

Human-centric Path Planning and Motion Behaviour Analysis in Hazardous Environments

by

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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

Hazardous work environments, such as nuclear facilities and construction sites, present critical safety challenges that need more attention. While nuclear operations expose workers to imperceptible radiation risks, construction activities involve physically demanding tasks that contribute to ergonomic injuries such as musculoskeletal disorders (MSDs). Persistent risks in hazardous environments require more effective solutions to address their unique occupational challenges through advanced technologies. This research explores the potential of augmented reality (AR) and virtual reality (VR) for improving safety through human-centric design, focusing on path planning in radiation environments and human motion analysis in masonry as potential use cases. The research addresses the practicality issues during their implementation and assesses the feasibility of the developed solutions.

The first study develops an AR-based path planning system in radiation environments. Here, path planning algorithms in existing methods only prioritize exposure minimization but result in routes poorly suited for human navigation, such as zigzagged paths with too many turns or paths that are unnecessarily long just to follow the lowest doses. To overcome this, I propose a two-stage human-centric path planning framework. First, the A*-based algorithm is enhanced with a novel multi-objective cost function to generate candidate paths that balance cumulative radiation exposure, travel distance, and the number of turns. Second, a parameter sweep procedure is introduced to select Pareto-optimal solutions. Unlike traditional methods that prioritize either radiation reduction or path length, this framework offers users a variety of path options tailored to their specific needs. Also, considering fewer turns for easier navigation, this approach is more intuitive than traditional robot-centric path planning methods, offering greater flexibility and safety for workers in real-world applications.

The second study evaluates VR's efficacy for training in masonry work to reduce ergonomic risks like MSDs while lifting heavy blocks. While VR training is effective in training for various fields, its effectiveness in teaching proper ergonomic posture and reducing injury risks has not been thoroughly explored. This study conducted experiments to compare real lifts (lifting physical blocks in a real-world setting) and VR lifts (lifting virtual weightless blocks in a VR-simulated environment), assessing motion behaviour in both contexts. In both experiments, while performing the same tasks of lifting blocks, participants were asked to wear a motion capture suit to record the motion data. The

collected data were processed for analysis using the Rapid Upper Limb Assessment (a standard test for ergonomic risk), followed by a detailed analysis of the scores for body sections, including upper arm, lower arm, neck, and trunk. Experimental results demonstrate a significant statistical difference in motion behaviour between VR and real-life tasks, particularly in the trunk and neck. We conclude that VR training developments for the trades must recognize this limitation.

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Dedication

To my mother

Danyan Huang

And to the rest of the family and friends

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List of Abbreviations

MSD	Musculoskeletal Disorders
OHSA	Occupational Health and Safety Act
PPE	Personal Protective Equipment
VR	Virtual Reality
AR	Augmented Reality
CMDC	Canadian Masonry Design Center
CMU	Concrete Masonry Unit
OL	Open List
CL	Closed List
RULA	Rapid Upper Limb Assessment
REBA	Rapid Entire Body Assessment
OWAS	Ovako Working Posture Analysing System
CTSE	Construction Safety Training And Education
PN3	Perception Neuron 3
BVH	BioVision Hierarchy
OHSCO	Occupational Health And Safety Council Of Ontario
SD	Standard Deviations

Chapter 1

Introduction

1.1 Background

The nuclear industry is a major contributor to Canada's economy, which drives GDP growth, generates government revenue and creates jobs. Since the establishment of Atomic Energy of Canada Limited in 1952 and the subsequent development of the domestically designed CANDU reactor technology, Canada has played a pioneering role in advancing nuclear energy globally. As of 2022, nuclear power stands as the second largest source of non-emitting electricity in the country (IAEA, 2022). Commercial electricity generation from nuclear power in Canada dates back to the early 1960s. With 22 reactors currently operating, nuclear energy supplies approximately 15 percent of the nation's total electricity (Government of Canada, 2025). By 2024, the nuclear industry in Canada has expanded its workforce to 89,000, representing a 17% growth since 2019. This growth aligns with a substantial \$22 billion annual contribution to the national GDP, reflecting the industry's growing economic importance (Canadian Nuclear Association, 2025). Currently, multiple new reactor facility projects are ongoing within Canada, led by New Brunswick Power, Ontario Power Generation, and Bruce Power. These initiatives are expected to contribute significantly to the nation's future economic growth (Government of Canada, 2025).

The construction industry represents an even more substantial driver of economic growth in Canada, employing over 1.6 million people, which is nearly 8% of this nation's workforce (Statistics of Canada, 2025). It creates job opportunities, bolsters supply chains and stimulates investments (Canadian Construction Association, 2024). Over the past decade, the industry has consistently contributed approximately \$150 billion annually to the national economy (Statistics Canada, 2024). Beyond direct employment through on-site labour, the construction industry significantly influences all three economic sectors. It impacts the primary sector by driving the extraction of raw materials, such as quarrying and mining activities required to procure construction inputs like cement and aggregates. It engages the secondary sector through manufacturing industries that produce prefabricated components used in construction. Additionally, it intersects with the tertiary sector by using professional services such as project management, engineering, architectural design, and surveying (Gruneberg, 1997). The influence of the construction industry on the economic sectors

underscores its ability to drive economic growth and create ripple effects across multiple sectors, reinforcing its critical role in the broader economy.

While these industries contribute substantially to Canada's economy, they share occupational safety challenges due to their hazardous work environments, which can seriously threaten worker health and safety. In nuclear facilities, workers are exposed to ionizing radiation from radioactive isotopes produced during reactor operations. At high exposure levels, ionizing radiation can cause acute health effects, including radiation sickness and, at extreme doses, death. Lower doses may lead to long-term health consequences such as cardiovascular disease, cataracts, and cancer. The carcinogenic effect occurs through DNA damage, which can create cancer-causing mutations when cells divide (NIH, 2022).

Similarly, in construction, workers encounter multiple physical hazards, including falls from elevation, struck-by injuries, and ergonomic risks from manual handling (MLITSD, 2017). Of these, ergonomic hazards represent a key concern for worker health and safety in the construction industry, with musculoskeletal disorders (MSDs), defined as painful conditions affecting muscles, tendons, and nerves, ranking among the most prevalent occupational health challenges worldwide (Canadian Center for Occupational Health and Safety, 2024). As of 2022, musculoskeletal conditions affected approximately 1.71 billion people worldwide, making them a leading contributor to disability. This burden continues to rise, driven by demographic shifts such as population growth and aging, which amplify the risk of chronic musculoskeletal impairments (World Health Organization, 2022). Within the construction industry, these risks are exacerbated by manual materials handling, including frequent heavy lifting and repetitive tasks, which increases workers' exposure to ergonomic hazards and significantly contributes to MSDs (Workplace Safety and Insurance Board, 2024).

To mitigate these occupational risks, Canada has established comprehensive legal frameworks, including the Occupational Health and Safety Act (OHSA) and its regulations, as well as Part II of the Canada Labour Code (Hess, Weinstein, & Welch, 2010). For radiation-specific hazards, additional regulatory measures have been implemented through the Nuclear Safety and Control Act (1997) and the Radiation Protection Regulations (2020). These legislative instruments are supported by practical safety interventions such as mandatory worker training programs, strict personal protective equipment (PPE) requirements, and systematic hazard control protocols.

Despite established safety protocols, emerging technologies like virtual reality (VR) and augmented reality (AR) demonstrate significant potential to enhance hazard prevention. AR-enabled wearable displays can provide real-time visualization of radiation hotspots and optimal low-exposure pathways, allowing workers to minimize cumulative doses during maintenance procedures or emergency response operations. Also, previous research has shown that VR training can be more effective in the construction industry for some skills than conventional in-person training, offering increased engagement, enhanced skill development, and reduced costs and risks, particularly in improving construction safety (Adami, et al., 2021). Therefore, this study explored and developed VR/AR technology applications to improve safety in construction and radiation environments.

1.2 Problem Statements

While the application of VR/AR technologies for safety enhancement in construction and radiation environments appears intuitively viable, such as AR applications for real-time radiation hazard visualization and guided navigation or VR platforms for immersive safety training, practical challenges that require further investigation may occur during the implementation. The feasibility of these solutions under real-world constraints has yet to be systematically validated, and their operational challenges remain underexplored.

For the first industry-partnered research project with MDA Space Ltd., focused on nuclear radiation decommissioning, I developed an AR application capable of visualizing radiation hazards through colour-coded representations of radiation intensity levels. The system integrated a path planning algorithm to identify and display optimal routes minimizing cumulative radiation dose. However, in complex radiation environments with abrupt intensity changes, the algorithm-generated paths often exhibit excessive zigzagging with frequent directional changes to follow the route with the lower radiation doses. While theoretically optimal for dose reduction, such paths introduce ergonomic challenges during human navigation, including increased cognitive load, operator fatigue, and elevated error potential (Fallah, Apostolopoulos, Bekris, & Folmer, 2013). A further limitation of current radiation safety path planning approaches is their exclusive focus on exposure minimization without considering human factors. These algorithms fail to account for the practical need to balance radiation avoidance with path efficiency, particularly during time-sensitive operations. For instance, in urgent scenarios where workers must complete tasks quickly, operators may prioritize shorter paths while maintaining radiation exposure at safe levels to ensure timely completion. This gap highlights

the need for research methods to reduce radiation exposure, shorten paths, and simplify navigation simultaneously, enabling AR applications to visualize paths that balance safety and practicality in radiation environments simultaneously.

For the second research project, conducted in partnership with Canadian Masonry Design Center (CMDC) and focused on reducing ergonomic risks for masonry workers, I developed a VR application replicating a work scenario where workers can lift and place blocks at designated locations for ergonomics training purposes. Their movements are tracked using motion capture suits, enabling detailed analysis to identify and mitigate ergonomic risks. However, while VR training has shown promise in training knowledge, skills, sequences and safety procedures, its application to ergonomics training, specifically in masonry work, has not been adequately explored due to VR's limitation in simulating the weight, mass and momentum of concrete masonry units (CMUs) in real-life tasks. In the context of masonry, no existing research empirically confirms that motion patterns in a VR simulation with weightless blocks replicate real-world block-lifting motion patterns. Lack of replication may render effective ergonomic training for masonry infeasible in VR. This lack of confirmation introduces a significant knowledge gap and research question.

1.3 Research Objectives

With this background, the overall research objectives of this thesis are to 1) develop VR/AR applications that improve worker safety in hazardous environments and 2) address practical implementation challenges and evaluate the feasibility of the solutions. The specific research objectives of this study are as follows.

- 1. To develop a human-centric path planning algorithm that generates navigation paths tailored for humans, which can be visualized and guided through an AR application:** I propose a framework that identifies Pareto-optimal path solutions using an A*-based path planning method enhanced with a new cost function. The proposed method addresses the multi-objective problem of balancing three key factors: minimizing radiation exposure, optimizing path length, and reducing the number of turns. Unlike conventional approaches, the proposed method offers greater flexibility, enabling the generation of human-centric navigation paths that align more closely with practical user needs in radiation-sensitive environments.

2. **To investigate the validity of using VR for ergonomics training, particularly in masonry work, by comparing human motion behaviour during block lifting in real and VR environments:** A VR simulation was developed to replicate a preceding real-life experiment, and the participants' motions were recorded using a wearable motion capture system. These allowed us to analyze the collected data using the Rapid Upper Limb Assessment (a standard test for ergonomic risk), followed by a detailed analysis of the scores for body sections, including upper arm, lower arm, neck, and trunk, to gain deeper insight into the findings.

1.4 Thesis Organization

This thesis integrates two complementary studies to fulfill its research objectives. The work is organized into five chapters, with Chapters 3 and 4 each dedicated to one study, including their respective research methodologies and alignment with specific research goals. The structure of the thesis is as follows:

Chapter 1: Introduction. This chapter covers the background, problem statements, objectives, and thesis organization.

Chapter 2: Literature Review. This chapter presents a comprehensive literature review, examining prior research and methodologies relevant to this study and the key techniques employed in this work.

Chapter 3: Human-Centric Path Planning in Radiation Environments. This chapter introduces a human-centric path planning method that can balance reduced radiation exposure, shorter path length, and easier navigation by minimizing the number of turns. A path selection procedure is also introduced to select Pareto-optimal solutions.

Chapter 4: Comparing Human Motion in Reality and Virtual Reality for Heavy Blocks Lifting to Assess the Feasibility of Using VR for Ergonomics Training in Masonry Work. This chapter details a comparative motion analysis study investigating the validity of adopting VR for ergonomics training. This study compares real lifts (lifting physical blocks in a real-world setting) and VR lifts (lifting virtual weightless blocks in a VR-simulated environment), assessing motion behaviour in both contexts.

Chapter 5: Conclusion and Recommendations. This chapter summarizes the key conclusions of this research and makes recommendations for future work.

Chapter 2

Literature Review

2.1 Techniques Used in Path Planning Algorithms

2.1.1 Grid-based Maps

The environment is discretized into a grid-based map, where each cell is labelled as either occupied or empty based on the occupancy grid mapping approach (Elfes, 1989). As illustrated in Figure 1, occupied cells (marked in black) represent impassable regions, including obstacles or map boundaries, while the remaining empty cells are traversable. Map boundaries are labelled as B, and obstacles are labelled as O. Each cell is also associated with a radiation dose rate $R(i,j)$, quantifying the radiation intensity at that location. The radiation dose rates are visually represented using a colour gradient, ranging from red (high radiation) to dark purple (low radiation). The path-planning algorithms operate under 8-directional movement constraints, enabling movement between a cell and its eight neighbouring cells (up, down, left, right, and the four diagonals). In Figure 1, the white arrows indicate possible node movements within the grid as current positions.

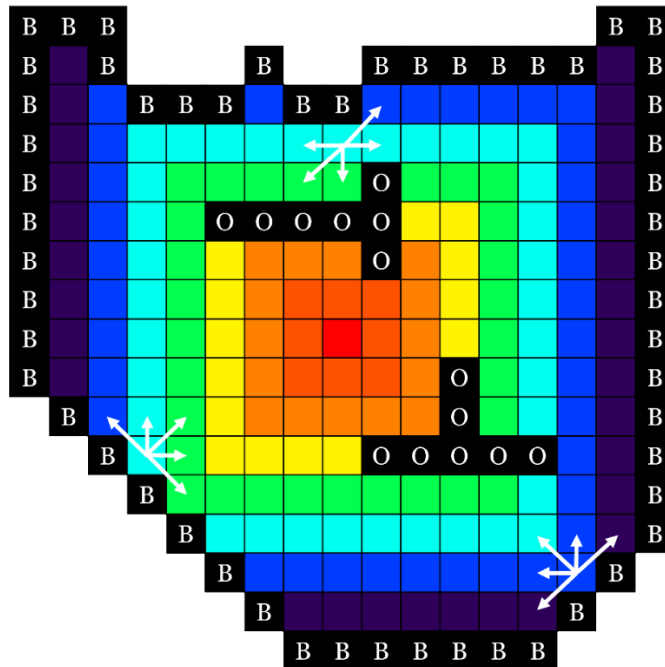


Figure 1. Grid-based Map to quantize the space and radiation values

2.1.2 Algorithms Used in Path Planning

Dijkstra's algorithm was developed by Dijkstra (1959), for finding the shortest path between two nodes in a graph. The method iteratively constructs the shortest paths from a starting node by organizing nodes into sets, prioritizing those with the smallest tentative distances, and updating the shortest known distances until the target node is reached. Dijkstra's approach remains a cornerstone in pathfinding, widely applied in fields such as network routing (Abderrahim, Hakim, Boujemaa, & Touati, 2019), transportation planning (Bozyiğit, Alankuş, & Nasiboğlu, 2017), and optimization (Akram, Habib, & Alcantud, 2021).

A* algorithm enhances search efficiency by estimating the remaining cost from the current node n to the goal using $H(n)$. Unlike Dijkstra's algorithm, which expands nodes uniformly based solely on the accumulated cost $G(n)$, A* prioritizes nodes using the total cost $F(n)$, balancing the actual cost of the path taken so far (G cost) with the estimated cost to reach the goal (H cost) with reduced number of explored nodes. The expression of $F(n)$ is defined in Equation 1.

$$F(n) = G(n) + H(n) \quad \text{Equation 1}$$

The $G(n)$ cost in the A* algorithm represents the actual cost of moving from the start node to the current node along the path being explored. It is calculated by summing the costs of all individual steps taken to reach the current node. As A* explores the graph, it uses the $G(n)$ cost to evaluate and compare paths, updating it whenever a cheaper route to a node is found. In a shortest distance problem, the $G(n)$ cost typically represents the actual physical distance travelled from the start node to the current node. Other than this, it can be extended to include additional factors like safety, fuel economy, navigation speeds, terrain difficulty, and more (Haider Jafri & Kala, 2015). By incorporating these factors into the $G(n)$ cost function, the A* algorithm can find paths that optimize for various objectives, making it highly adaptable to complex real-world problems.

Next, the heuristic-driven approach using $H(n)$ is particularly effective in structured environments, such as grid-based maps, where domain-specific heuristics, such as Euclidean or Manhattan distance, provide relatively accurate estimates of the remaining path cost when searching for the shortest-distance path. Notably, when the heuristic $H(n)$ is set to zero, A* is equivalent to Dijkstra's algorithm. A* algorithm has two lists to store nodes, Open List (OL) for the unexplored nodes and Closed List (CL) for the explored nodes. When the algorithm finishes exploring nodes by reaching the goal, if it exists, a path is constructed via backtracking from the goal using information of the parent nodes.

2.1.3 Path Planning in Radiation Environments

In Liu et al.'s (2015) study, the A* algorithm was adapted to prioritize minimizing cumulative radiation exposure in grid-based environments. The H(n) cost function is set to zero, which guarantees the result path has the minimum radiation exposure. The cost function G(n) that calculates the cumulative radiation dose from the start node to node n is defined as:

$$G(n) = \sum_{k=1}^{n-1} (R_k(i, j) + R_{k+1}(i, j)) \times l \times \frac{x_k}{2 \times v} \quad \text{Equation 2}$$

$$x_k = \begin{cases} 1.4, & \text{if diagonal} \\ 1, & \text{otherwise} \end{cases} \quad \text{Equation 3}$$

$R_k(i, j)$ and $R_{k+1}(i, j)$ represent the radiation dose of adjacent nodes along the path; l is the width of the grid, and v is the constant walk speed of the workers. x_k is set to 1.4 if the movement between the nodes is diagonal, and 1 if the movement is horizontal or vertical.

Liu et al. (2015) successfully integrated cumulative radiation exposure into the A* algorithm's G(n) cost function to identify paths that minimize radiation exposure. However, their single-factor approach can be impractical for real-world applications, as it overlooks essential trade-offs between safety and efficiency. Prioritizing radiation exposure exclusively can lead to undesired routing decisions in reality. For example, the algorithm may favor a path with an insignificant reduction in radiation exposure (e.g., <0.01%) over a significantly shorter alternative, even if the shorter route only has a marginal increase in radiation exposure. Similarly, it might prioritize a path requiring numerous turns, thereby increasing navigation complexity and error risk for workers, over a slightly higher exposure but more navigable alternative.

2.2 Techniques Used for Ergonomic Risk Assessment

2.2.1 Observational Assessment Methods

While numerous observational assessment methods have been developed to reduce ergonomic risks, the most prevalent in industry practice are the Rapid Upper Limb Assessment (RULA) (McAtamney & Corlett, 1993), Rapid Entire Body Assessment (REBA) (Hignett & McAtamney, 2000), and Ovako Working posture Analysing System (OWAS) (Karhu, Kansil, & Kuorinka, 1977). A systematic review of ergonomic assessment techniques (Joshi & Deshpande, 2019) found REBA (22%), RULA (21%), and OWAS (11%) to be the most commonly cited in the reviewed studies.

RULA is a standard and broadly used rule-based assessment system designed to assess risk factors linked to MSDs, with a primary focus on the upper body (Kee, 2022). RULA categorizes the human body into two groups: one comprising the lower and upper arms and wrists, and the other including the neck, trunk, and legs. The body section score for each group is determined by integrating individual joint scores using assessment tables, which also consider external loads and repetitive movements other than the posture (Ryu, Banting, Abdel-Rahman, & Haas, 2023). In the end, a RULA grand score, describing the overall risk index for a given posture, is calculated by integrating the body section scores.

Similarly, REBA is a widely used tool for evaluating MSD risks. Unlike RULA, which primarily assesses upper body postures, REBA provides a more comprehensive analysis by incorporating the entire body. In addition to posture, external loads, and repetitive movements, factors also considered in RULA, REBA accounts for coupling effects and dynamic postural loading (Kee, 2022). REBA follows a similar body categorization approach, dividing the human body into two groups (neck/trunk/legs and upper/lower arms/wrists). However, the scoring order of REBA is the opposite of RULA. REBA evaluates the neck, trunk, and legs before assessing the arms and wrists. The final REBA grand score integrates these body section scores with an additional activity score, which is not included in RULA.

In contrast to RULA and REBA, OWAS individually assesses three body sections: back, arms, and legs. Each body section has specific posture classifications with corresponding risk scores. For instance, the back section includes four postural categories: upright (score = 1), bent (score = 2), twisted (score = 3), and bent-and-twisted (score = 4), where higher scores indicate greater risk. Similarly, arms and legs have their posture classifications and scoring systems. During assessment, each recorded posture at the sampling frequency receives individual scores for all three body sections. These scores, along with the score of the loading assessment, are then summed to calculate the final OWAS score.

Given their widespread adoption in various industries, extensive research has been conducted to compare the effectiveness of RULA, REBA, and OWAS. For example, Cremasco et al. (2019) compared RULA and REBA in assessing the risk of MSDs during manual loading operations of a wood chipper. Their findings indicated that RULA is a more effective tool for evaluating operators'

postures in human-machine interactions, especially for the upper limbs. This is attributed to RULA's greater sensitivity, as it consistently identified higher risk levels than REBA across all observed tasks. In a study by Yarandi et al. (2019) comparing the effectiveness of the Novel Ergonomic Postural Assessment (NERPA), RULA, and REBA for MSD assessment, RULA was identified as the most effective method for predicting MSD risk across various occupational tasks. Furthermore, when evaluating postural loads and their association with MSDs, RULA demonstrated greater suitability, as its assessed risk levels showed a stronger correlation with MSDs compared to those identified by OWAS and REBA (Kee, 2022). Additionally, Joshi & Deshpande (2021) pointed out that the weight of the load should be considered when selecting an ergonomic assessment method. OWAS is more appropriate for evaluating risks associated with loads under 5 kg, while REBA is better suited for loads between 5 kg and 10 kg. For tasks involving loads greater than 10 kg, RULA is considered the most suitable.

As the lower back and upper limbs are the most critical body joints for MSD risks (Ryu, Banting, Abdel-Rahman, & Haas, 2023), this study focuses on upper body assessment. Based on the literature review, RULA was selected for this study for three reasons: (1) RULA is designed for assessing the upper body postures, matching this study's focus; (2) Research shows RULA is more effective for MSD risk assessment because of its higher sensitivity, consistently showing higher risk levels in observed tasks; and (3) the weight of CMUs masons handle in this study is 16.6 kg (exceeding 10 kg), making RULA the most suitable choice.

2.2.2 Motion Capture

Extensive research studies have proven that the use of wearable inertial sensors for motion capture is suitable for various motion analysis applications, aligning with the performance of standard optoelectronic systems. Huang et al.'s (2020) experiment revealed that motion data captured from wearable inertial sensors produced risk assessments that were highly consistent with expert evaluations using RULA and REBA methods, validating the use of inertial sensors for ergonomic analysis. Nath et al. (2017) performed an ergonomic assessment of construction workers' trunk and shoulder postures using wearable inertial sensors, demonstrating strong agreement between sensor measurements and observational data. Specifically, Wu et al. (2022) validated the use of Perception Neuron Studio, an affordable and widely used commercial inertial motion capture system. Their comparison with OptiTrack, the gold-standard optical system, demonstrated that the Perception

Neuron system delivers sufficiently accurate upper body kinematic measurements, even for biomechanical analysis purposes.

Chapter 3

Human-Centric Path Planning in Radiation Environments

3.1 Design of the New Multi-objective Cost Function G'

This study introduces a new multi-objective cost function, $G'(n)$, designed to better balance path safety and efficiency, as defined in Equation 4. The function incorporates $G(n)$ for radiation exposure, $\delta(n)$ for distance, and a weighting parameter α to adjust the trade-off between. Additionally, a turning penalty coefficient, λ , is included to reduce turns for simpler navigability. Similar to Liu et al.'s (2015) study, the heuristic estimation is not included, and the $H(n)$ cost is set to zero.

$$G'(n) = \lambda[\alpha \cdot G(n) + (1 - \alpha) \cdot \delta(n)] \quad \text{Equation 4}$$

$$\lambda = \begin{cases} 1, & \text{if the direction is the same as the previous step} \\ > 1, & \text{if the direction changes from the previous step} \end{cases} \quad \text{Equation 5}$$

$$\delta(n) = \sum_{k=1}^{n-1} \left(\sqrt{(i_{k+1} - i_k)^2 + (j_{k+1} - j_k)^2} \right) \cdot \bar{R} \quad \text{Equation 6}$$

With the weighting parameter (α) ranging from 0 to 1, this weighting mechanism enables users to adjust priorities between minimizing path distance and minimizing radiation exposure. Here, $G(n)$ retains the definition from Liu et al.'s work (2015), representing cumulative radiation exposure. The path distance term $\delta(n)$, defined in Equation 6, is calculated as the Euclidean distance between grid nodes with coordinates expressed as (i,j) , multiplied by the map's average radiation dose ($\bar{R}$). This scaling ensures unit consistency between the radiation-based function $G(n)$ and the distance-based function $\delta(n)$. Since $\bar{R}$ is constant across all nodes, it maintains a proportional relationship with distance while ensuring unit compatibility between radiation exposure and path length.

When α is set to 0, the proposed method focuses entirely on radiation minimization, which is equivalent to the minimum dose method. When α is set to 1, the proposed method prioritizes shorter paths, which is equivalent to the minimum distance method. Conversely, when α is set to 0.5, the algorithm focuses entirely on radiation minimization, which is equivalent to the minimum dose method. Intermediate values of α allow the algorithm to balance these objectives, generating paths that trade off radiation safety and path length. This flexibility is particularly beneficial for time-sensitive tasks, where operators may prioritize shorter paths to meet time constraints while maintaining acceptable radiation exposure levels. The turning penalty coefficient (λ) is applied to cost

calculations whenever a directional change occurs in the path. This results in a slightly higher cumulative cost for nodes associated with turns, making them less favourable during the pathfinding process. As defined in Equation 5, λ is set to 1 when no directional change occurs from the previous step, leaving the cost unaffected. Conversely, λ exceeds 1 when a directional change occurs, slightly increasing the cumulative cost. The introduction of λ reduces unnecessary turns in generated paths, particularly beneficial in scenarios where alternative routes with fewer turns exhibit comparable cumulative radiation doses. Furthermore, the resulting paths are smoother and more navigable, enhancing practicality and human operability in radiation environments without significantly compromising radiation safety.

3.2 Path Generation and Metric Computation

Figure 2 illustrates the pseudocode of the algorithm of path generation and metric computation. By running the A* algorithm with the new multi-objective cost function G' defined in the last section, a path (P) can be generated with the specified α and λ . In order to evaluate the path, three metrics are computed, including the number of turns (T), the cumulative dose (C), and the path distance (D).

Algorithm 1 Path Generation and Metric Computation - $PGenMetricsComp(M, \alpha, \lambda)$

Input: Map information M , weighting parameter α , turning penalty coefficient λ

Output: Number of turns T , cumulative radiation dose C , and path distance D .

- 1: **Initialize:** $T = 0, C = 0, D = 0$
 - 2: **Define the new cost function** G'
 - 3: $P = AStar(M, \alpha, \lambda, G')$
 - 4: **Calculate** T of P
 - 5: **Calculate** C of P
 - 6: **Calculate** D of P
 - 7: **Return** T, C, D
-

Figure 2. Pseudocode of Algorithm 1

Figure 3 illustrates examples of metric calculations. The grid cell width is denoted as l , and the radiation dose or the grid cell is denoted as R . The number of turns (T) is determined by counting directional changes along the path: Path A has 5 turns, Path B has 1 turn, and Path C has 2 turns. The cumulative radiation dose is computed by averaging the radiation dose rates of consecutive grid cells and multiplying by the distance travelled. For instance, the cumulative dose for Path B is calculated as:

$$\frac{R6 + R5}{2} \times l + \frac{R5 + R4}{2} \times l + \frac{R4 + R10}{2} \times l + \frac{R10 + R16}{2} \times l$$

Path distance is determined using the Euclidean distance formula. For example, the total distance for Path C is:

$$l + \sqrt{2} \times l + l$$

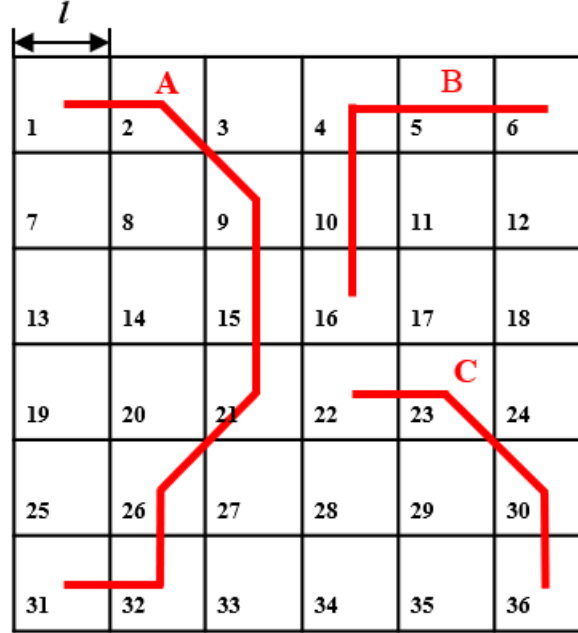


Figure 3. Calculation of the Metrics

Since the resulting path depends on these two input parameters, operators have numerous options to choose from based on their specific needs. However, adjusting either parameter can significantly alter the values of T, C, and D, generating a wide range of potential paths that may overwhelm operators. For example, increasing alpha to prioritize radiation minimization might not always achieve the desired exposure reduction while substantially increasing path distance, producing undesirable alternatives. This highlights the need for a systematic evaluation and selection process to identify non-dominated solutions where at least one metric shows clear improvement.

3.3 Path Selection with Multi-Objective Criteria

Parameter sweep strategy is employed in the path selection procedure to systematically explore the trade-offs between radiation safety, path efficiency, and navigational simplicity. This involves testing a predefined set of values for the weighting parameter, which balances radiation exposure and path

distance, and the turning penalty coefficient λ . For each combination of α and λ , the algorithm generates paths and evaluates them based on three metrics: the number of turns (T), cumulative radiation dose (C), and total path distance (D). These metrics are designed to solve this multi-objective challenge: reducing turns improves human navigability, lowering cumulative dose prioritizes radiation safety, and shortening distance enhances operational efficiency. As Pareto efficiency is adopted in the evaluation process, the outputs are Pareto optimal solutions. Among all candidate paths in the test space, only non-dominated solutions, meaning no other solution performs better across all three evaluation metrics, are retained, while inferior solutions are eliminated. Table 1 summarizes the notations and nomenclature used in the pseudocode of the path selection procedure.

Table 1: Notations and Nomenclature

Notation	Definition
M	Map information
R	2D grid containing radiation dose values
O	Obstacle set
B	Boundary set
S	Start node
E	End node
α	Weighting parameter balancing minimizing distance and radiation dose
λ	Turning penalty coefficient
ASet	Set of α values to be tested
LSet	Set of λ values to be tested
VP	Set of valid path tuples
PGenMetricsComp()	Algorithm for path generation and metrics computation
T	Number of turns in the path
C	Cumulative radiation dose
D	Path distance
v	Boolean indicating if the current path is valid
IP	Set of invalid path tuples

Figure 4 illustrates the pseudocode for the SelectPath() algorithm. The algorithm accepts three primary inputs: map information (M), a predefined set of weighting coefficients (ASet), and a set of turning penalty values (Lset). The map M encodes the radiation environment as a grid, including radiation dose values (R), obstacle set (O), boundary set (B), and start and end nodes (S, E). The output is a set of valid paths (VP), where each path is represented by a tuple containing its parameter values (α , λ) and performance metrics: T, C, and D.

Algorithm 2 *SelectPath*($M, ASet, LSet$)

```
1: Initialize:  $VP = \emptyset$ 
2: for each  $\alpha \in ASet$  do
3:   for each  $\lambda \in LSet$  do
4:      $T, C, D = PGenMetricsComp(M, \alpha, \lambda)$ 
5:     Initialize:  $v = TRUE$ 
6:     Initialize:  $IP = \emptyset$ 
7:     for each  $vp$  in  $VP$  do
8:       if  $T \geq vp[2]$  and  $C \geq vp[3]$  and  $D \geq vp[4]$  then
9:          $v = FALSE$ 
10:        BREAK
11:      end if
12:      if  $T \leq vp[2]$  and  $C \leq vp[3]$  and  $D \leq vp[4]$  then
13:         $IP.append((\alpha, \lambda, vp[2], vp[3], vp[4]))$ 
14:      end if
15:    end for
16:    if  $v == TRUE$  then
17:      for each  $ip$  in  $IP$  do
18:         $VP.remove(ip)$ 
19:      end for
20:       $VP.append((\alpha, \lambda, T, C, D))$ 
21:    end if
22:  end for
23: end for
24: Return  $VP$ 
```

Figure 4. Pseudocode for SelectPath() Algorithm

The SelectPath() algorithm begins by initializing an empty set VP. PGenMetricsComp() algorithm, described in the previous section, is executed iteratively across all combinations of α and λ defined in Aset and Lset, applying the A* algorithm with new cost function $G'(n)$ to compute the number of turns (T), cumulative radiation dose (C), and total path distance (D) for each generated path. Pareto efficiency is applied in the evaluation process, ensuring only Pareto-optimal solutions are retained for this multi-objective problem (Ngatchou, Zarei, & El-Sharkawi, 2005). The remaining result paths are obtained through iterative comparisons of the metrics during the parameter sweep process (Fitzpatrick, 2012). As the algorithm tests combinations of α and λ , it discards paths that are universally dominated in all three metrics while retaining those that are Pareto-optimal. A candidate path is invalidated ($v = FALSE$) if it is dominated by any path in VP, which is, if it does not outperform existing paths in at least one metric T, C, or D. In such cases, the algorithm proceeds to the next iteration without retaining the path. For instance, consider a candidate path with $T = 6$, $C = 50 \mu Sv$, and $D = 20$ m. If VP contains a path with superior values for all metrics ($T = 5$, $C = 40 \mu Sv$, $D = 15$ m), the candidate path is dominated and thus eliminated from consideration. Conversely, a

candidate path remains valid if it is non-dominated, meaning no existing path in VP universally outperforms it across all three metrics. This means the path is retained as long as it performs better in at least one metric (T, C, or D). For example, if all existing paths in VP have more than 10 turns, a candidate path with 10 or fewer turns will be kept regardless of its other two metric values. During each iteration, the SelectPath() algorithm also checks whether the candidate path dominates existing solutions in the valid path set (VP), i.e., whether it is superior in all three metrics (T, C, D).

Dominated paths are temporarily appended to the invalid path set (IP) and subsequently removed from VP. This iterative process guarantees that the final output, VP, contains only non-dominated solutions, ensuring decision-makers are presented with Pareto-optimal solutions.

3.4 Simulation Experiments

Four simulation cases were conducted to validate the proposed methodology in grid-based radiation environments, each with a consistent configuration: a $0.25\text{ m} \times 0.25\text{ m}$ grid resolution, obstacles and boundaries marked in black, radiation intensity visualized via a colour gradient ranging from dark to red (low to high radiation dose rates), and a worker walking speed of 1.5 m/s . The cases evaluate simple radiation environments with a few concentrated radiation hotspots and obstacles to more complex environments.

3.4.1 Simulation Case 1: One Radiation Source and a Few Obstacles

Figure 5(a) illustrates the radiation distribution for simulation case 1. This case simulates a simple radiation environment with only one radiation source and a few obstacles. Figure 5(b) presents the path generated by the A* algorithm using the minimum dose method, achieving a low radiation exposure of $17.33\text{ }\mu\text{Sv}$ but requiring 4 turns and a longer path length of 24.6 m . In contrast, Figure 5(c) shows the path from the minimum distance method, which prioritizes efficiency with a shorter 15.75-meter route and no turns but incurs significantly higher radiation exposure of $63.35\text{ }\mu\text{Sv}$.

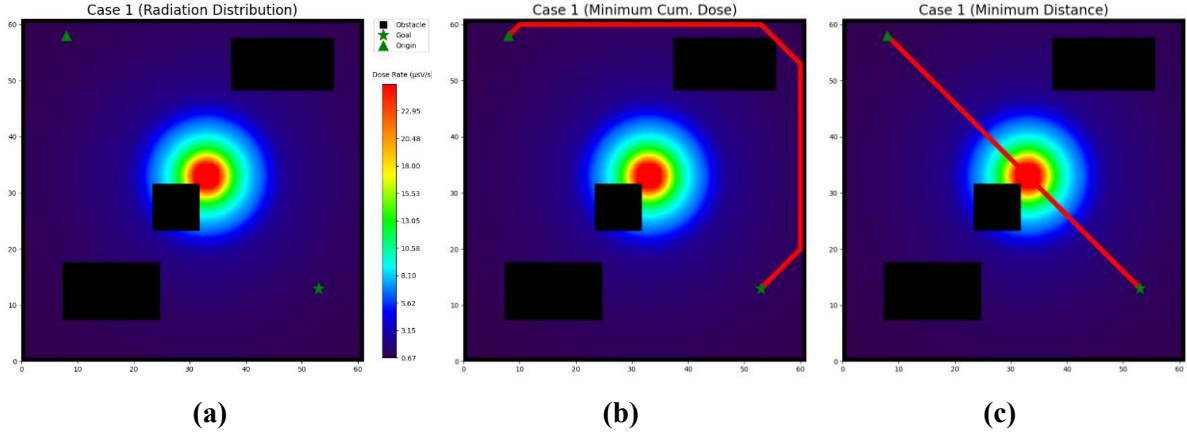


Figure 5. (a) Radiation Distribution; (b) Min. Dose Method; and (c) Min. Distance Method of Case 1

3.4.1.1 Path Selection Results

Figure 6 illustrates the path selection results of case 1, showing the trade-offs between number of turns, total distance, and cumulative radiation dose for all the paths in the final output. Marker colours differentiate the number of turns. Two benchmark paths are also plotted for comparison: the minimum dose method ($T = 4$, $C = 17.33 \mu\text{Sv}$, $D = 24.6 \text{ m}$) prioritizes safety but requires a longer, more circuitous route, and the minimum distance method ($T = 0$, $C = 63.35 \mu\text{Sv}$, $D = 15.75 \text{ m}$) optimizes efficiency at the expense of very high radiation exposure. Valid paths occupy intermediate regions, demonstrating Pareto-optimal trade-offs. The inverse relationship between cumulative dose and path distance is evident: shorter paths correlate with higher radiation exposure, while safer routes require longer distances.

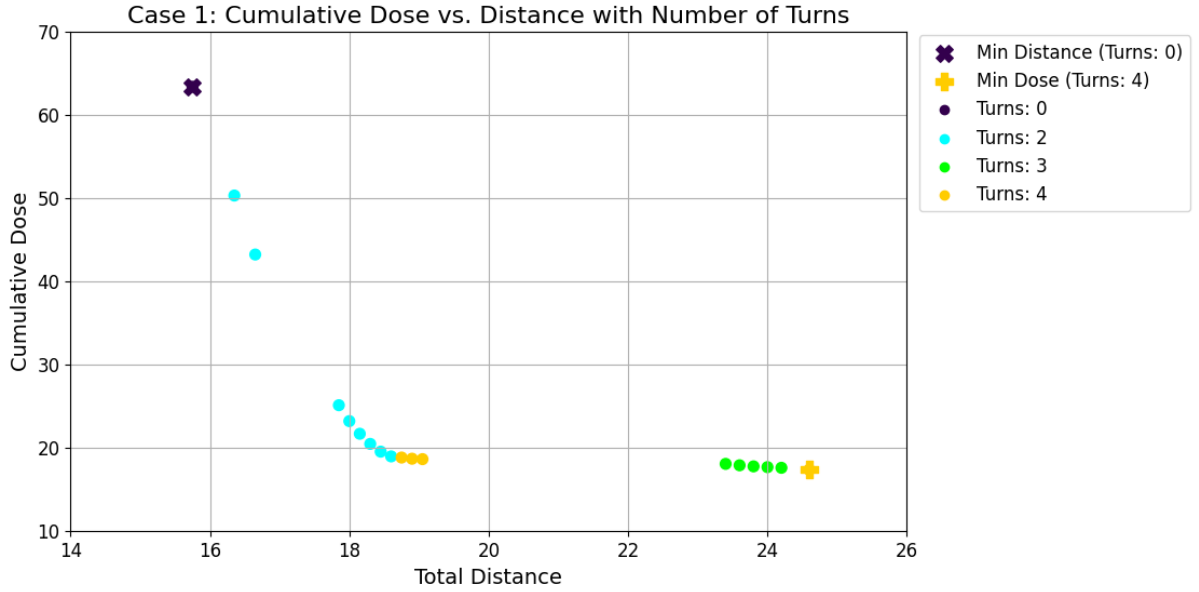


Figure 6. Cumulative Dose vs. Distance with Number of Turns (Case 1)

Figure 7 visualizes the path results for Case 1, showing paths (a) to (f) with different α and λ combinations. Table 2 details the results for these paths, along with the minimum distance and minimum dose paths, including the turning penalty coefficient, weighting parameter, number of turns, cumulative dose, and distance.

Paths (a) to (d) demonstrate the impact of increasing α values (0.15, 0.25, 0.40, 0.95) with λ fixed at 1, isolating the trade-off between radiation avoidance and path efficiency. At lower α values, such as 0.15, the algorithm prioritizes minimizing path distance by avoiding high radiation zones, resulting in paths like path (a). Compared with the minimum distance path, the distance of path (a) only slightly increases by around 13% from 15.75 m to 17.85 m. This small increase in distance reduces radiation exposure significantly by over 60% from 63.35 μSv to 25.08 μSv . With increasing alpha values, the algorithm progressively focuses more on the radiation avoidance. Moderate alpha values can lead to path results with balanced radiation exposure and path length like path (c). Comparing path (c) with the minimum dose path, when α is set to 0.4, the cumulative dose of path (c) increases by approximately 9%, while its distance is reduced by nearly 25%. In this case, operators might prefer path (c) over the minimum dose path, as a 9% increase in cumulative dose may be negligible in certain scenarios. When α is set to higher values, such as 0.95, the algorithm prioritizes radiation avoidance, resulting in a path like path (d), which is identical to the minimum dose path.

The comparison of paths (d) and (e) highlights the impact of λ with α fixed at 0.95. Increasing λ to 1.06 generates path (e), eliminating a turn near the origin with negligible impact on radiation exposure or path distance compared with path (d). Similarly, with λ set to 1.02, path (f) avoids an unnecessary turn compared to the minimum dose path, demonstrating how slight adjustments to the turning penalty coefficient simplify navigation without compromising radiation safety or efficiency. Unnecessary turns like this should be avoided as they have almost negligible impact on the cumulative radiation dose. This can enhance path practicality for human operators, underscoring the algorithm's ability to reduce navigational complexity through parameter tuning.

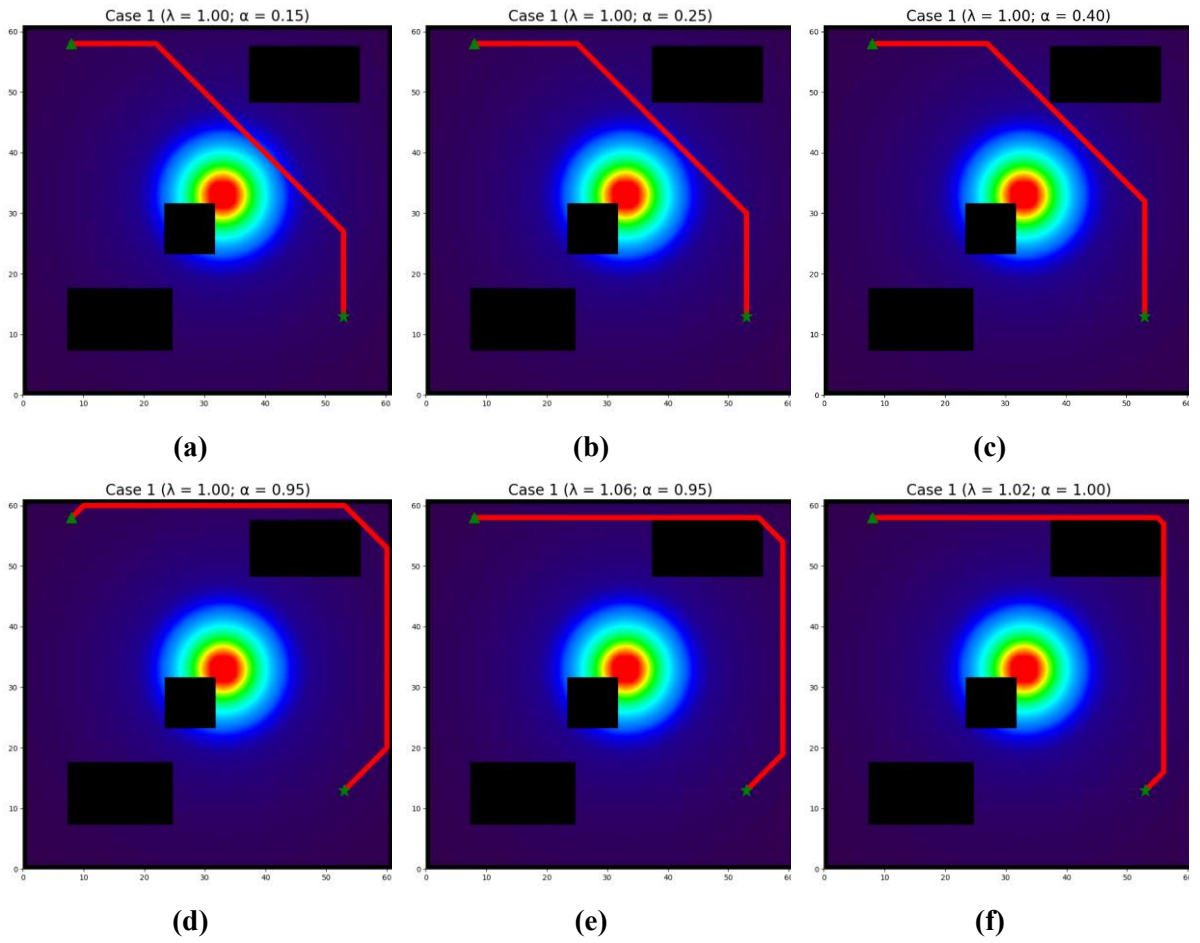


Figure 7. Visualization of Paths (a) to (f) with Combinations of Specified α and λ Values (Case 1)

Table 2: Results of Paths (a) to (f), Min. Dose and Min. Distance Paths: turning penalty coefficient, weighting parameter, number of turns, cumulative dose, and distance (Case 1)

Path	Turning Penalty Coeff. (-) [λ]	Weighting Parameter (-) [α]	Number of Turns (-) [T]	Cumulative Dose (μSv) [C]	Distance (m) [D]
Min. Distance	1.00	0.00	0	63.35	15.75
(a)	1.00	0.15	2	25.08	17.85
(b)	1.00	0.25	2	20.43	18.30
(c)	1.00	0.40	2	18.93	18.60
(d)	1.00	0.95	4	17.33	24.60
(e)	1.06	0.95	3	17.64	24.00
(f)	1.02	1.00	3	18.03	23.40
Min. Dose	1.00	1.00	4	17.33	24.60

3.4.2 Simulation Case 2: One Radiation Source and a Maze-like Obstacle Configuration

Figure 8(a) depicts the radiation distribution for simulation case 2, featuring a single high-intensity radiation source and a maze-like obstacle configuration. Figure 8(b) presents the path generated by the A* algorithm using the minimum dose method, which minimizes radiation exposure to 34.58 μSv but requires six turns and a longer path length of 26.95 m. In contrast, Figure 8(c) shows the minimum distance path, which prioritizes efficiency with a shorter 18.75 m route but results in significantly higher radiation exposure of 83.71 μSv . Due to the maze-like obstacles, the minimum distance path still requires many turns.

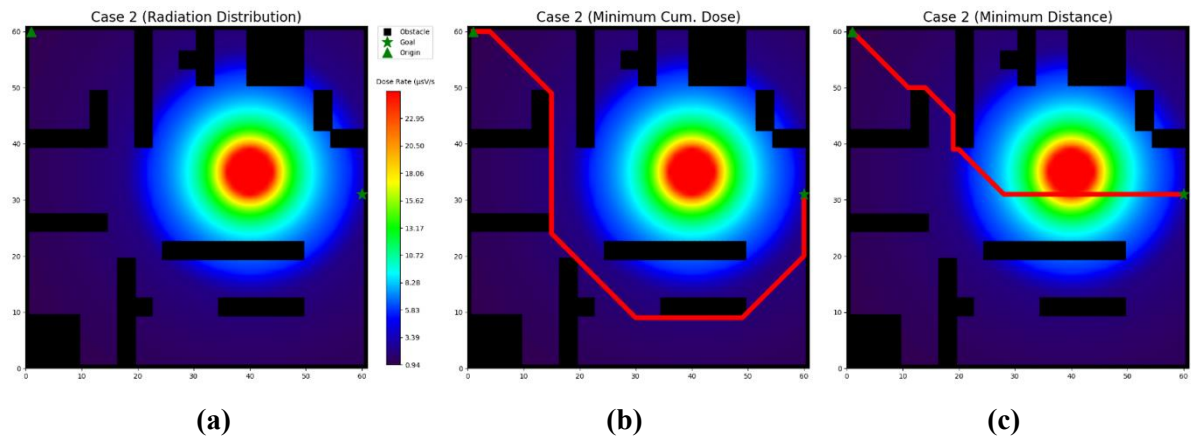


Figure 8. (a) Radiation Distribution; (b) Min. Dose Method; and (c) Min. Distance Method of

Case 2

3.4.2.1 Path Selection Results

Figure 9 illustrates the path selection results for case 2, highlighting the trade-offs between the number of turns, cumulative radiation dose, and distance for all paths in the final output. Marker colors distinguish the number of turns. Two benchmark paths are plotted for comparison: the minimum dose path ($T = 6$, $C = 34.58 \mu\text{Sv}$, $D = 26.95 \text{ m}$) prioritizes safety but requires a longer distance, while the minimum distance path ($T = 6$, $C = 83.71 \mu\text{Sv}$, $D = 18.75 \text{ m}$) maximizes efficiency at the cost of high radiation exposure. Valid paths occupy intermediate regions, demonstrating Pareto-optimal trade-offs. This case also reveals an inverse relationship between the cumulative dose and path distance, where shorter paths correlate with higher radiation exposure, while safer routes require longer distances.

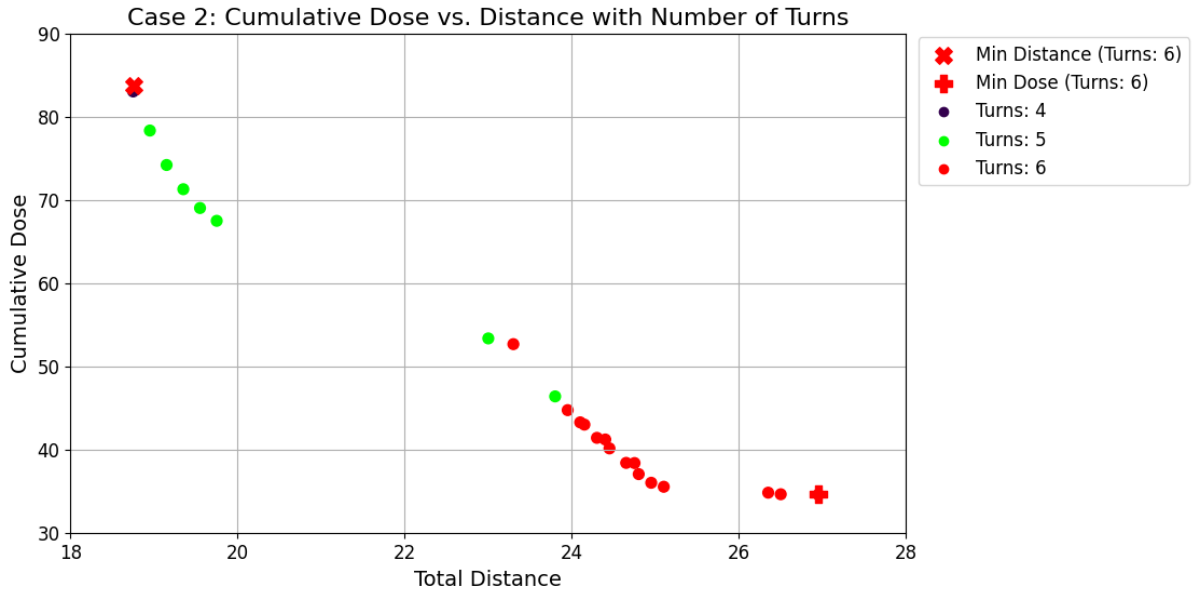


Figure 9. Cumulative Dose vs. Distance with Number of Turns (Case 2)

Figure 10 visualizes the path results for case 2, showing paths (a) to (f) with different α and λ combinations. Table 3 details the results for these paths, along with the minimum distance and minimum dose paths, including the turning penalty coefficient, weighting parameter, number of turns, cumulative dose, and distance.

Paths (a) to (e) demonstrate the impact of increasing α values (0.05, 0.30, 0.40, 0.80, 0.95) with λ fixed at 1. The gradual transition in these paths reveals that, as α increases, the algorithm gradually shifts its focus towards radiation avoidance, resulting in paths that prioritize lower exposure over

shorter distances. These path options can be valuable for operators in nuclear facilities. For instance, when radiation levels remain below the threshold requiring strict avoidance, and efficiency is a priority for work tasks, path (c), with α set to 0.4, could be a suitable choice. Compared to the minimum distance path, it increases travel distance by only about 5% while reducing radiation exposure by approximately 20%. The comparison of paths (e) and (f) highlights the impact of λ with α fixed at 0.95. Increasing λ to 1.02 generates path (f), removing a turn while having minimal effect on radiation exposure and path length.

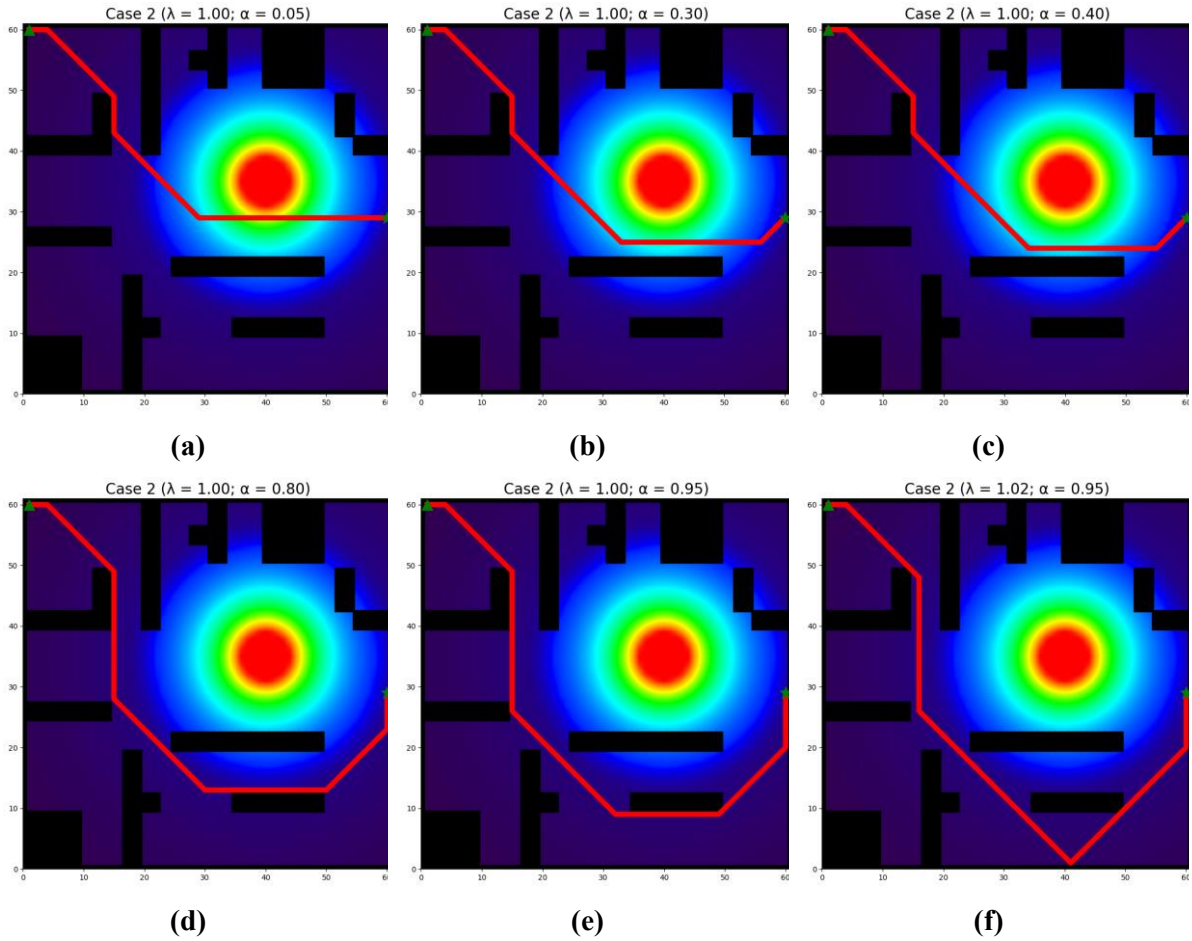


Figure 10. Visualization of Paths (a) to (f) with Combinations of Specified α and λ Values (Case 2)

Table 3: Results of Paths (a) to (f), Min. Dose and Min. Distance Paths: turning penalty coefficient, weighting parameter, number of turns, cumulative dose, and distance (Case 2)0

Path	Turning Penalty Coeff. (-) [λ]	Weighting Parameter (-) [α]	Number of Turns (-) [T]	Cumulative Dose (μSv) [C]	Distance (m) [D]
Min. Distance	1.00	0.00	6	83.71	18.75
(a)	1.00	0.05	4	83.03	18.75
(b)	1.00	0.30	5	69.02	19.55
(c)	1.00	0.40	5	67.48	19.75
(d)	1.00	0.80	6	35.52	25.1
(e)	1.00	0.95	6	34.63	26.65
(f)	1.02	0.95	5	36.01	28.1
Min. Dose	1.00	1.00	6	34.58	26.95

3.4.3 Simulation Case 3: Multiple Radiation Sources and Obstacles

Figure 11 (a) depicts the radiation distribution for simulation case 3, characterized by multiple radiation sources and obstacles. Figure 11 (b) presents the path generated by the A* algorithm using the minimum dose method, which minimizes radiation exposure to 35.13 μSv but requires a longer path length of 24.65 m with 6 turns. In contrast, Figure 11 (c) shows the minimum distance path, which prioritizes efficiency with a shorter 15.65 m route but results in significantly higher radiation exposure of 78.66 μSv . In order to avoid obstacles, the minimum distance path requires 7 turns.

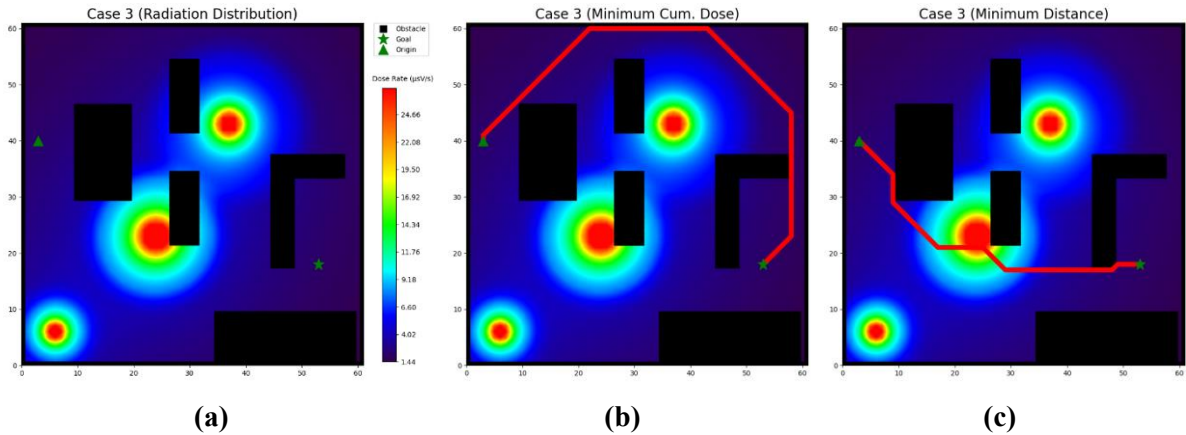


Figure 11. (a) Radiation Distribution; (b) Min. Dose Method; and (c) Min. Distance Method of Case 3

3.4.3.1 Path Selection Results

Figure 12 illustrates the path selection results for case 3, highlighting the trade-offs between the number of turns, cumulative radiation dose, and distance for all paths in the final output. Marker

colors distinguish the number of turns. Two benchmark paths are plotted for comparison: the minimum dose path ($T = 5$, $C = 35.13 \mu\text{Sv}$, $D = 24.65 \text{ m}$) prioritizes safety but requires a longer distance, while the minimum distance path ($T = 7$, $C = 78.66 \mu\text{Sv}$, $D = 15.65 \text{ m}$) maximizes efficiency at the cost of high radiation exposure. Valid paths occupy intermediate regions, demonstrating Pareto-optimal trade-offs. This case also reveals an inverse relationship between cumulative dose and path distance, where shorter paths correlate with higher radiation exposure, while safer routes require longer distances.

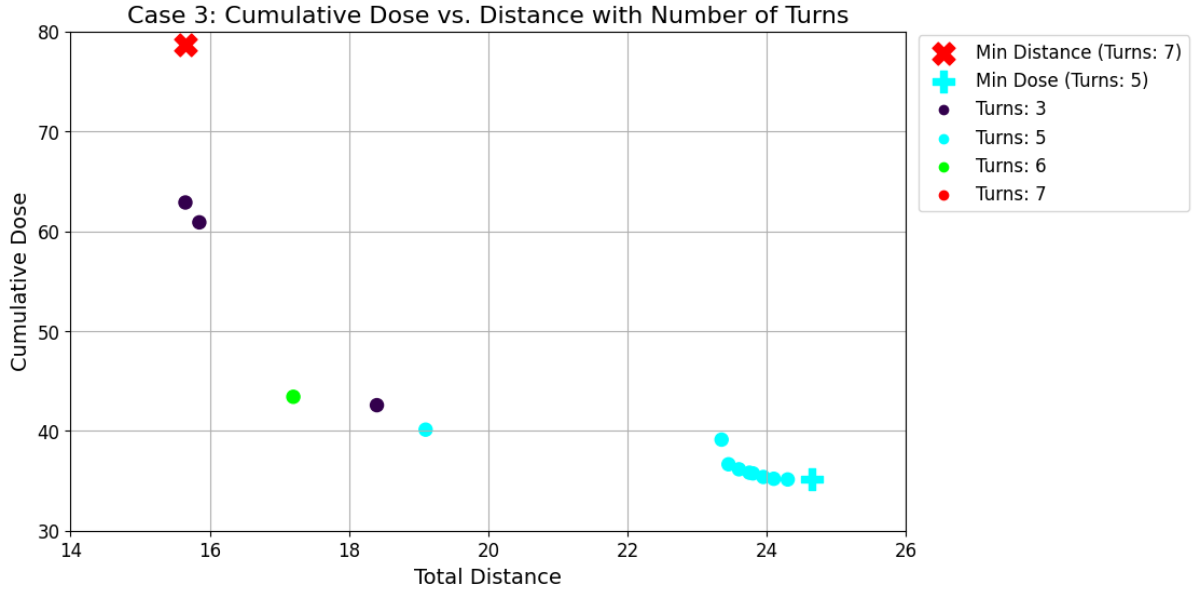


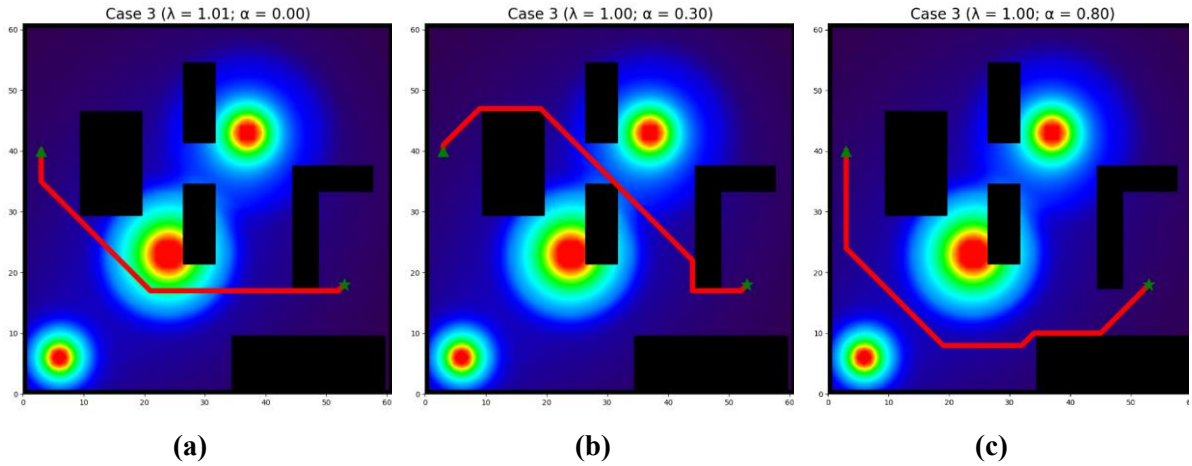
Figure 12. Cumulative Dose vs. Distance with Number of Turns (Case 3)

Figure 13 visualizes the path results for case 3, showing paths (a) to (f) with different α and λ combinations. Table 4 details the results for these paths, along with the minimum distance and minimum dose paths, including the turning penalty coefficient, weighting parameter, number of turns, cumulative dose, and distance.

Paths (b), (c), (e), and (f) demonstrate the impact of increasing α values (0.30, 0.80, 0.85, 0.95) with λ fixed at 1. The gradual transition in these paths shows that as α increases, the algorithm progressively prioritizes radiation avoidance, leading to longer routes with lower exposure. This trend is particularly evident when comparing paths (b), (c), and (e). When α is set to 0.3, the algorithm prioritizes shorter path distance, generating path (b), which takes a more direct route through the space between the central radiation hotspot and the top-right hotspot. Compared to the minimum distance path, path (b)

increases distance by around 9% while reducing radiation exposure by over 43%. As noted in previous cases, this trade-off may be preferable for some operators, as a 9% increase in distance has a minimal impact on efficiency, whereas a 43% reduction in radiation exposure significantly enhances safety. When α is set to 0.80, the algorithm prioritizes radiation minimization, generating path (c), which takes a longer route with reduced radiation exposure by passing between the bottom-left and central radiation hotspots. As α increases to 0.85, the algorithm emphasizes radiation minimization even more, generating path (e), which makes a detour away from all three radiation hotspots, with less radiation exposure and longer distance.

Comparing path (a) with the minimum distance path highlights the advantage of incorporating a turning penalty in the new cost function. With λ set to 1.01 and α fixed at 0.00, the algorithm generates path (a), reducing the number of turns by 4 without affecting path distance. As a fortunate side effect, radiation exposure also decreases by approximately 20%. However, this reduction is incidental rather than guaranteed, as λ primarily functions to minimize turns rather than optimize radiation exposure. Comparing paths (c) and (d) further demonstrates the benefit of the turning penalty. With λ set to 1.01 and α fixed at 0.80, the algorithm reduces the number of turns by two, generating path (d). While path (d) maintains a similar distance and radiation exposure to path (c), it offers smoother navigation for operators.



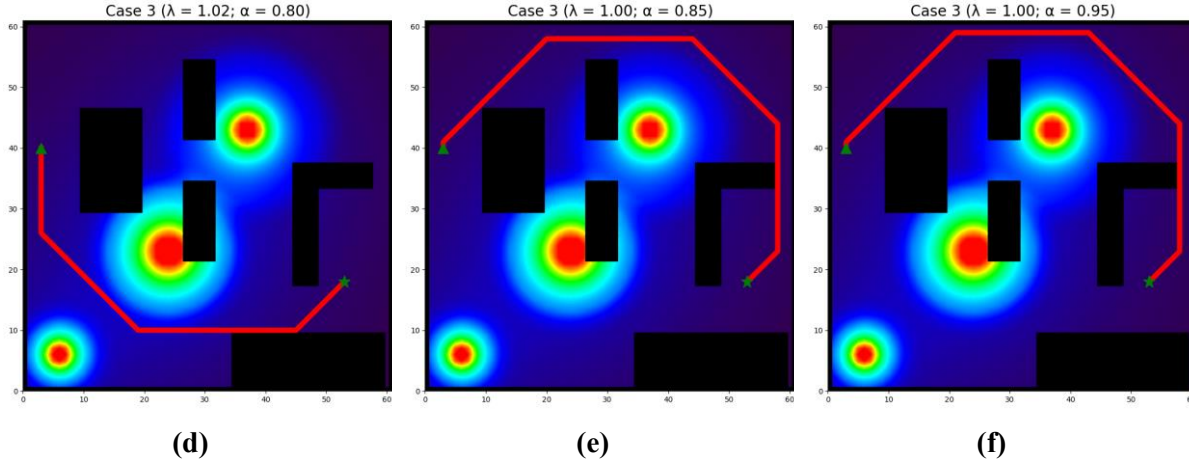


Figure 13. Visualization of Paths (a) to (f) with Combinations of Specified α and λ Values (Case 3)

Table 4: Results of Paths (a) to (f), Min. Dose and Min. Distance Paths: turning penalty coefficient, weighting parameter, number of turns, cumulative dose, and distance (Case 3)

Path	Turning Penalty Coeff. (-) [λ]	Weighting Parameter (-) [α]	Number of Turns (-) [T]	Cumulative Dose (μSv) [C]	Distance (m) [D]
Min. Distance	1.00	0.00	7	78.66	15.65
(a)	1.01	0.00	3	62.87	15.65
(b)	1.00	0.30	6	43.41	17.20
(c)	1.00	0.80	5	40.12	19.10
(d)	1.02	0.80	3	42.57	18.40
(e)	1.00	0.85	5	35.20	24.10
(f)	1.00	0.95	5	35.13	24.30
Min. Dose	1.00	1.00	5	35.13	24.65

3.4.4 Simulation Case 4: Intricate Radiation Environment with Widely Dispersed Obstacles

Figure 14 (a) illustrates the radiation distribution for simulation case 4, which features a more complex radiation environment characterized by irregularly distributed radiation and widely dispersed obstacles. Figure 12 (b) presents the path generated by the A* algorithm using the minimum dose method, which minimizes radiation exposure to 148.86 μSv but requires a longer path length of 26.90

m with 6 turns. In comparison, Figure 12 (c) displays the minimum distance path, emphasizing efficiency with a shorter route of 21.10 m and a more straightforward trajectory with only 3 turns. However, this path results in a substantially higher radiation exposure of 305.72 μSv .

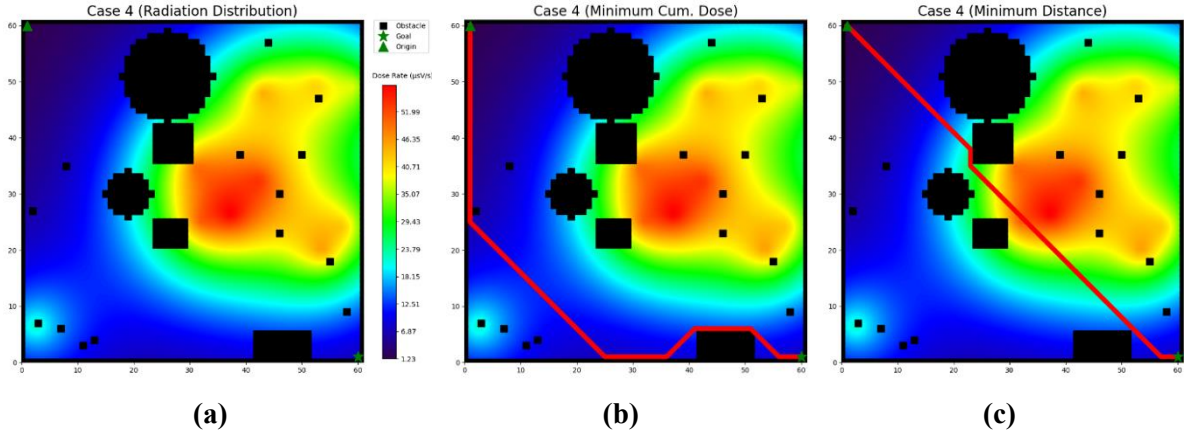


Figure 14. (a) Radiation Distribution; (b) Min. Dose Method; and (c) Min. Distance Method of Case 4

3.4.4.1 Path Selection Results

Figure 15 illustrates the path selection results for case 4, highlighting the trade-offs between the number of turns, cumulative radiation dose, and distance for all paths in the final output. Marker colors distinguish the number of turns. Two benchmark paths are plotted for comparison: the minimum dose path ($T = 6$, $C = 148.86 \mu\text{Sv}$, $D = 26.90 \text{ m}$) prioritizes safety but requires a longer distance, while the minimum distance path ($T = 3$, $C = 305.72 \mu\text{Sv}$, $D = 21.10 \text{ m}$) maximizes efficiency at the cost of high radiation exposure. Valid paths occupy intermediate regions, demonstrating Pareto-optimal trade-offs. This case also reveals an inverse relationship between cumulative dose and path distance, where shorter paths correlate with higher radiation exposure, while safer routes require longer distances.

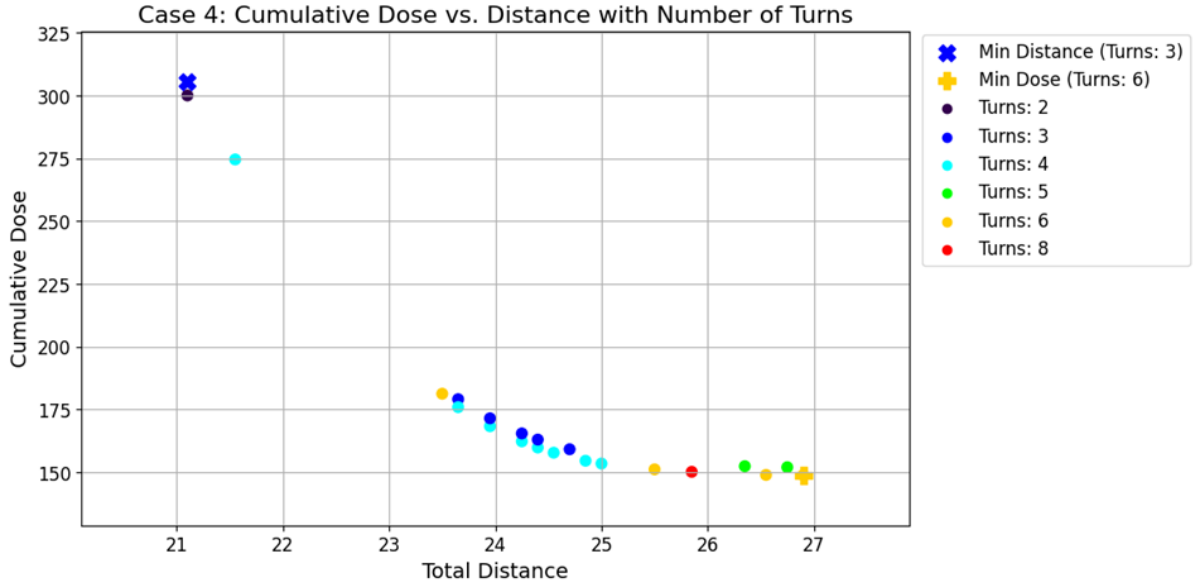


Figure 15. Cumulative Dose vs. Distance with Number of Turns (Case 4)

Figure 16 visualizes the path results for case 4, showing paths (a) to (f) with different α and λ combinations. Table 5 details the results for these paths, along with the minimum distance and minimum dose paths, including the turning penalty coefficient, weighting parameter, number of turns, cumulative dose, and distance.

Paths (b), (c), and (d) demonstrate the impact of increasing α values (0.30, 0.40, 0.85) with λ fixed at 1. The gradual transition in these paths shows that as α increases, the algorithm progressively prioritizes radiation avoidance, leading to longer routes with lower exposure.

When α is set to 0.3, the algorithm prioritizes shorter path distances, generating path (b). This path follows a more direct route, bypassing the red region with higher radiation intensity. As α increases to 0.40, the algorithm places slightly more emphasis on radiation avoidance, resulting in path (c). This path is shifted further toward the bottom-left side of the map, taking a detour to avoid the red region with higher radiation intensity. When α increases to higher values, such as 0.5, the resulting path (d) is pushed even further toward the bottom-left side, taking a longer detour to maintain a greater distance from the high-radiation area.

Comparing path (a) with the minimum distance path underscores the benefit of incorporating a turning penalty into the new cost function. With λ set to 1.01 and α fixed at 0.00, the algorithm generates path (a), which reduces the number of turns to 2 without altering the path distance. As a

fortunate side effect, similar to simulation case 3, the radiation exposure also decreases slightly. The comparison between paths (d) and (e) further illustrates the advantages of the turning penalty. With λ set to 1.01 and α fixed at 0.85, the algorithm generates path (e), reducing the number of turns by 3. While path (e) maintains a similar distance and radiation exposure to path (d), it offers smoother navigation for operators. Similarly, the comparison between path (f) and the minimum dose path highlights this advantage, demonstrating how the turning penalty contributes to more efficient and human-centric route planning.

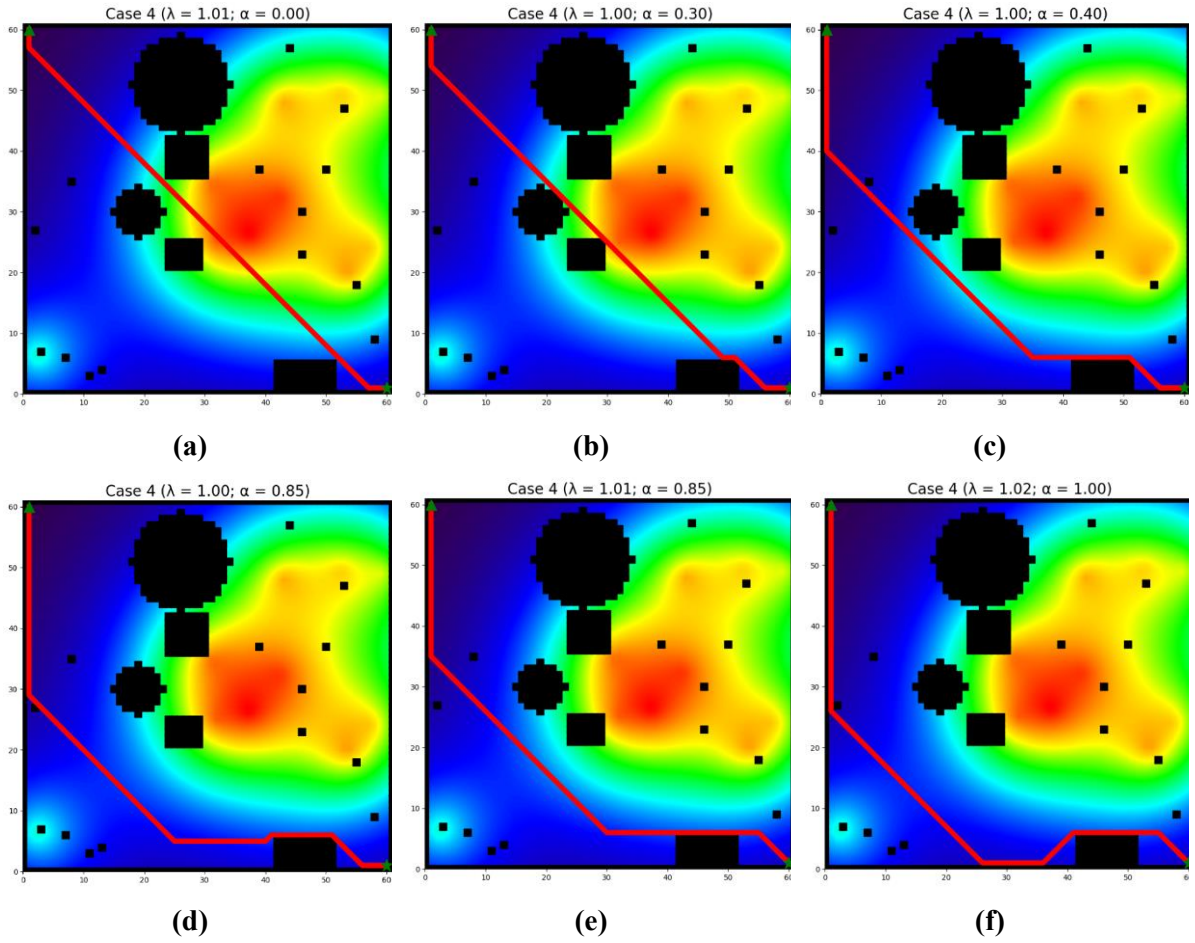


Figure 16. Visualization of Paths (a) to (f) with Combinations of Specified α and λ Values (Case 4)

Table 5: Results of Paths (a) to (f), Min. Dose and Min. Distance Paths: turning penalty coefficient, weighting parameter, number of turns, cumulative dose, and distance (Case 4)

Path	Turning Penalty Coeff. (-) [λ]	Weighting Parameter (-) [α]	Number of Turns (-) [T]	Cumulative Dose (μSv) [C]	Distance (m) [D]
Min. Distance	1.00	0.00	3	305.72	21.10
(a)	1.01	0.00	2	300.08	21.10
(b)	1.00	0.30	4	274.59	21.55
(c)	1.00	0.40	4	175.95	23.65
(d)	1.00	0.85	6	151.17	25.50
(e)	1.01	0.85	3	163.02	24.40
(f)	1.02	1.00	5	152.02	26.75
Min. Dose	1.00	1.00	6	148.86	26.90

Chapter 4

Comparing Human Motion in Reality and Virtual Reality for Heavy Blocks Lifting to Assess the Feasibility of Using VR for Ergonomics Training in Masonry Work

4.1 Introduction

There are various conventional methods for addressing MSD risks in construction, such as legal regulations, guidelines, surveying, in-person training, and observational assessments, often face challenges like high costs, limited engagement, and scalability issues. Recent advancements in technology have led to the adoption of VR applications in construction training as a promising solution. Previous research has shown that VR training is more effective than conventional in-person training in construction safety training and education (CTSE), offering increased engagement, enhanced skill development, and reduced costs and risks (Adami et al., 2021; Man et al., 2024; Nykänen et al., 2020; Sacks et al., 2013). This presents a potential concern: there may be an implicit or explicit assumption that VR applications inherently outperform traditional methods in effectiveness. However, deploying VR in contexts where conventional approaches are more suitable can lead to suboptimal outcomes. To avoid this, researchers should fully study and evaluate the use of VR applications in different scenarios, carefully considering when and how VR should be used, rather than assuming it is always the best option. In recent years, a growing body of research has explored and evaluated the use of VR applications.

In some cases, VR proves to be effective. For example, Jurchis and Dienes (2023) explored if it's possible to do implicit learning by teaching realistic body movements in VR, for example, teaching VR users to recognize the boxing postures, and confirmed that the implicit learning for full body movements, which is unconscious acquisition of patterns, can be achieved by VR. The limitations of VR are evident in scenarios involving human motion. Realistic human motion generation remains one of VR's most persistent challenges. While studies like Ye et al. (2022) attempt solutions to predict full body movements, VR still has many limitations in reliably replicating real-world motion due to the complexity of natural movement. Rogers et al. (2019) recognized a fidelity issue in VR games and found that the extent to which VR interactions mimic real-world actions can affect user experience.

While they conducted a user survey on motion fidelity, their study did not empirically compare VR-based human interactions with real-world human actions.

These considerations are relevant in the context of adopting VR in ergonomics training. Specifically, in masonry work, this application has not been adequately explored due to VR's limitation in simulating the weight, mass and momentum of Concrete Masonry Units (CMUs) in real-life tasks. To date, in the field of masonry trades, no existing research has empirically confirmed that motion patterns in a VR simulation with weightless blocks replicate real-world block lifting motion patterns. Lack of replication may render effective ergonomic training for masonry infeasible in VR. This lack of confirmation introduces a significant knowledge gap and research question.

4.2 Methodology

To address this question, this study investigated the validity of using VR for ergonomics training, particularly in masonry work, by comparing human motion behaviour during block lifting in real and VR environments. RULA is a standard and broadly used rule-based assessment system designed to assess risk factors linked to MSDs, with a primary focus on the upper body. The RULA score, computed based on captured motion data in the form of joint locations, was used to quantitatively assess musculoskeletal loadings and ergonomic risks (McAtamney & Corlett, 1993). A VR simulation was developed to replicate a preceding real-life experiment, and the participants' motions were recorded using a wearable motion capture system. These allowed us to compute body section scores, including the upper arm, lower arm, neck, and trunk, which were also analyzed to gain deeper insight into the findings.

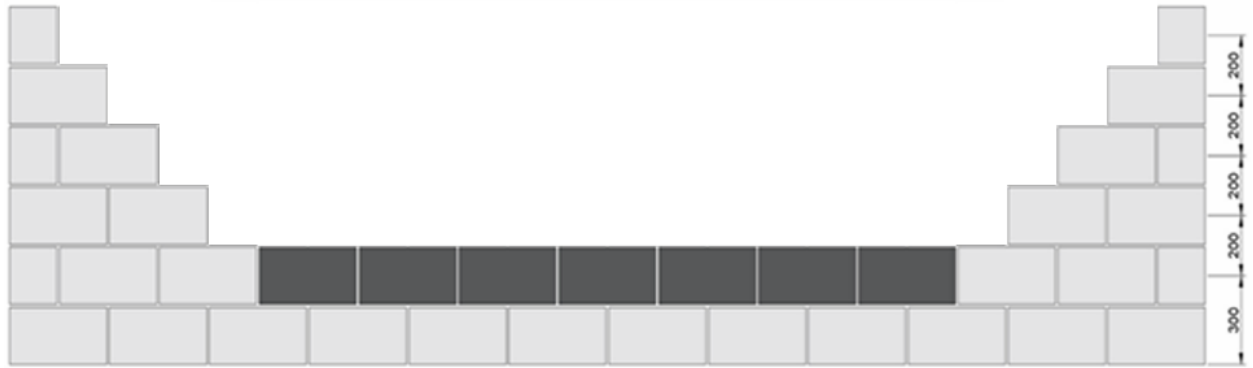
4.2.1 Data Collection

In Ontario, Canada, the 3-year masonry apprenticeship program consists of on-site and in-school training, allowing apprentices to apply for journeyman certification upon completion. This study used a subset of data from previous research that included human motion data of block lifting from 66 healthy masons with varying levels of work experience, collected at the Ontario Masonry Training Centre in Waterloo and the Canada Masonry Design Center in Mississauga, Ontario (Ryu, Alwasel, Haas, & Abdel-Rahman, 2020). Specifically, this study uses and analyzes the motion data from one group of participants to complete the second and sixth courses of a partially pre-built wall using both

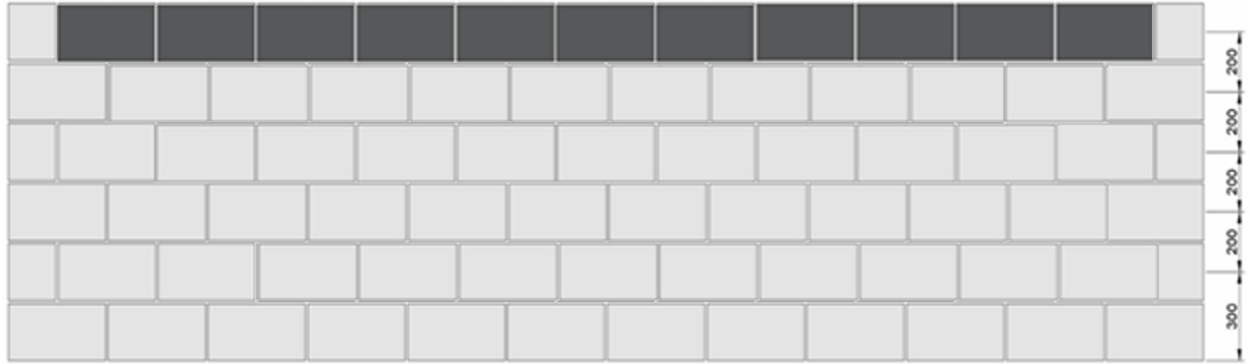
hands to handle the masonry unit. As this study focuses on double-hand lifts, the data on single-hand lifts from these previous real-world motion data collection exercises were excluded.

To facilitate comparison, a VR simulation was developed in the Unity game engine to replicate as closely as possible the real-life wall building data collection exercises. Accordingly, The VR simulation also employed two-hand interaction, requiring participants to grasp the CMUs with both hands. The motion data were recorded as participants wore the motion capture suit during the VR simulation. Each participant was instructed to complete the second and sixth courses of a pre-built wall in VR using a total of 18 CMUs, with a translucent yellow box indicating the designated placement location. This study included motion data from 74 lifts for course 2 and 96 lifts for course 6 from the previous real-life experiment. The VR simulation experiment collected motion data from 42 lifts for course 2 and 66 lifts for course 6.

Specifically, this study uses two scenarios for the experiment, shown in Fig. 1. The pre-built wall consisted of 27 CMUs laid into six courses (lighter grey shade). The participants laid down CMUs on the second course (Figure 17 (a)) and the sixth course (Figure 17 (b)). In the previous real-life wall building exercises, 16.6 kg CMUs with dimensions of $0.19 \times 0.19 \times 0.39$ m were organized in three piles approximately one meter from the pre-built lead wall (Ryu, Alwasel, Haas, & Abdel-Rahman, 2020).



(a)



(b)

Figure 17. Configuration of the Pre-built Wall: (a) Second Course Scenario; and (b) Sixth Course Scenario

In the VR simulation, the setup, including the wall configuration and the dimension of each CMU, was identical to that in the real-life exercises. The key distinction was that participants lifted virtual CMUs without weight in the VR simulation and laid them without spreading mortar. The scope of both sets of exercises is limited to analyzing the motion behaviour of participants while lifting blocks, with no consideration of other activities such as mixing or spreading mortar. Reflecting this, the VR simulation involved only block lifting and placement, and the motion analysis of associated activity was conducted. Figure 18 provides a visual representation of the setup used in the prior real-life exercise (Fig. 18 a - b) and the VR simulated exercise (Fig. 18 c - d).

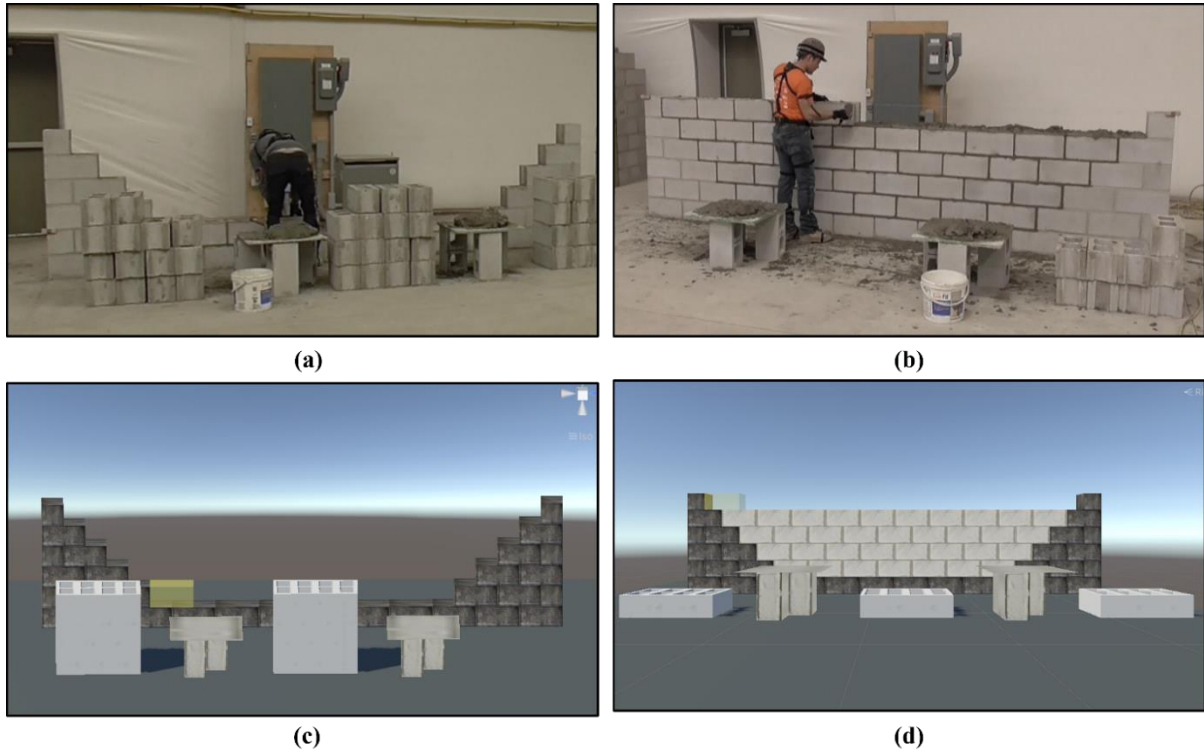


Figure 18. Set-ups: (a) Real-life Exercise – Course 2; (b) Real-life Exercise – Course 6; (c) VR Simulation – Course 2; (d) VR Simulation – Course 6

Both sets of exercises captured whole-body motion data. The real-life exercises used two wireless motion capturing systems, MVN Awinda and Perception Neuron (McFarland, Ryu, Haas, & Abdel-Rahman, 2023), whereas the VR simulation exercises utilized Perception Neuron 3 (PN3), an upgraded version of the latter (Noitom Ltd., 2024). This system supports unobtrusive motion capture, minimizing distraction and interference with the participants' tasks. The PN3 system uses 17 inertial measurement units (IMUs) integrated with a three-axis accelerometer, a three-axis gyroscope, and a three-axis magnetometer (Noitom Ltd., 2024). Each IMU was attached to the head, back, both shoulders, upper and lower arms, hands, thighs, legs, and feet using elastic straps (Fig. 19). The use of inertial sensors for motion capture has been proven suitable for various upper body motion analysis applications, aligning with the performance of standard optoelectronic systems (Seo, Alwasel, Lee, Abdel-Rahman, & Haas, 2017; Sers, et al., 2020).

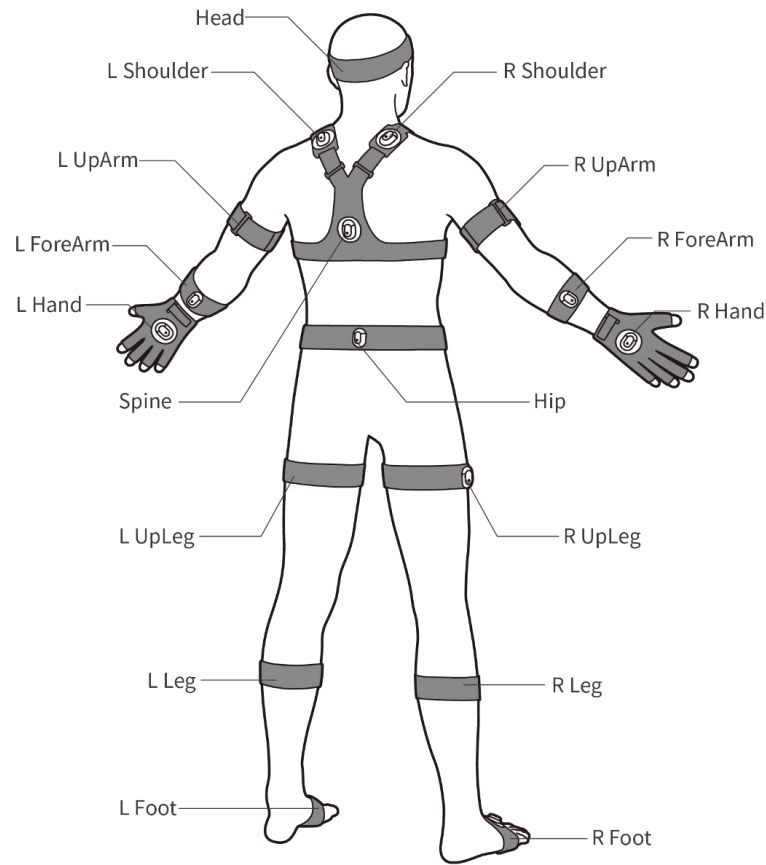


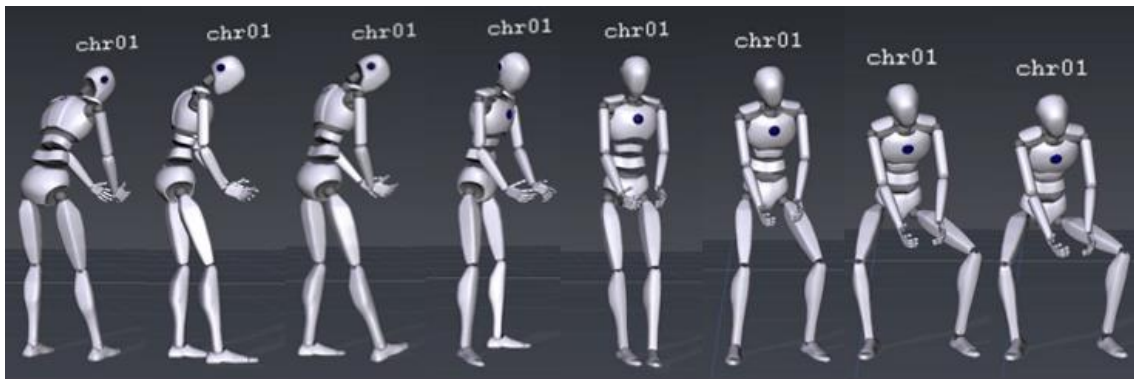
Figure 19. PN3 sensors (image from Noitom Ltd. (2024))

Motion data from both experiments were recorded and subsequently exported in the BioVision Hierarchy (BVH) format using the proprietary software (Axis Studio) provided by the respective PN3 by Noitom Ltd (2024).

Participants retrieved the CMUs individually, applied mortar and placed them in the designated locations in the wall. Figure 20 illustrates a single CMU lift sequence, showcasing the process from pickup to placement from three perspectives: in real life, as a skeleton model in Axis Studio, and from a first-person view in the VR simulation.



(a)



(b)



(c)

Figure 20. A Single CMU Lift Sequence from Pickup to Placement with Perspectives Synchronized Horizontally of: (a) Participant Wearing Motion Capture Suit in Real Life; (b) Skeleton Model in Axis Studio; and (c) First-Person View in VR Simulation

4.2.2 Data Processing

The exported motion data from the real-life experiment (referred to as real lifts) had a frame rate of 125 frames per second (fps), while the motion data from the VR simulation experiment (referred to as VR lifts) was capped at 60 fps due to a software update. For alignment, the real lift data were down-

sampled to match the frame rate of the VR lift data at 60 fps. For each frame, the 3D joint locations were extracted from the BVH files using the software BVH Viewer. Using MATLAB scripts, the data were segmented and stored in MAT-files for each lift, documenting the whole body's joint center coordinates for each frame across the complete lift motion, from CMU pickup to placement for individual lifts.

4.2.3 Data Analysis

A standard and broadly used rule-based assessment system, RULA, was used to compare the human motion behaviour during real and VR lifts. It is used in practice to assess risk factors linked to MSDs, specifically focusing on the upper body (Kee, 2022). RULA categorizes the human body into two groups: one comprising the lower and upper arms and wrists, and the other including the neck, trunk, and legs. The body section score for each group is determined by integrating individual joint scores using assessment tables, which also consider external loads and repetitive movements (Ryu, Banting, Abdel-Rahman, & Haas, 2023; Ryu, Diraneyya, Haas, & Abdel-Rahman, 2021). As the lower back and upper limbs are the most critical body joints for MSD risks (Ryu, Banting, Abdel-Rahman, & Haas, 2023), this study focuses on the upper body. For each frame, a RULA grand score, describing the overall risk index for a given posture, is calculated by integrating the body section scores. This study compares the RULA grand score between real and VR lifts, and it delves deeper into body section scores (upper arm, lower arm, neck, and trunk) to identify the primary sources of postural differences between the two lifting conditions. In accordance with the Occupational Health and Safety Council of Ontario (OHSCO) Musculoskeletal Disorders Prevention Series guidelines, instead of the cumulative effects of all movements during a lift, this study analyzed the most critical postures observed by identifying the peak score (RULA grand, upper arm, lower arm, neck and trunk scores) from all frames of each lift (OHSCO, 2007). To ensure score comparability between real and VR lifts and to focus on motion patterns, the load penalty was excluded from the score calculation for real lifts, as the scores were highly saturated due to the external load of 16.6 kg.

4.3 Results

4.3.1 Descriptive Results

Notable differences in RULA grand scores and body section scores between real and VR lifts can be observed when comparing mean values and standard deviations (SD) for the second and sixth courses

of the wall, as illustrated in Figure 21. The second and sixth courses of masonry units are named C2 and C6, respectively, which is the nomenclature used in Figure 21. Figure 21 (a) shows that real lifts yield higher RULA grand scores across both courses. This difference is primarily attributed to the trunk and neck due to the absence of weight in VR, while the upper and lower arm scores are nearly identical between real and VR lifts. In Figure 21 (b), VR lifts show higher variability in SD across the RULA grand score and all body section scores, particularly for the neck and trunk. This increased variability may stem from the less consistent and constrained movements involved in VR lifts, as the weightless virtual CMUs used in VR simulation do not replicate the 16.6 kg weight of the physical CMUs in the real-life experiment.

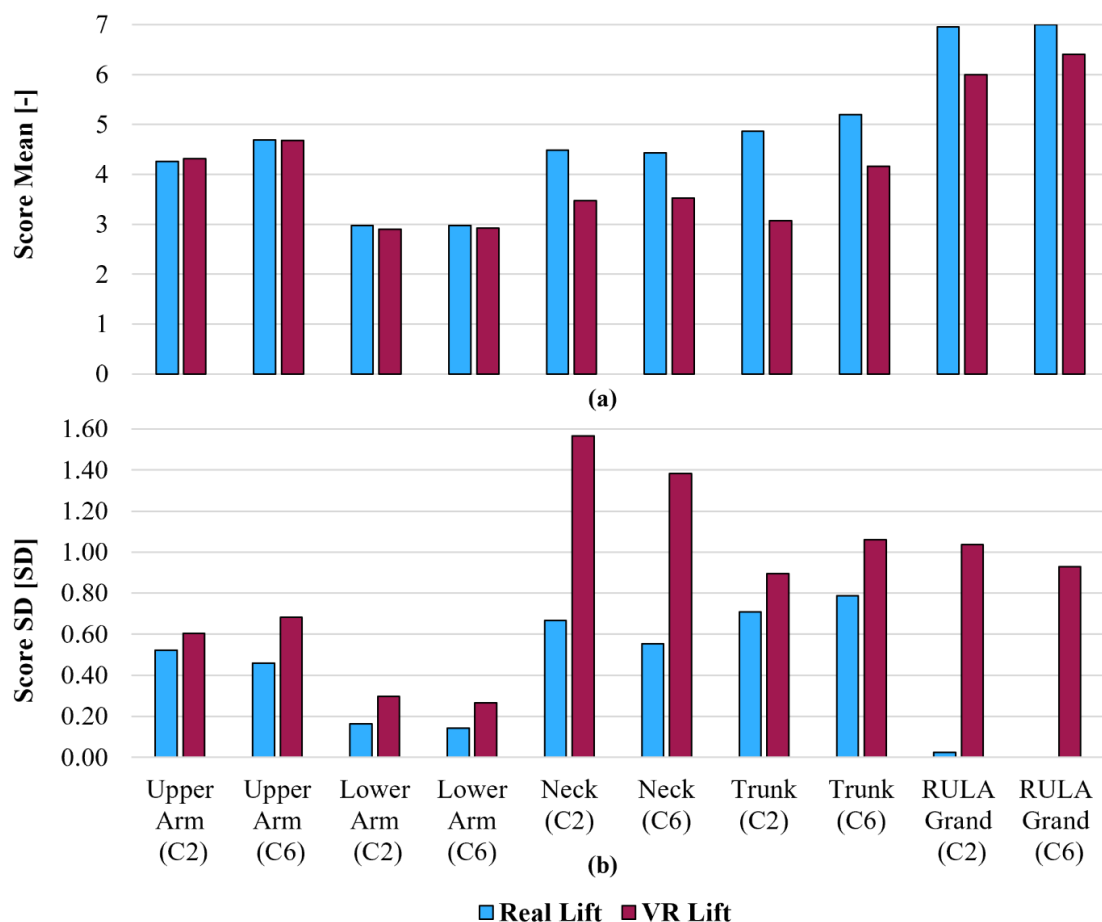


Figure 21. Comparison of RULA Grand Score and Body Section Scores Between Real and VR Lifts: (a) Mean and (b) SD (Standard Deviation)

Table 6 presents the mean RULA grand scores, individual body section scores, and the score differences between real and VR lifts for course 2 and course 6. Score differences were calculated by subtracting VR lift scores from real lift scores (i.e., Real – VR). Among all body sections, the most significant difference between real and VR lifts occurs in the trunk; specifically, for course 2, the mean score of real lifts exceeds that of VR lifts by approximately 1.79 (or about 60%), and for course 6, the increase is around 1.03 (or about 25%). The second most notable difference is in the neck, with the mean score of real lifts surpassing that of VR lifts by approximately 1.01 in course 2 and 0.90 in course 6.

Table 6: Comparison of RULA Grand Score and the Body Section Scores between Real and VR lifts (Mean)

Body Section	Real Lift	VR Lift	Real - VR
Upper Arm (C2)	4.26	4.31	-0.05
Upper Arm (C6)	4.69	4.68	0.01
Lower Arm (C2)	2.97	2.90	0.07
Lower Arm (C6)	2.98	2.92	0.06
Neck (C2)	4.49	3.48	1.01
Neck (C6)	4.43	3.53	0.90
Trunk (C2)	4.86	3.07	1.79
Trunk (C6)	5.19	4.17	1.03
RULA Grand (C2)	6.96	6.00	0.96
RULA Grand (C6)	7.00	6.41	0.59

Another noticeable trend in the mean scores is that, apart from the upper and lower arm body sections, which show similar scores for real and VR lifts across both courses, the differences in neck, trunk, and RULA grand scores are more pronounced in course 2 than in course 6. The most prominent example is the trunk score, where the difference between real and VR lifts is substantially more significant in course 2 (1.79) compared to course 6 (1.03), indicating a greater ergonomic divergence in this condition.

Table 7 illustrates the differences in score SD between C2 and C6 for real and VR lifts across various body sections. The tabulated values were derived by subtracting scores of C2 from those of C6 (i.e., $C6 - C2$). The SD differences across courses reveal distinct trends between real and VR conditions. The SD of the grand RULA scores remains relatively stable for real lifts between courses 2 and 6, while VR lifts show a decline of approximately 0.11 moving from course 2 to 6. For real lifts, the grand RULA score SD remains stable ($\Delta = -0.02$), indicating relatively consistent variability in postural risk across courses. In contrast, VR lifts exhibit a more notable decline in SD of grand RULA scores ($\Delta = -0.11$), suggesting less variability in scores of C6 compared to C2. Across all body sections, both real and VR lifts show a decrease in the SD of the neck score and an increase in the SD of the trunk score for course 6; however, this change is more pronounced for VR lifts. A contrasting trend is observed in the SD of the upper arm score: real lifts experience a decrease of 0.06 ($\Delta = -0.06$), whereas VR lifts show an increase of 0.08 in course 6 ($\Delta = 0.08$).

Table 7: The differences between C2 and C6 in Score SD for Real and VR lifts across Body Sections

Body Section	Real Lift $\Delta(C6 - C2)$	VR Lift $\Delta(C6 - C2)$
Upper Arm	-0.06	0.08
Lower Arm	-0.02	-0.03
Neck	-0.11	-0.18
Trunk	0.08	0.17
RULA Grand	-0.02	-0.11

The observed patterns demonstrate the distinct differences in both the mean and SD of scores between real and VR lifts. These trends suggest that there is a measurable divergence in human motion behaviour between real-world and VR-simulated brick-laying tasks. However, while these differences are evident descriptively, further statistical is required to determine whether the observed divergences are statistically significant, ensuring that observed trends reflect meaningful systemic differences rather than random variation.

4.3.2 Statistical Analysis

To determine whether there is a statistically significant difference in human motion behavior between real and VR lifts, the Mann-Whitney U test was performed using the SPSS software with a significance level of 5%. This non-parametric test that does not require a normal distribution of data was selected in this study as the experiment data are not strictly normally distributed (McKnight & Najab, 2010).

Figure 22 presents the distributions of upper arm, lower arm, neck, trunk, and RULA grand scores for course 2 and 6. Figure 22 (e) shows that the distributions of RULA grand scores for real and VR lifts differ significantly in both courses. The RULA grand scores for real lifts are predominantly concentrated around 7, whereas VR lifts exhibit a broader distribution, with a considerable proportion of scores around 5 and 6.

The distributions of upper and lower arm scores exhibit similar patterns in both real and VR lifts. Upper arm scores are primarily concentrated between 4 and 5 across both courses, while lower arm scores are predominantly clustered around 3.

However, the distribution of neck scores varies between real and VR lifts. In real lifts, neck scores are primarily concentrated at higher values, specifically 4 and 5. In contrast, while some VR lift scores also cluster at 4 and 5, a substantial proportion is distributed at lower values like 1 and 3.

Trunk score distributions exhibit notable differences not only between real and VR lifts but also between courses. In course 2, real lift scores are primarily concentrated between 4 and 6, with the majority at 5, whereas VR lifts show a broader range from 2 to 6, with most scores clustered at 2 and 3. In course 6, real lifts display a wider distribution from 3 to 6 compared to course 2, with the highest concentration at scores 5 and 6. Notably, in course 6, score 5 accounts for the largest proportion, marking a clear distinction from course 2.

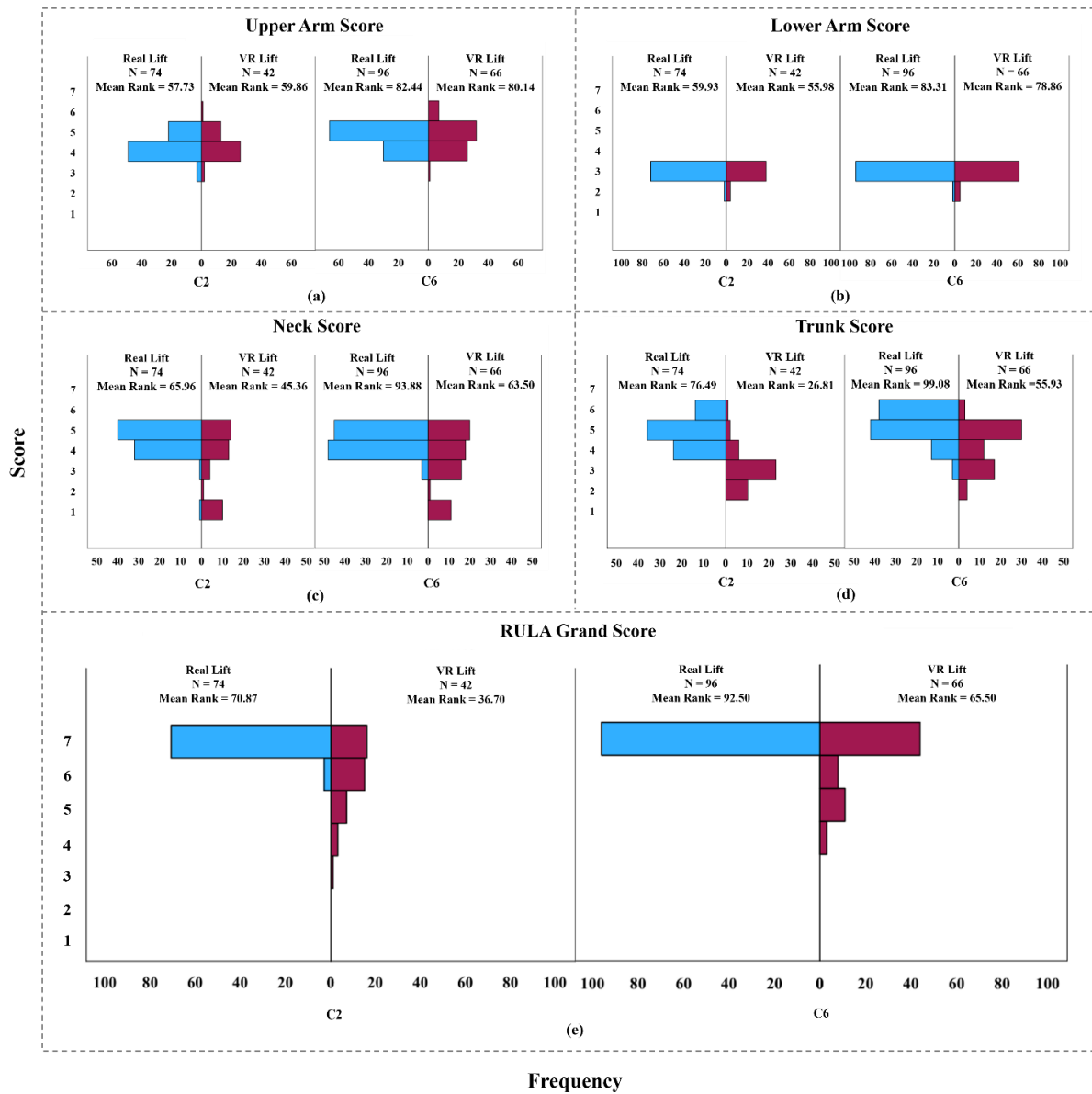


Figure 22. Score Distribution: (a) Upper Arm Score; (b) Lower Arm Score; (c) Neck Score; (d) Trunk Score; and (e) RULA Grand Score

Tables 8 and 9 show the results of the Mann-Whitney U test for courses 2 and 6, respectively, listing the score, lift category, sample size, mean rank, sum of ranks, u-value and p-value. The null hypothesis of this test is that the distribution of the scores is the same for VR lifts and real lifts. At a significance level of 5%, a p-value below 0.05 leads to rejecting the null hypothesis, while a p-value exceeding 0.05 results in retaining the null hypothesis. The p-value of RULA grand scores for both

courses is smaller than 0.001, which confirms that, for both courses, there is a statistically significant difference in RULA grand score between VR lifts and real lifts. The test results for the body section scores further indicate that the difference is primarily driven by the trunk and neck scores, whereas the upper arm and lower arm scores show similarity: for both courses, neck and trunk scores have a p-value smaller than 0.001, leading to the rejection of the null hypothesis; in contrast, upper arm and lower arm scores have a p-value greater than 0.05 retaining the null hypothesis. Overall, the Mann-Whitney U test results validate the findings from the descriptive results, confirming that the observed differences in ergonomic performance between real and VR lifts are statistically significant.

Table 8: Mann-Whitney U Test Results (Course 2)

Score	Lift Category	N	Mean Rank	Sum of Ranks	U	P
RULA Grand	Real Lift	74	70.87	5244.38	2469.50	< 0.001
	VR Lift	42	36.70	1541.4		
Upper Arm	Real Lift	74	57.64	4265.36	1490.50	0.664
	VR Lift	42	60.01	2520.42		
Lower Arm	Real Lift	74	59.93	4434.82	1660.00	0.112
	VR Lift	42	55.98	2351.16		
Neck	Real Lift	74	65.96	4881.04	2106.00	< 0.001
	VR Lift	42	45.36	1905.12		
Trunk	Real Lift	74	76.49	5660.26	2885.00	< 0.001
	VR Lift	42	26.81	1126.02		

Table 9: Mann-Whitney U Test Results (Course 6)

Score	Lift Category	N	Mean Rank	Sum of Ranks	U	P
RULA Grand	Real Lift	66	92.50	6105.00	4224.00	< 0.001
	VR Lift	96	65.50	6288.00		
Upper Arm	Real Lift	66	82.54	5447.64	3268.00	0.694
	VR Lift	96	79.98	7678.08		
Lower Arm	Real Lift	66	83.31	5498.46	3342.00	0.092
	VR Lift	96	78.86	7570.56		
Neck	Real Lift	66	93.76	6188.16	4345.00	< 0.001
	VR Lift	96	63.67	6112.32		
Trunk	Real Lift	66	99.06	6537.96	4854.00	< 0.001
	VR Lift	96	55.95	5371.20		

4.4 Discussion

Different human motion patterns between the real-world and the VR simulation when participants perform the same tasks were observed in this study. These differences align with broader challenges in replicating interaction fidelity in virtual environments. Prior research has highlighted that discrepancies between VR and real-world interactions often stem from the physical difficulties in accurately simulating actions and interactions with objects, which can, in turn, affect users' movement. In this study, the significantly higher RULA scores for real lifts, along with greater variability observed in VR lifts, emphasize how the absence of load simulation in VR alters human motion behaviour, suggesting that VR may not effectively train workers for real-world ergonomic risks, particularly in load-intensive tasks like masonry.

These findings are consistent with existing literature that underscores VR's limitations in providing physical resistance; in this study, the lack of weight and momentum in the VR simulation specifically contributed to unrealistic motion patterns during block lifting. This implies that when designing VR training modules, developers should carefully consider the limitations of VR in tasks involving load handling. Another implication for researchers evaluating VR's efficacy in various scenarios is that, instead of conducting surveys on users and draw conclusions based on their feedback, they should consider empirically quantify the difference on their movements or performance between in real-world and in VR.

One limitation of this study is participant variability. Different groups of participants were used for the VR and real-world lifting tasks due to scheduling constraints and participant availability.

Differences in participants' physical fitness and prior experience may have influenced movement patterns. Importantly, this study demonstrates that VR is not suitable for ergonomic training in tasks involving loads, while further investigation is needed to determine its effectiveness in tasks with little or no load.

Chapter 5

Conclusion

5.1 Summary and Contributions

This thesis addresses the research problem arising from the implementation of VR/AR technologies as safety solutions in hazardous environments, such as construction sites or radiation-exposed settings. While these technologies hold promise for mitigating risks, their feasibility under real-world operational constraints remains insufficiently validated, and the practical challenges of deployment are underexplored. To bridge this gap, the research objectives focus on 1) develop VR/AR applications that improve worker safety in hazardous environments and 2) address practical implementation challenges and evaluate the feasibility of the solutions. The principal contributions of this work, aligned with the objectives outlined in Chapter 1, are as follows:

Objective 1: develop a human-centric path planning algorithm that generates navigation paths tailored for humans, which can be visualized and guided through an AR application.

To enable flexible, human-centric navigation for operators in radiation-prone environments, Chapter 3 introduced a two-stage methodology. In the first stage, a new cost function that incorporates a weighting mechanism was developed, allowing users to prioritize either radiation avoidance or shorter path length according to task-specific needs. Additionally, a turning penalty was introduced into the cost function to discourage excessive directional changes, resulting in smoother, more navigable paths with fewer turns. In the second stage, a path selection procedure using parameter sweep was developed to select Pareto-optimal solutions for the users. To validate this algorithm's effectiveness, the proposed method was compared with the minimum dose method and minimum distance method through simulation cases. Together, these innovations generate paths that balance three critical objectives: reduced cumulative radiation exposure, shorter traversal distance, and easier navigation, addressing both safety and practicality in radiation environments. The key contributions include (1) the flexibility to prioritize radiation-averse routes or shorter paths based on task-specific requirements, (2) the generation of smoother, more intuitive paths with fewer directional changes tailored for human navigation, and (3) the ability to present only the Pareto-optimal path solutions to the user for informed decision-making.

Objective 2: investigate the validity of using VR for ergonomics training, particularly in masonry work, by comparing human motion behaviour during block lifting in real and VR environments.

Although it is intuitively expected that different motion patterns will emerge in the VR simulation due to the absence of physical weight, there is a lack of research to confirm this. Chapter 4 examined the use of VR for ergonomic training in masonry work by comparing human motion behaviour during block lifting in real and VR environments. A VR simulation was developed to replicate the previous real-life exercises with the same scenario and setup. The key findings reveal a significant difference in motion behaviour between real and VR lifts, which is likely primarily due to the limitation of VR simulation in including the physical weight and momentum involved in real-life masonry work. As a result, real lifts yielded higher RULA grand scores than VR lifts, with the higher scores being attributed to the trunk and neck. This suggests that while VR offers valuable training opportunities in construction, it cannot simulate the physical demands of masonry tasks, limiting its effectiveness for ergonomics training. Based on these findings, it's concluded that using VR for ergonomic training in masonry is not recommended.

5.2 Limitations and Future Work

The human-centric path planning algorithm developed in Chapter 3 was designed to visualize navigation routes in AR environments. While simulations were used to validate the algorithm's effectiveness, this study did not include implementation testing in an AR platform. Future investigations could integrate the algorithm into an AR application to assess its performance in real-world scenarios. Additionally, the nuclear environment in this study was assumed to be static due to the static radiation datasets provided by our industry partner, MDA Space Ltd., in the original sponsored research project. For future work, if real-time radiation monitoring data becomes accessible, the algorithm could be extended to handle dynamic radiation fields and moving obstacles, thereby enabling real-time adaptive path planning as environmental conditions change.

In the study presented in Chapter 4, one limitation was participant variability. Due to scheduling constraints and availability, different groups were used for the VR-based and real-world lifting tasks. Variations in physical fitness, experience, and familiarity with lifting tasks may have influenced participants' movement patterns. Additionally, the findings demonstrate that VR is not well-suited for ergonomic training in tasks involving loads, such as masonry. However, this study did not investigate

the use of VR for ergonomic training in tasks with minimal or no load. Future research on VR-based training applications should be cautious about the physical demands of the real-world tasks. However, further investigation is needed to explore whether VR can be effectively used for ergonomic training in tasks that involve minimal or no physical load, unlike masonry, which is load intensive. Tasks focused on posture and movement without load handling may be more suitable. For example, sports such as golf or tennis, where proper posture and swing mechanics are critical, can be simulated in VR to train movements like swinging a golf club or racket. Similarly, activities such as yoga, stretching routines, or occupational tasks involving seated or standing postures, may also benefit from VR-based posture training without the need for load simulation. These scenarios present promising opportunities to explore VR's potential in posture-focused training. In the context of masonry and other load-intensive trades, future research should explore alternative methods that incorporate the physical weight of materials and offer more immediate and automated feedback to enhance training outcomes.

References

- Noitom Ltd. (2024). *Perception Neuron 3 hardware list*. Retrieved from Perception Neuron: <https://support.neuronmocap.com/hc/en-us/articles/4401815074203-Perception-Neuron-3-Hardware-List>
- Abderrahim, M., Hakim, H., Boujemaa, H., & Touati, F. (2019). A Clustering Routing based on Dijkstra Algorithm for WSNs. *2019 19th International Conference on Sciences and Techniques of Automatic Control and Computer Engineering (STA)* (pp. 605-610). Sousse, Tunisia: IEEE.
- Adami, P., Rodrigues, P. B., Woods, P. J., Becerik-Gerber, B., Soibelman, L., Copur-Gencturk, Y., & Lucas, G. (2021). Effectiveness of VR-based training on improving construction workers' knowledge, skills, and safety behaviour in robotic teleoperation. *Advanced Engineering Informatics*, 50, 101431.
- Adeyemi, O., Adejuyigbe, S., Akanbi, O., Ismaila, S., & Adekoya, A. (2013). Enhanced Ergonomics Training; A Requisite to Safe Body Postures in Manual Lifting Tasks. *Global Journal of Researches in Engineering*, 13(6). 37-42.
- Akram, M., Habib, A., & Alcantud, J. (2021). An optimization study based on Dijkstra algorithm for a network with trapezoidal picture fuzzy numbers. *Neural Comput & Applic* 33, 1329–1342.
- Ansari, N. A., & Sheikh, M. J. (2014). Evaluation of work Posture by RULA and REBA: A Case Study. *IOSR Journal of Mechanical and Civil Engineering (IOSR-JMCE)*, 11(4), 8-23.
- Bozyiğit, A., Alankuş , G., & Nasiboğlu, E. (2017). Public transport route planning: Modified dijkstra's algorithm. *International Conference on Computer Science and Engineering (UBMK)* (pp. 502-505). Antalya, Turkey: IEEE.
- Canadian Center for Occupational Health and Safety. (2024). *What are work-related musculoskeletal disorders (WMSDs)?* Retrieved from Canadian Center for Occupational Health and Safety: <https://www.ccohs.ca/oshanswers/diseases/rmirsi.html>

- Canadian Construction Association. (2024). *Value of the Industry*. Retrieved from Canadian Construction Association: <https://www.cca-acc.com/about-us/value-of-industry/>
- Canadian Nuclear Association. (2025). *Canadian Nuclear Industry: A Powerhouse of Job Creation and Economic Growth*. Retrieved from Canadian Nuclear Association: <https://cna.ca/2024/09/24/canadian-nuclear-industry-a-powerhouse-of-job-creation-and-economic-growth/>
- CCOHS. (2024). *What are work-related musculoskeletal disorders (WMSDs)?* Retrieved from Canadian Center for Occupational Health and Safety: <https://www.ccohs.ca/oshanswers/diseases/rmirsi.html>
- Cook, T. M., Rosecrance, J. C., & Zimmermann, C. L. (1996). Work-Related Musculoskeletal Disorders in Bricklaying: A Symptom and Job Factors Survey and Guidelines for Improvements. *Applied Occupational and Environmental Hygiene*, 11(11), 1335–1339.
- Cremasco, M. M., Giustetto, A., Caffaro, F., Colantoni, A., Cavallo, E., & Grigolato, S. (2019). Risk Assessment for Musculoskeletal Disorders in Forestry: A Comparison between RULA and REBA in the Manual Feeding of a Wood-Chipper. *International Journal of Environmental Research and Public Health*, 16(5), 793.
- Dijkstra, E. (1959). A note on two problems in connexion with graphs. *Numer. Math.* 1, 269–271.
- Elfes, A. (1989). Using occupancy grids for mobile robot perception and navigation. *Computer*, vol. 22, no. 6, 46-57.
- Fallah, N., Apostolopoulos, I., Bekris, K., & Folmer, E. (2013). Indoor Human Navigation Systems: A Survey. *Interacting with Computers*, Volume 25, Issue 1, 21–33.
- Government of Canada. (2011). *The Fundamentals – Ergonomics*. Retrieved from Government of Canada: <https://www.canada.ca/en/government/publicservice/wellness-inclusion-diversity-public-service/health-wellness-public-servants/disability-management/fundamentals-ergonomics.html>
- Government of Canada. (2025). *New reactor facility projects*. Retrieved from Government of Canada: <https://www.cnsccsn.gc.ca/eng/reactors/power-plants/new-reactor-facilities/>

- Government of Canada. (2025). *Nuclear power plants*. Retrieved from Government of Canada: <https://www.cnsccsn.gc.ca/eng/reactors/power-plants/>
- Gruneberg , G. L. (1997). Construction and the Economy. In S. L. Gruneberg , *Construction Economics* (pp. 37-67). London: Palgrave.
- Haider Jafri, S. M., & Kala, R. (2015). Path Planning of a Mobile Robot in Outdoor Terrain. *Intelligent Systems Technologies and Applications* (pp. 187–195). Kochi, India: Springer.
- Hess, J., Weinstein, M., & Welch, L. (2010). Ergonomic Best Practices in Masonry: Regional Differences, Benefits, Barriers, and Recommendations for Dissemination. *Journal of Occupational and Environmental Hygiene*, 7(8), 446–455.
- Hess, J., Weinstein, M., & Welch, L. (2010). Ergonomic Best Practices in Masonry: Regional Differences, Benefits, Barriers, and Recommendations for Dissemination. *Journal of Occupational and Environmental Hygiene*, 7(8), 446–455.
- Hignett, S., & McAtamney, L. (2000). Rapid Entire Body Assessment (REBA). *Applied Ergonomics*, 201-205.
- Huang, C., Kim, W., Zhang, Y., & Xiong, S. (2020). Development and Validation of a Wearable Inertial Sensors-Based Automated System for Assessing Work-Related Musculoskeletal Disorders in the Workspace. *Int. J. Environ. Res. Public Health*, 17(17), 6050.
- IAEA. (2022). *Country Nuclear Power Profiles 2022 Edition - Canada*. Retrieved from IAEA: <https://www-pub.iaea.org/MTCD/publications/PDF/cnpp2022/countryprofiles/Canada/Canada.htm#:~:text=Canada's%20nuclear%20sector%20contributes%20CAD13,15%25%20of%20Canada's%20electricity%20needs.>
- Joshi, M., & Deshpande, V. (2019). A systematic review of comparative studies on ergonomic assessment techniques. *International Journal of Industrial Ergonomics*.
- Joshi, M., & Deshpande, V. (2021). Study of association between OWAS, REBA and RULA with perceived exertion rating for establishing applicability. *Theoretical Issues in Ergonomics Science*, 23(3), 313–332.

- Jurchiș, R., & Dienes, Z. (2023). Implicit learning of regularities followed by realistic body movements in virtual reality. *Psychon Bull Rev*, 30, 269–279.
- Karhu, O., Kansii, P., & Kuorinka, I. (1977). Correcting working postures in industry: A practical method for analysis. *Applied Ergonomics*, 8.4, 199-201.
- Kee, D. (2022). Systematic comparison of OWAS, RULA, and REBA based on a literature review. *Int. J. Environ. Res. Public Health*, 19(1), 595.
- Liu, Y. K., Li, M. K., Xie, C. L., Peng, M. J., Wang, S. Y., Chao, N., & Liu, Z. K. (2015). Minimum dose method for walking-path planning of nuclear facilities. *Annals of Nuclear Energy*, Volume 83, 161-171.
- Man, S. S., Wen, H., & So, B. C. (2024). Are virtual reality applications effective for construction safety training and education? A systematic review and meta-analysis. *Journal of Safety Research*, 88, 230–243.
- McAtamney, L., & Corlett, E. N. (1993). RULA: A survey method for the investigation of work-related upper limb disorders. *Appl. Ergon.*, 24(2), 91-99.
- McFarland, T. C., Ryu, J., Haas, C., & Abdel-Rahman, E. (2023). Crafting safe and efficient masonry practices: Quantitative assessment of postural characteristics in movement strategies. *Journal of Construction Engineering and Management*, 150(2).
- McKnight, P. E., & Najab, J. (2010). Mann-Whitney U Test. In *The Corsini Encyclopedia of Psychology* (eds I.B. Weiner and W.E. Craighead).
- MLITSD. (2017). *Key hazards in construction health and safety*. Retrieved from Ministry of Labour, Immigration, Training and Skills Development: <https://www.ontario.ca/document/construction-sector-plan-2017-2018/key-hazards-construction-health-and-safety>
- Nath, N. D., Akhavian, R., & Behzadan, A. H. (2017). Ergonomic analysis of construction worker's body postures using wearable mobile sensors. *Applied Ergonomics*, 107-117.
- NIH. (2022, May 12). *Accidents at Nuclear Power Plants and Cancer Risk*. Retrieved from National Cancer Institute at the National Institutes of Health: <https://www.cancer.gov/about-cancer/causes-prevention/risk/radiation/nuclear-accidents-fact-sheet>

- Noitom Ltd. (2024). *Complete professional motion capture software solution*. Retrieved from Perception Neuron: <https://neuronmocap.com/pages/axis-studio>
- Noitom Ltd. (2024). *Perception Neuron 3 FAQ*. Retrieved from Perception Neuron: <https://support.neuronmocap.com/hc/en-us/articles/4401823551515-Perception-Neuron-3-FAQ>
- Nuclear Safety and Control Act*. (1997). S.C. 1997, c. 9.
- Nykänen, M., Puro, V., Tiikkaja, M., Kannisto, H., Lantto, E., Simpura, F., . . . Teperi, A. M. (2020). Implementing and evaluating novel safety training methods for construction sector workers: Results of a randomized controlled trial. *Journal of Safety Research*, 75, 205–221.
- OHSCO. (2007). *Musculoskeletal disorders prevention series part 3C: MSD prevention toolbox – more on in-depth risk assessment methods*. Retrieved from OHSCO: https://www.iwh.on.ca/sites/iwh/files/iwh/tools/msd_prevention_toolbox_3c_2007.pdf
- Power, J. D., Perruccio, A. V., Paterson, J. M., Canizares, M., Veillette, C., Coyte, P. C., . . . Rampersaud, Y. R. (2022). Healthcare utilization and costs for musculoskeletal disorders in Ontario, Canada. *The Journal of Rheumatology*, 49(7), 740–747.
- Radiation Protection Regulations*. (2020). SOR/2000-203.
- Rogers, K., Funke, J., Frommel, J., Stamm, S., & Weber, M. (2019). Exploring interaction fidelity in virtual reality: Object manipulation and whole-body movements. *CHI '19: Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (pp. Paper No.: 414, Pages 1 - 14). Glasgow, Scotland UK: Association for Computing Machinery.
- Ryu, J. H., Alwasel, A., Haas, C. T., & Abdel-Rahman, E. (2020). Analysis of relationships between body load and training, work methods, and work rate: Overcoming the novice mason's risk hump. *Journal of Construction Engineering and Management*, 146(8).
- Ryu, J., Banting, B., Abdel-Rahman, E., & Haas, C. T. (2023). Ergonomic characteristics of expert masons. *Journal of Construction Engineering and Management*, 149(1).
- Ryu, J., Diraneyya, M. M., Haas, C. T., & Abdel-Rahman, E. (2021). Analysis of the limits of automated rule-based ergonomic assessment in bricklaying. *Journal of Construction Engineering and Management*, 147(2), 04020163.

- Sacks, R., Perlman, A., & Barak, R. (2013). Construction safety training using immersive virtual reality. *Construction Management and Economics*, 31(9), 1005–1017.
- Seo, J., Alwasel, A., Lee, S., Abdel-Rahman, E. M., & Haas, C. (2017). A comparative study of in-field motion capture approaches for body kinematics measurement in construction. *Robotica*, 37(5), 928-946.
- Sers, R., Forrester, S., Moss, E., Ward, S., Ma, J., & Zecca, M. (2020). Validity of the Perception Neuron inertial motion capture system for upper body motion analysis. *Measurement*, 149, 107024.
- Statistics Canada. (2024). *Gross domestic product (GDP) at basic prices, by industry, annual average (x 1,000,000)*. Retrieved from Statistics Canada:
<https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=3610043406>
- Statistics Canada. (2025). *Labour Force Survey, January 2025*. Retrieved from Statistics Canada:
<https://www150.statcan.gc.ca/n1/daily-quotidien/250207/dq250207a-eng.htm#:~:text=In%20Ontario%2C%20employment%20increased%20by,rate%20held%20steady%20at%207.6%25>.
- Statistics of Canada. (2025). *Labour Force Survey, January 2025*. Retrieved from Statistics Canada:
<https://www150.statcan.gc.ca/n1/daily-quotidien/250207/dq250207a-eng.htm?indid=3587-1&indgeo=0>
- Workplace Safety and Insurance Board. (2024). *Musculoskeletal Disorder Report -- by Rate Group: Rate Group Code: 412, Rate Group Description: G2: Infrastructure Construction.* .
- Workplace Safety and Insurance Board. (2024). *Musculoskeletal Disorder Report -- by Rate Group: Rate Group Code: 437, Rate Group Description: G3: Foundation, Structure and Building Exterior Construction.*
- Workplace Safety and Insurance Board. (2024). *Musculoskeletal Disorder Report -- by Rate Group: Rate Group Code: 487, Rate Group Description: G5: Specialty Trades Construction.*
- Workplace Safety and Insurance Board. (2024). *Musculoskeletal Disorder Report -- by Rate Group: Rate Group Code: 493, Rate Group Description: G6: Non-Residential Building Construction.*

- World Health Organization. (2022). *Musculoskeletal health*. Retrieved from World Health Organization: <https://www.who.int/news-room/fact-sheets/detail/musculoskeletal-conditions>
- World Health Organization. (2022). *Musculoskeletal health*. Retrieved from World Health Organization: <https://www.who.int/news-room/fact-sheets/detail/musculoskeletal-conditions>
- Wu, Y., Tao, K., Chen, Q., Tian, Y., & Sun, L. (2022). A Comprehensive Analysis of the Validity and Reliability of the Perception Neuron Studio for Upper-Body Motion Capture. *Sensors*, 22(18), 6954.
- Yarandi, M. S., Soltanzadeh, A., Koohpaei, A., Sajedian, A. A., Ahmadi, V., Sakari, S., & Yazdanirad, S. (2019). Effectiveness of Three Ergonomic Risk Assessment Tools, Namely NERPA, RULA, and REBA, for Screening Musculoskeletal Disorders. *Arch Hyg Sci*, 8 (3) :188-201.
- Ye, Y., Liu, L., Hu, L., & Xia, S. (2022). INeural3Points: Learning to Generate Physically Realistic Full-body Motion for Virtual Reality Users. *Computer Graphics Forum*, 41(8), 183-194.