, in particular, demands increased length and breadth to accommodate the nature of tasks performed in that zone.

- Extra dwell zone: An additional dwell zone has emerged at the bottom left of the factory. This suggests the need for a properly designed extra workbench to support the activities conducted there effectively. The location of this extra workbench should be properly located to minimize the movements.
- Off-centered worker positioning: Worker 4 is notably off-centered relative to their allocated workbench. This misalignment may stem from the assembly inflow between Rigs 2 and 3 to Rig 4 and the outflow to Rig 6. Adjustments to the factory layout should be considered to better align with these assembly flow patterns.
- Emerging collaboration zones: The clustering indicates collaborative activity between workers. Notable examples include collaboration between Worker 2 and Worker 1, as well as Worker 6 and Worker 2 in their respective workbenches.
- Overlap analysis of dwell regions: Figure 4 further explores collaboration through an overlap analysis of dwell regions (constructed using the box plot of clustered dwell zones). Significant overlaps were identified between Worker 4 and Worker 5 (11.1% of dwell points) and between Worker 1 and Worker 6 (6.3% of dwell points). These overlaps highlight areas of joint effort and potential interdependencies in tasks.

The clustering analysis of dwell regions provides actionable insights for improving workspace design and task coordination.

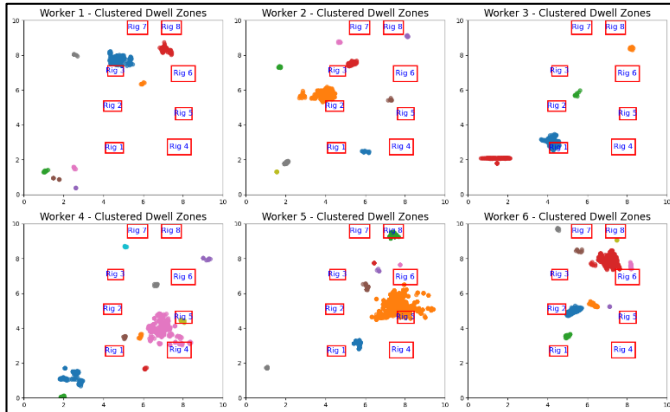


Figure 3. Dwell regions of six workers

5.3 Transit trajectories

Table 3 summarises the distribution of the number of workers simultaneously in transit during the assembly task. The data reveals that the scenario where all workers are dwelling simultaneously is relatively rare, occurring only 2.4% of the time. In contrast, the scenario with five workers in transit simultaneously is the most common, accounting for 28.3% of the total time. These high transit percentages, especially with multiple workers in motion simultaneously, highlight the complexity of coordinating tasks during the assembly process.

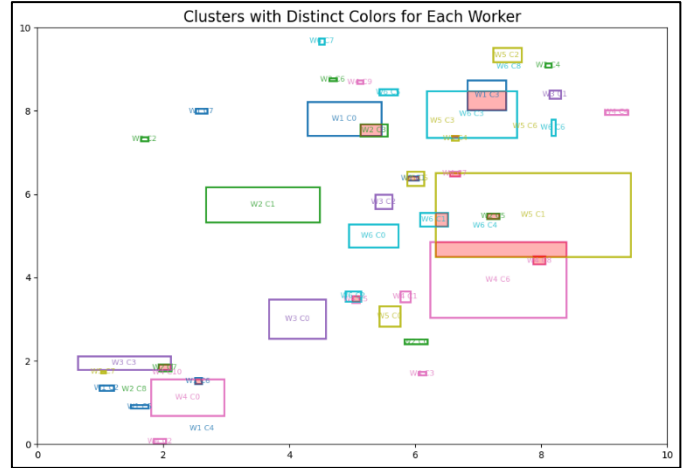


Figure 4. All dwell clusters (box plot) with overlap zones highlighted (shaded orange). Worker and cluster number are specified for each cluster.

To ensure safety and efficiency, each transit scenario must be carefully analyzed to understand the interactions between workers. The subsequent subsections delve into key aspects of these scenarios, including: proximity analysis (evaluating the distances between workers during transit to identify potential safety risks); Frequent interaction zones (identifying areas where worker interactions occur most frequently); Frequent interactive workers (highlighting pairs or groups of workers with high interaction rates); Trajectory characteristics (analyzing speed variations, changes in direction, and trajectory overlap to assess movement patterns); and Common trajectories (investigating shared pathways to understand task dependencies and workflow overlaps). These detailed analyses aim to enhance the understanding of worker interactions, mitigate safety risks, and improve coordination during the assembly process.

Table 3. Number of workers in transit simultaneously from dwell and transit movement points classification

Number of workers in transit	0	1	2	3	4	5	6
Percentage of points	2.4	8.2	18.1	9.1	21.4	28.3	12.5

5.3.1 Trajectory cluster analysis

Figure 5 visualizes the trajectories of workers, with transit points clustered using the DBSCAN algorithm (eps = 0.3). The subplots illustrate the distinct trajectories of each worker, highlighting core clusters. These clusters clearly identify the frequent common pathways used by workers, providing valuable insights into movement patterns. Various trajectory properties are analysed based on these clusters. Figure 6 classifies transit clusters by total distance and average speed. Two cluster categories—'High Distance and High Speed' and 'Low Distance and High Speed'—emerge as critical to address. These movement patterns should be minimized when designing the factory layout to enhance safety and efficiency. Figure 7 maps the temporal colocations of three or more workers within 0.5 meters of Euclidean distance. The analysis reveals that most colocations occur around Rigs 5 and 6, as well as along the interaction pathways connecting Rigs 2, 3, 5,

and 6. Notably, Workers 2, 3, and 4 exhibit the highest colocation rates, each accounting for 30% of the plotted colocation points in Figure 7.

The identified clusters and common trajectories underline areas of high worker movement, emphasizing the need for optimized workflow paths. Transit clusters with high speed and distance pose safety risks and inefficiencies, suggesting these patterns should be mitigated in the factory's design. High colocation rates around specific rigs and pathways indicate zones of frequent interaction and potential congestion. These areas require careful planning to balance collaboration and safety. The insights from Figures 5–7 will guide the redesign of the factory layout, focusing on minimizing high-risk trajectories, reducing unnecessary interactions, and improving overall workflow efficiency.



Figure 7. Temporal colocation of three or more workers within 0.5 m of Euclidean distance.

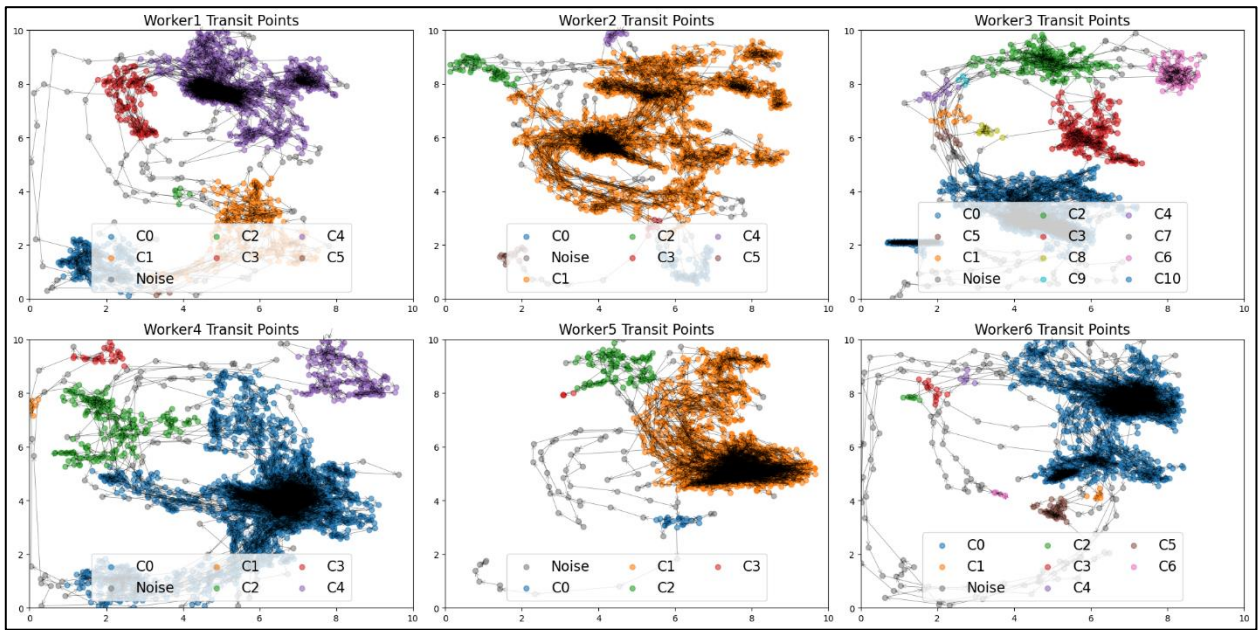


Figure 5. Transit clusters for all workers

5.4 Suggestions for safety and productivity improvements.

From the dwell and transit analyses, the following improvements are recommended:

Task sharing: The process sequence is constrained by the tricycle design and cannot be altered. However, effective task sharing strategies can be implemented to mitigate undesirable worker behaviours, such as excessive transit, frequent state changes, and prolonged dwell periods. For instance, task-sharing percentages can be allocated through a pairwise distribution approach to encourage more efficient worker behaviour.

Factory layout redesign: The analysis indicates a need to redesign the factory layout to reduce significant transit occurrences. Figure 8 illustrates an expanded layout that integrates dwell cluster zones into each work area. The rig size includes the necessary dwell zones. Key adjustments include: A new workbench has been added closer to Rig 1 and Rig 4, as these locations are frequently accessed by workers. Rig 4 has been repositioned off-centre to facilitate smoother inflow and outflow of materials and workers. Rig 2 has been rotated by 90° to enhance proximity to Rigs 2 and 6, promoting better collaboration among workers. This adjustment also reduces

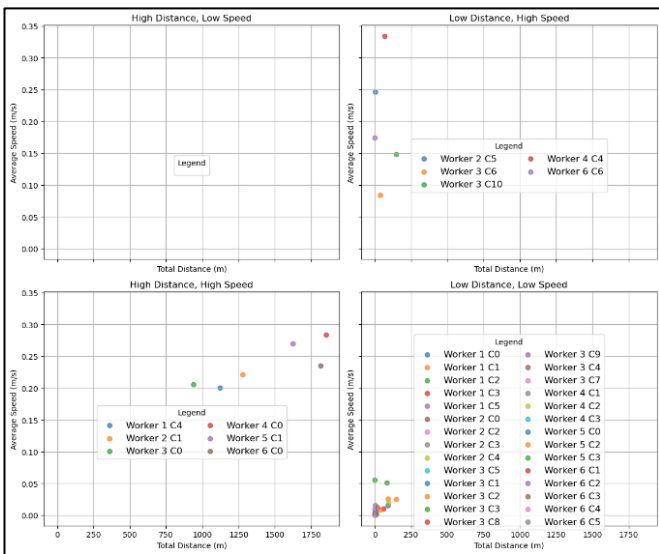


Figure 6. Transit cluster classification for total distance and average speed. Each label associated with cluster label in Figure 5.

colocation concentration events in the central transit areas. Given the significant movements between Rigs 5 and 6, their positions remain adjacent. To improve material flow, these rigs could be redesigned, eliminating unnecessary transfer movements in this region. These changes aim to enhance workflow efficiency, minimize unnecessary movement, and foster better collaboration between workers.

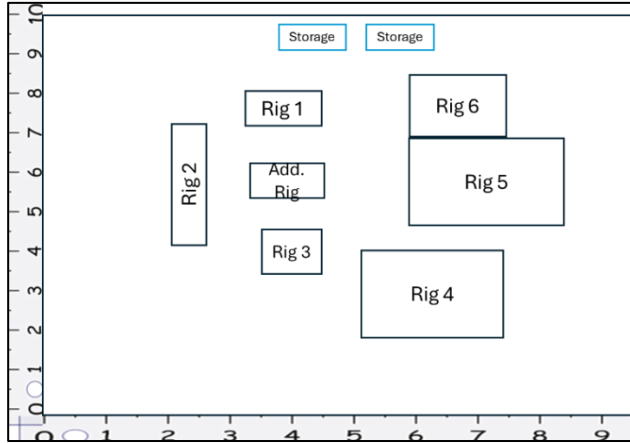


Figure 8. Layout redesign by considering dwell and transit zones. The rig size includes the necessary dwell zones.

6. CONCLUSIONS AND FUTURE WORK

This research highlights the critical role of spatio-temporal dynamics in understanding worker movement behaviour, workspace utilization, collaboration and coordination among workers, and the identification of safety risk zones. The findings provide actionable insights to enhance safety by minimizing unnecessary worker movement and transitions. Through this foundational framework, the study aims to further improve operational efficiency and safety by developing robust semantic representations of movement trajectories and interactions. The proposed approach has the potential to enable real-time support systems for workers, offering features such as identification of risk zones, adaptive modifications to spatio-temporal trajectories, and dynamic control strategies for task coordination. Future work involves validating the proposed approach, particularly the speed threshold and minimum duration for classifying dwell and transit points and receiving feedback from industrial workers.

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