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Optimization of Safety Control System for Civil Infrastructure Construction Projects

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OPTIMIZATION OF SAFETY CONTROL SYSTEM FOR CIVIL INFRASTRUCTURE CONSTRUCTION PROJECTS

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Sudip Subedi

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To: Dean John L. Volakis
College of Engineering and Computing

This dissertation, written by Sudip Subedi, and entitled Optimization of Safety Control System for Civil Infrastructure Construction Projects, having been approved in respect to style and intellectual content, is referred to you for judgment.

We have read this dissertation and recommend that it be approved.

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The dissertation of Sudip Subedi is approved.

Dean John L. Volakis
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Andrés G. Gil
Vice President for Research and Economic Development
and Dean of the University Graduate School

Florida International University, 2021

DEDICATION

I dedicate my work...

to my dearest wife, Surakshya Giri, who was always by my side in all the ups and downs. Without her support, I would have never completed my doctoral degree.

to my respected parents, Mr. Govinda Subedi and Mrs. Durga Subedi, who always motivated me to aim higher in life. Irrespective of any hardship, they ensured the necessities required for my success.

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to my respected teachers, professors, and mentors, who guided me throughout my life journey.

Finally, with the hope that my research work will facilitate in improving the construction workers' safety, I would like to dedicate it to the entire construction workforce and the brave ones who lost their lives while working in construction sites.

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ABSTRACT OF THE DISSERTATION

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Labor-intensive repetitive activities are common in civil construction projects. Construction workers are prone to developing musculoskeletal disorders-related injuries while performing such tasks. The government regulatory agency provides minimum safety requirement guidelines to the construction industry that might not be sufficient to prevent accidents and injuries in a construction site. Also, the regulations do not provide insight into what can be done beyond the mandatory requirements to maximize safety and underscore the level of safety that can be attained and sustained on a site. The research addresses the aforestated problem in three stages: (i) identification of theoretical maximum attainable level of safety, safety frontier, (ii) identification of underlying system inefficiencies and operational inefficiencies, and (iii) identification of achievable level of safety, sustainable safety.

The research proposes a novel approach to identify the safety frontier by kinetic analysis of the human body while performing labor-intensive repetitive tasks. The task is a combination of different unique actions, which further involve several movements. For identifying a safe working procedure, each movement frame needs to be analyzed to compute the joint stress. Multiple instances of repetitive tasks can then be analyzed to identify unique actions exerting minimum stress on joints.

The safety frontier is a combination of such unique actions. For this, the research proposes to track the skeletal positional data of workers performing different repetitive tasks. Unique actions involved in all tasks were identified for each movement frame. For this, several machine learning techniques were implemented. Moreover, the inverse dynamics principle was used to compute the stress induced by essential joints. In addition to the inverse dynamics principle, several machine learning algorithms were implemented to predict lower back moments. Then, the safety frontier was computed, combining the unique actions exerting minimum stress to the joints. Furthermore, the research conducted a questionnaire survey with construction experts to identify the factors affecting system inefficiencies that are not under the control of the project management team and operational inefficiencies that are under control. Then, the sustainable safety was computed by adding system inefficiencies to the safety frontier and removing operational inefficiencies from observed safety.

The research validated the applicability of the proposed methodology in a real construction site. The application of random forest classifier, one-vs-rest classifier, and support vector machine approach were validated with high accuracy (>95%). Similarly, random forest regressor, lasso regression, gradient boosting evaluation, stacking regression, and deep neural network were explored to predict the lower back moment. Random forest regressor and deep neural network predicted the lower back moment with an explained variance of 0.582 and 0.700, respectively. The computed safety frontier and sustainable safety can potentially facilitate the construction sector to improve safety strategies by providing a higher safety benchmark for monitoring, including the ability to monitor postural safety in real-time. Moreover, different industrial sectors such as manufacturing and agriculture can implement the similar approach to identify safe working postures for any labor-intensive repetitive task.

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CHAPTER 1

INTRODUCTION

Workplace safety has always been of primary concern in civil infrastructure construction projects. Construction researchers and industrialists are working hand-in-hand to enhance the overall safety of the construction site [1–4]. In the past few decades, there has been a significant improvement in construction safety [5–10]. Researchers have done several studies and implemented them to improve the construction methodology [11], equipment safety [6, 12–14], and workers' safety [8, 15–17]. Also, researchers have identified numerous technologies, such as inertial measurement unit (IMU) [18, 19], motion sensor [20–23], computer vision [24–29], and depth sensor camera [30–33], among others, to ensure the safety of materials, equipment, and workers in the construction field. Besides, safety regulation agencies, such as the Occupational Safety and Health Administration (OSHA), continuously monitor workplace safety. These improvements have significantly reduced the rate of fatal and non-fatal injuries occurring on a construction site. Figure 1.1 shows the decreasing trend of rate of fatal injuries for construction workers and the overall construction industry [34] due to the availability and implementation of advanced technologies. Despite the decreasing trend, the rate of fatal injuries has always been higher for construction workers than the average for the overall construction industry.

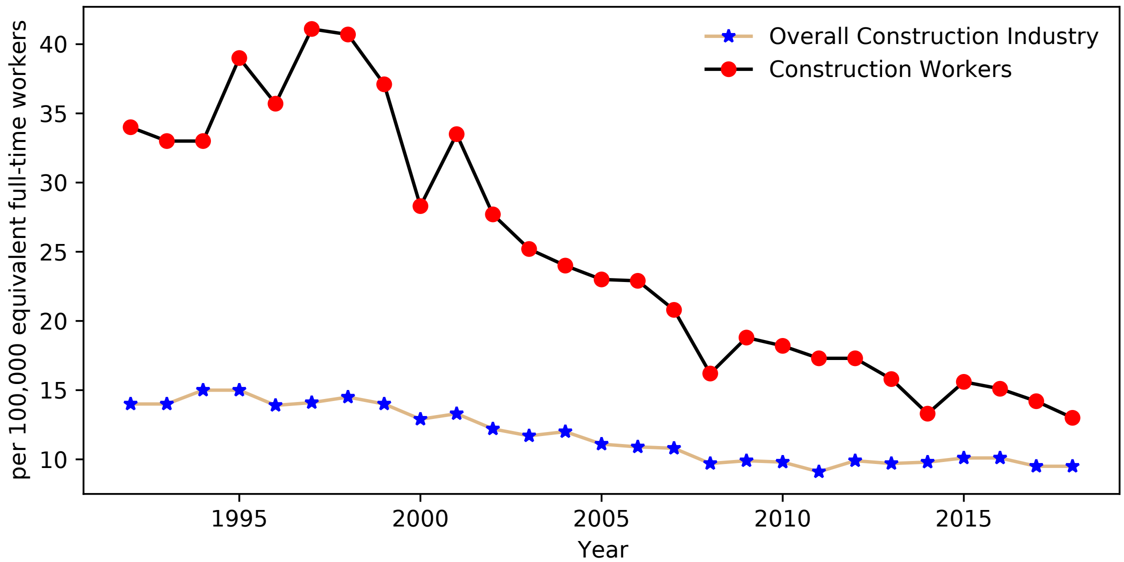

Fig. 1.1. Rate of fatal injuries

Notwithstanding the advancement in technology, most construction activities are still labor-intensive and repetitive such as manual material handling, concreting work, reinforcement bars fabrication and installation, masonry work, and formwork. A brief literature review showed musculoskeletal disorders (MSDs) as one of the major problems among the construction workers performing repetitive labor-intensive tasks [35–37]. Neck disorder, wrist/hand disorder, lower back disorder, shoulder disorder, and knee disorder were identified as the major MSDs from which the construction workers were suffering [35]. The survey among the construction workers identified the back, knee, and shoulder as the three body regions with the highest prevalence of MSDs [36]. Repetitive tasks induce fatigue, causing a change in multi-joint kinematics and postural stability [38]. [39] identified a significant difference in the lifting technique of industrial manual material handlers between those who develop lower back pain and those who do not. The stress generated in the back muscles while lifting an object increases significantly with the increase in the inclination of the back [40], further highlighting the importance of ergonomic safety of construction workers.

Similarly, a brief literature review showed several studies related to assessing MSDs among construction workers with the implementation of technologies, such as computer vision [41], inertial measurement unit (IMU) [19], and electromyogram (EMG) [42], among others. Although several studies have been performed regarding the MSDs and their effects, many workers are still suffering from MSDs related injuries [37]. Construction workers are dispersed randomly in a whole construction site with only a handful of safety personnel to monitor the overall site safety. Moreover, a handful of safety personnel cannot monitor the construction workers individually. The aforementioned problem necessitates developing an automated control system to monitor the construction workers' activity, maximize the safety level and thrive for the higher safety benchmark in construction projects. In order to develop such a system, it is crucial to identify the factors affecting workers' safety and the availability of different methods and technologies to track and monitor those factors. For this, we conducted an extensive literature review, covered in Chapter 2. Section 1.1 provides a brief description of the dissertation outline.

1.1 Dissertation Outline

The dissertation provides a framework for identification of theoretical maximum achievable level of safety, *safety frontier*, *system* & *operational inefficiencies*, and *sustainable safety*, that can be achieved and sustained in a construction site. The dissertation is divided into different chapters addressing the literature review, three hypotheses, and a conclusion. The following subsections provide a summary of each chapter.

1.1.1 Chapter 1 - Introduction

Chapter 1 provides brief information about the existing safety-related researches in the construction sector. It identifies MSDs as one of the significant issues among construction workers performing repetitive labor-intensive activities. Moreover, the chapter identifies the need to develop a safety monitoring system to track and monitor workers' safety.

1.1.2 Chapter 2 - Literature Review

Chapter 2 presents an in-depth systematic literature review to identify factors affecting construction workers' safety. It identifies different technology that we can implement for monitoring several safety factors. The chapter also identifies legal issues and disputes resulting from the workers' injuries and provides information about the possible technologies we can use to resolve these issues.

1.1.3 Chapter 3 - Objective and Scope

Chapter 3 provides the objective of the research. The research framework includes three research questions, three hypotheses, limitations, and the scope of the study.

1.1.4 Chapter 4 - Safety Frontier

Chapter 4 explains and validates a proposed framework to identify the theoretical maximum achievable level of safety, *safety frontier*. The research discussed in the chapter is published in *Automation in Construction* and presented in the journal format. It partially answers the first two hypotheses of the study.

1.1.5 Chapter 5 - System and Operational Inefficiencies

Chapter 5 identifies several crucial factors affecting workers' safety while performing repetitive labor-intensive activities such as masonry, manual material handling, and concrete work. It categorizes the identified factors into the *system* and *operational inefficiencies* based on expert opinions obtained from the questionnaire survey. It also provides a framework to indexify the *system* and *operational inefficiencies*. The chapter partially addresses the third hypothesis of the research.

1.1.6 Chapter 6 - Sustainable Safety

Chapter 6 validates the research framework developed in Chapter 4 using real construction site data. In addition, it indexifies the *system* and *operational inefficiencies* as discussed in Chapter 5. Then it describes a methodology to compute *sustainable safety* that can be achieved and sustained in the construction site. The chapter answers all three hypotheses of the study.

1.1.7 Chapter 7 - Conclusions

Chapter 7 summarizes the overall dissertation research framework and discusses research findings, major contributions, significance, applicability in real construction sites, and limitations. It also provides insights for future work.

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CHAPTER 2

LITERATURE REVIEW

Mapping the "Datafication" in Construction Worker Safety Research to Minimize the Injury Related Disputes[a]

Sudip SUBEDI[1], Nipesh PRADHANANGA[2]

Abstract

The construction workers are susceptible to work-related injury which increases the probability of workers' compensation claim. But the workers' compensation claim can cause dispute due to several reasons such as whether injury occurred on the job, suspicion of fraud, and lack of evidence, among others. This highlights the necessity of improvement in workers' safety and the recording of evidence to reduce the dispute occurrence. The rapid "datafication" of construction processes implementing the available technologies can be a potential solution. This chapter aims to trace the trends of such "datafication" by investigating the available scientific literature to create a novel tabular index of what data is (or can be) generated and leveraged, for what purpose, following what methodologies, and when. This chapter identifies different technology that can be used to monitor workers' safety and provide data for dispute resolution, if any. The author proposes the use of

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systematic literature review (SLR) for this study to provide reliable data-based mapping. The methodology includes identification of safety factors and technology implemented from published scholarly articles and their applicability in dispute resolution. A tabular index was created containing information such as factors tracked, technology used, type of data, and accuracy, among others. Similarly, multiple visual maps were generated aiding in the identification of the important safety factors and most reliable technologies fit to be implemented for data collection, that can help to reduce the chance of injury and identify the reason behind the injury, if any. This literature review will serve as an index for researchers and practitioners working on construction safety or wanting to learn about real-time construction safety research. The visual maps reported in the literature review contributes as a guide to understand what data type is required for a specific safety issue, how to collect them, and how the data can be analyzed. The maps will also reveal trends in the rise and fall of distinct types of analysis methods and technologies in construction safety research. Finally, the construction practitioners can use the map to identify the technology which can be used to collect different data that could help to reduce the chance of injury as well as identify the reason behind the injuries if occurred, reducing the probability of disputes.

2.1 Introduction

Construction is one of the oldest activities of humankind, and its methodology is ever-changing to improve the cost, quality, time, and safety [1]. Numerous studies have already been done and implemented to improve the construction methodology [2], safety (materials, equipment, and laborers), and use of technology [3–7]. Despite all these improvements, the injuries in the construction industry are significantly high, and the rate of fatal and non-fatal injuries is higher compared to most of the other industries. Out of 5,147 fatal occupational injuries in the USA, 4,674 of them were in the private sector in 2017 [8]. Moreover, out of 4,674 worker fatalities in the private sector, 971 (20.8%) were in construction [8] which is very high compared to the 3.98% contribution of the construction industry to overall gross domestic product (GDP) [8].

Construction workers are directly and indirectly affected by the injuries occurring in the accidents [9]. Pain and suffering, moral and psychological suffering (especially in the case of death and permanent disability), among others, are some of the indirect effects, whereas loss of salary, reduction of professional capacity, loss of time (medical treatment), site compliance of health, and safety issues are some of the direct effects of injuries to construction workers [9]. And researchers have identified the workplace injuries and their effects as one of the major cause of disputes and delays in construction site [10–12]. As construction accidents usually cause serious injuries or death to workers, and many parties are involved in the accidents, disputes are very common over issues such as causes, reliability, and compensation [13]. Disputes mainly arise if there is doubt that the injury is job-related or when the extent of disability is difficult to measure since total compensation payments are typically a function of time off the job or reduced earning capacity [14]. These disputes can eventually lead to litigation, causing delay and loss in the construction project. So, there is a need for improvement in construction methodology, which ensures better safety as well as provides evidence for dispute resolution. Several researchers have validated the implementation of technology to enhance the construction methodology and safety [5, 6, 15] such as computer vision [16–19], motion sensor [20–23], and range camera [24–29], among others. These technology have quantitative data associated with them, which can be used for enhancing construction safety as validated by the researchers. Besides, these data can be used to find the reasons behind the accidents, if any.

Even though there have been numerous studies regarding the implementation of technology to enhance the construction methodology and safety [5, 6, 15], it is difficult for the construction safety personnel to find the proper technology suitable for their construction site and similarly for the new researchers to keep track of the technology previously researched. The authors identified a lack of a systematic mapping that keeps track of all the information, such as research proposed by whom, used for what purpose, the methodology implemented, and cost versus reliability. This chapter tries to address this issue by creating an index map containing the implementation methodology and technical details of different technology used for tracking and enhancing the construction safety obtained from a pool of published research papers.

The authors aim to track the trends of “Datafication” in the construction industry, by reviewing the available scientific literature to create a novel visualization maps of what data is generated, for what purpose, who generated the data, following what methodologies, and when was it generated. “Datafication” is the digitization of different aspects of our life, and it aids in real-time tracking and predictive analysis. This chapter explores the implementation of technology in tracking and enhancing construction safety through literature review. Similarly, this chapter provides an index for extracting quantitative data regarding workers’ behavior which can be used for dispute resolution in case of any injury.

2.2 Background

As mentioned in the previous section, injuries are present in construction industry. There is a higher risk of dispute arisal with the occurrence of the injury. An injured worker has to prove his/her engagement in work activities when the injury occurred, the nature of work activities contributed to the injury's development, whether or not recovery has occurred, and whether or not the worker refused a legitimate offer from the employer [30–32]. This can be very challenging in absence of data or witness. Also the disputes are partially motivated by the fact that the workers' compensation program in the US generally prevents an injured worker from suing his/her employer for damages [33]. This forces injured workers to seek other sources of recovery including other party's involved in the project such as design firms [33]. The typical allegation includes the design firm's responsibility to visit the job site to review the contractor's work for conformance with the plans and specifications gave rise to a duty to prevent unsafe conditions at the job site [33].

In *Reese v. Triple D. Truss, LLC*, lack of data resulted into the dispute regarding the liability of claim against negligence. Similarly, in *Purcell v. Visting Nurses Found. Inc.*, lack of real-time monitoring resulted into an accident injuring a construction worker and lack of recorded data resulted into the discrepancy regarding how the accident occurred and the extent of injury. And, in *Am. Nat'l Bk. Tr. Co. v. Nat'l Adv. Co.*, lack of real-time monitoring resulted in a fatal electrocution while painting a billboard. The real stimuli of the electrocution was hard to determine due to lack of real-time data causing dispute regarding the liability of the death. All these dispute cases further enhance the necessity of identification of proper technology that can be implemented in the construction site, which can primarily prevent accidents from happening and provide hard data in case of injury.

Also, from the preliminary literature review, it was found that researchers prioritized legal disputes related to change orders [34], cost overruns [35, 36], ambiguous contracts [37], schedule delays[35, 36], low quality [36], among others. A gap was identified regarding the research related to remedial of the workers' compensation claims related dispute and the possible implementation of recent technology.

Today's technology, in coordination with ultra-fast computer systems, can generate a vast amount of data. Researchers from the University of Berkeley estimated that every year about 1 Exabyte (= 1 Million Terabyte) of data are generated, of which a significant portion is available in digital form [38]. Daniel A. Keim has proposed different data types to be visualized such as one-, two-, or multidimensional data, text, hypertext, hierarchies, graphs, algorithms and software as well as different visualization technique like standard 2D/ 3D displays (bar chart, x-y plots), geometrically transformed displays (landscapes and parallel coordinates), icon-based displays (needle icons and star icons), dense pixel displays (recursive patterns and circle segment technique), and stacked displays (treemaps) [39]. We used the stacked displays visualization technique for mapping and indexing of all the available information of technology implemented to track and enhance construction workers' safety. The obtained visual indexing can provide different ways to capture real-time workers' safety related data to assist in minimizing the injuries as well as the workers' compensation related disputes.

2.3 Objective

Although construction safety includes materials, equipment, and workers' safety, the literature review was limited to tracking construction workers' safety. The study was further limited to track the academic research papers only, and any commercial products or patents were not tracked in this literature review. Moreover, only the information such as data transfer rate, accuracy, and range, among others, that were available in the published research papers were tabulated. The technological advancement might have enabled higher frequency rates or larger ranges and better accuracy, but those were not included in the scope of this literature review.

2.4 Methodology

After a thorough study of different types of literature reviews such as traditional/ narrative, systematic, meta-analysis, meta-synthesis, and critical literature review, the authors employed the systematic literature review (SLR) to carry out further study [40]. The SLR has been widely used for conducting literature reviews [41–44]. The SLR methodology clearly specifies its "criterion based selection" process [43]. By definition, the systematic literature review is a means of identifying, evaluating, and interpreting all available research relevant to a particular research question, or topic area, or phenomenon of interest [45]. Since the primary purpose of this study is to provide reliable data-based mapping for construction safety personnel and new researchers, this study is based on the guidelines proposed and implemented by Kitchenham [45, 46] and [47]. Although more sophisticated methods are available for scientometric analysis (including but not limited to co-citation analysis, citation burst analysis, co-authorship analysis, among others), the scope of this chapter is limited to building an index for extracting quantitative data regarding workers' behavior. Figure 2.1 shows the flowchart of the implemented methodology.

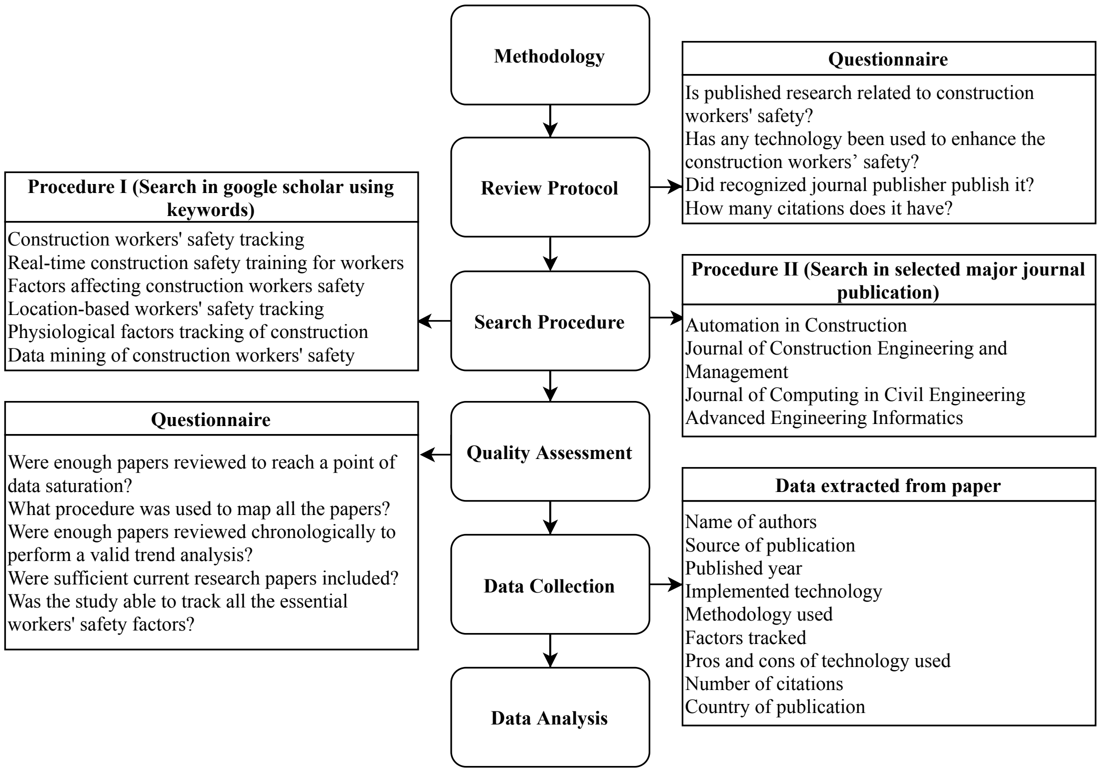

Fig. 2.1. Flowchart of the Implemented Methodology

2.4.1 Review Protocol

To conduct an unbiased literature review, a predefined protocol is necessary that specifies the method used to undertake a systematic literature review (SLR) [45]. The authors created the questionnaire to find a list of research papers answering those questions. Table 2.1 shows the questions needed to be answered positively to select the research papers for review.

Table 2.1. Questionnaire for research paper selection

SN	Question
1	Is published research related to construction workers' safety?
2	Has any technology been used to enhance the construction workers' safety?
3	Did recognized journal publisher publish it?
4	How many citations does it have?

The first question aided in filtering the papers related to the construction workers' safety. Then, the second question helped to sort out the papers that had implemented one or more technology, directly or indirectly aiding to the construction workers' safety. As it was virtually impossible to find all the papers, priority was given to the papers published in recognized journal publishers, such as Automation in Construction, Journal of Computing in Civil Engineering, and Safety Science, among others, enlisted in the following step. The authors also prioritized the number of citations to find the papers. While searching for papers using keywords, the inclusion of papers with higher citations was assured.

2.4.2 Search Procedure

The authors implemented two different search procedures to address two critical aspects of the literature review, first, the inclusion of relevant research papers, and second, the inclusion of recent research papers. The *Search Procedure I* addressed the first aspect of the review, and the *Search Procedure II* addressed the second aspect.

Search Procedure I

Google Scholar was used as the only search engine to find the relevant research papers for *Search Procedure I* due to ease of accessibility. Through the preliminary review of some research papers related to the implementation of technology to track and maintain construction workers' safety, the list containing keywords, phrases, and major technology was prepared as enlisted in Table 2.2. To narrow down the scope of *Search Procedure I*, only the first thirty papers were reviewed for each phrase as the papers beyond that were not relevant to the keyword used. Not all the reviewed papers were relevant to our scope of review, which were filtered either by reading the abstract or the whole research paper. References from the obtained papers were thoroughly reviewed to find additional research papers.

Table 2.2. List of primary keywords used to search the journal papers and conference proceedings.

Keywords	Phrases
Construction Workers, Safety, Physiological Factors, Safety Training, Real-Time Tracking, Data Mining, Location-based Tracking, Workers' Safety Factors	Construction workers safety tracking
	Real-time construction safety training for workers
	Factors affecting construction workers safety
	Location-based workers' safety tracking
	Physiological factors tracking of construction workers
	Data mining of construction workers' safety

During this search procedure, the authors found that the search engine showed the most viewed or most cited papers in the top. Also, since this procedure was retrospective, the inclusion of enough recent research papers became virtually impossible. This warranted the need for another search procedure, which should be able to include enough numerous research papers for which the *Search Procedure II* was implemented.

Search Procedure II

From the list of the research papers identified from the *Search Procedure I*, the authors identified the principal journal publications. Then the title and abstract of each research paper were reviewed, from each issue and volume, to filter the relevant papers from all major journal publication. The authors narrowed down the scope of *Search Procedure II* to finding research papers published in the range $2000 - 2018$, as no significant papers were found before 2000 from the *Search Procedure I*. The authors identified four major journal publications with the highest number of study related papers for the thorough review from *Search Procedure I*, as listed in Table

2.3. This search procedure made sure that recent as well as old research papers were incorporated in the study, making the trend analysis possible during the data analysis phase.

Table 2.3. List of journal publications reviewed for additional papers.

SN	Journal Publications
1	Automation in Construction
2	Journal of Construction Engineering and Management
3	Journal of Computing in Civil Engineering
4	Advanced Engineering Informatics

2.4.3 Quality Assessment

The quality, as well as the number of papers reviewed, plays a crucial role in determining the quality of the review itself. Therefore, the authors created a questionnaire based on the guidelines of SLR to assess the quality of the data obtained for the review, as shown in Table 2.4. Besides, to maintain the integrity of the obtained data from reviewed papers, data extracted by one reviewer was cross-checked and verified by another reviewer.

Table 2.4. Questionnaire for research paper selection.

SN	Question
1	Were enough papers reviewed to reach a point of data saturation?
2	What procedure was used to map all the papers?
3	Were enough papers reviewed chronologically to perform a valid trend analysis?
4	Were sufficient current research papers included?
5	Was the study able to track all the essential workers' safety factors?

2.4.4 Data Collection

Table 2.5 shows the list of information extracted by the researcher from each of the reviewed papers. A mapping index was created for visualization of technology implementation for construction workers' safety from the extracted information. The name of the authors were tracked to see the trend and continuity of researchers' involvement in such researches. The source of publication provided key information for selecting the major journal publications for *Search Procedure II*. The published year was valuable for trend analysis. The major information collected for indexing included implemented technology, the methodology used, factors tracked, and the pros and cons of technology. The number of the citation was considered as an indirect measurement of the research paper's importance and used to find papers for *Search Procedure I*.

Table 2.5. List of information extracted from the review paper.

SN	Journal Publications
1	Name of authors
2	Source of publication
3	Published year
4	Implemented technology
5	Methodology used
6	Factors tracked
7	Pros and cons of technology used
8	Implemented technology
9	Country of publication

2.4.5 Data Analysis

The data analysis was carried out to create a visual mapping of all the available information. The data analysis computer software, NVIVO, was used for mapping and trend analysis. NVIVO is "a qualitative data analysis (QDA) computer software package produced by QSR International, has many advantages and may significantly improve the quality of research" [48]. This software eases the five essential tasks in the analysis of qualitative data: managing data, managing ideas, query data, modeling visually, reporting [49].

2.5 Theoretical Definitions

For proper mapping and visualization of the available information regarding the use of different technology to track and enhance the construction workers' safety, the classification of these technology based on different factors affecting the workers' safety was paramount. Also, for unbiased classification throughout the study, a clear theoretical definition for each identified major factor was deemed necessary so that if any confusion arose during the classification of technology, these definitions could be referred for clarification.

2.5.1 Technology

For this literature review, the authors divided the technology into four major categories, hardware, software, tools and environment, and medium. The authors primarily focused on tracking the hardware that provided the right data of interest.

Hardware The hardware consists of all the equipment that can measure and provide data, directly or indirectly, helpful for the analysis of construction workers' safety. It can be touched and felt, unlike software. Global Positioning System (GPS), Physiological Status Monitoring (PSM) Device, and Ultra-Wide Band (UWB), among others, are some of the examples of hardware providing direct data and Laser Scanner and Robotic Total Station (RTS), among others, are the examples of hardware providing indirect data for worker safety. Direct data are directly related to the construction workers' physical, physiological, psychological, and visualization factors. Whereas, indirect data provides additional information about the construction workers' working environment.

Software The software plays the role of interface between the hardware and the user, and cannot be touched like hardware. MS Project, Autodesk Revit, and Unity 3D, among others, are some of the examples of the software that help a user to visualize the data obtained from the hardware and find the proper analysis tools.

Tools and Environment For this literature review, the environment is a digital representation of the physical and functional characterization of the construction environment. Augmented Reality (AR), Virtual Reality (VR) combined with Machine Learning (ML) and Artificial Intelligence (AI) can facilitate as interactive digital tools and construction environments in which users can perform different construction workers' safety-related research without putting construction workers into any real danger. Users may use one or many hardware and software in the environment to take advantage of it.

Medium Programming languages like Matlab, C, C+, and C++, among others, play a crucial role in the analysis part of the research. Moreover, these languages act as a medium between the technology and people to deduce results from analysis and get into a conclusion.

2.5.2 Techniques

There are specific tools that have been and are currently in use, such as surveys, questionnaires, training, and educational program for enhancing construction workers' safety. Although these cannot be classified into any sub-heading of technology, which is the key focus, they play a vital role in construction workers' safety enhancement, and they have been incorporated in the scope of the study.

2.5.3 Construction Workers' Safety

It is the discipline of preserving the health of those who build, operate, maintain, and demolish the engineering works and of others affected by those works [50]. It is the overall safety of all the workers working in the construction site from any potentially fatal or non-fatal injuries. From the literature review, many factors affecting the workers' safety were identified and categorized into three major factors; personal, environmental, and organizational. Not all factors can be tracked using existing technology.

2.5.4 Personal Factors

Personal factors are related to an individual that can influence how they act and behave, such as attitude, motivation, and ability to perform a task. Personal factors can be categorized into different sub-factors.

Physical Factors Physical factors are properties that can be observed without the need for a device or a tool [51]. For instance, common physical measures used to detect stress are posture, eye gaze, voice, pupil diameter, and hand and finger movement. However, sophisticated equipment and sensors that can analyze visual and audio cues are still needed to obtain physical signals at sampling rates enough for data analysis. It involves the anticipation of or confrontation with a situation that is characterized by physical harm, danger, pain, or discomfort [52].

Physiological Factors Physiological factors are properties that require a device and a tool to be attached to individuals to detect wide fluctuations [51]. It relates to the factors affecting the functioning in the body, such as heart rate, blood volume pulse, and blood pressure, among others.

Psychological Factors These are the factors regarding the influence of training levels, propensity to accept danger or risk-taking, skill levels, supervisor carefulness, and worker carelessness, among others. [53]. It involves the anticipation of or confrontation with situations that are potential threats to self-esteem and that often involve fear of failure or personal evaluation [52].

Cognitive Factors The cognitive factors refer to characteristics of the person that affect perceiving, remembering, thinking, problem-solving, decision making that is reflective of information processing regularities [54]. It affects the performance and learning of a person.

2.5.5 Environmental Factors

These are the factors that relate to site conditions such as tidiness, the interrelationship between construction groups, inter- and intragroup cooperation, control and supervision of work activities, the influence of site planning, and worker safety observance [53].

2.5.6 Organizational Factors

These relate to factors such as group interactions, interrelationships, trade union involvement, safety policy, safety propaganda, and safety climate, among others [53].

2.6 Data Collection and Analysis

Two hundred and seventy six published research papers were reviewed in total using the defined search protocol. *Search Procedure I* was used for 134 papers, and *Search*

Procedure II for the remaining 142 papers. Thirty-seven percent of the reviewed papers were extracted from Automation in Construction, 16% from Journal of Construction Engineering and Management, 11% from Journal of Computing in Civil Engineering, and 6% from Advanced Engineering Informatics. Table 2.6 shows the details about the publications from where the papers were reviewed.

Table 2.6. List of journal publications reviewed for additional papers.

SN	Journal Publications	No. of Papers
1	Automation in Construction	103
2	Journal of Construction Engineering and Management	44
3	Journal of Computing in Civil Engineering	30
4	Advanced Engineering Informatics	15
5	Others	84
	Total Number of Papers	**276**

After data collection from 276 reviewed papers, the qualitative data analysis was performed using the qualitative data analysis software, NVIVO, for visualization and mapping of the vital information. The authors identified the primary factors affecting the construction workers' safety from the reviewed papers and coded into the NVIVO as a 1st tier node. The authors further subdivided the primary factors into secondary factors and coded as 2nd tier node, which was further subdivided into tertiary factors and coded as 3rd tier node. Similarly, the authors coded different technology used to track and enhance construction safety (both directly and indirectly) as 4th tier node in each tertiary factors. Then, each 4th tier node was coded with the relevant information from the reviewed paper. Figure 2.2 shows an example of 1st, 2nd, 3rd, and 4th tier nodes created, and the information details for one of the technology coded in 4th tier node.

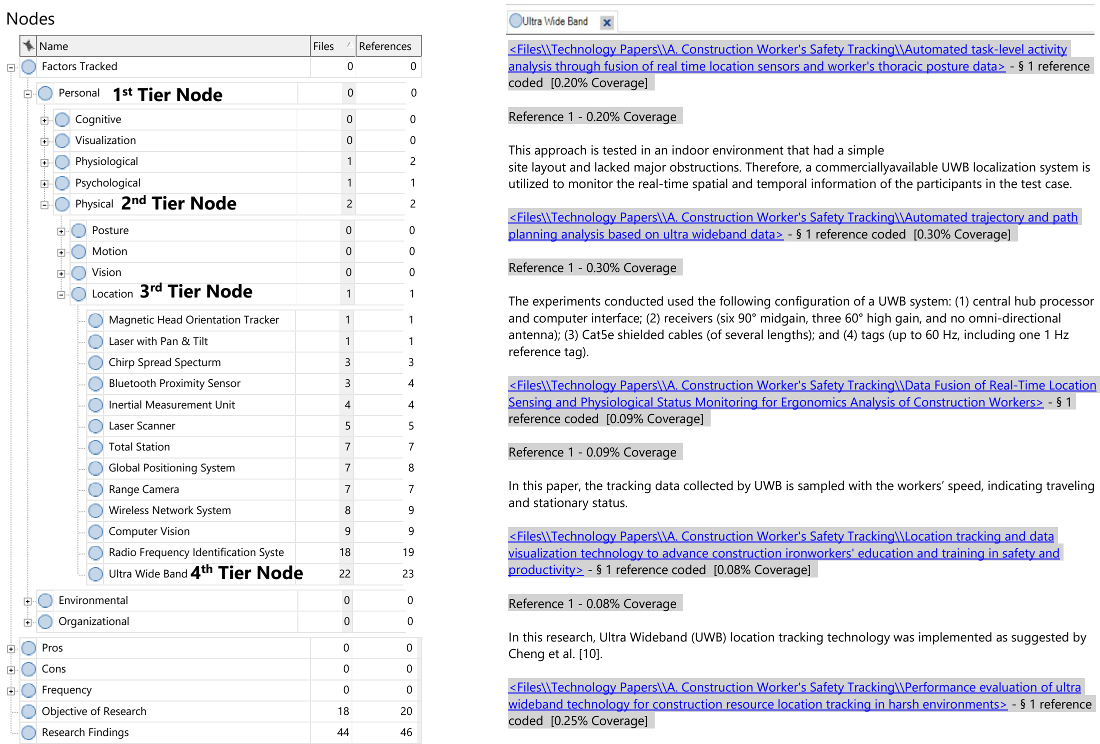

Fig. 2.2. Example of different tier nodes coded in NVIVO with information details for Ultra-Wideband

2.7 Results and Finding

The authors analyzed the journal papers extracted using the defined search protocols using the qualitative analysis software, NVIVO, and MATLAB. Figure 2.3 shows the comparative trend line for overall published papers and the ones published in the United States between the numbers of journal papers and published year from January 2000 to December 2018. It can be observed that the trend of the number of studies regarding the use of technology for workers' safety tracking has been increasing rapidly since 2006. Also, the maximum number of the published journal was 44 in 2016 and 2018. Similar trend can be observed for researches from just the

United States. This shows that the researchers are trying to implement technology in a construction site for the enhancement and tracking of workers' safety.

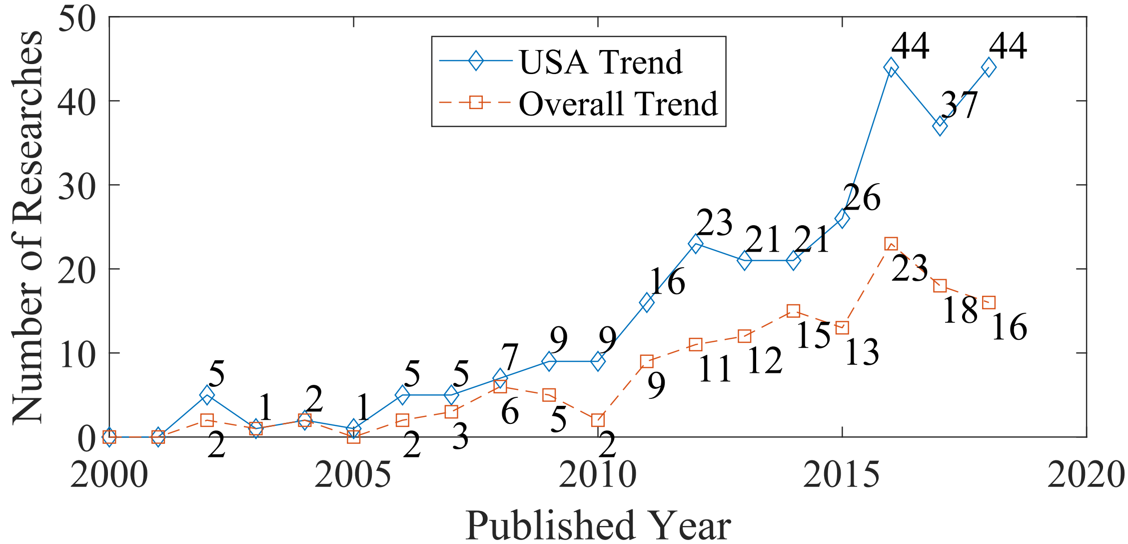

Fig. 2.3. Chronological plot of journal papers reviewed

2.7.1 Geographical Networking of Construction Workers' Safety Research

The authors reviewed the inter-country collaboration network based on the location of university or institute conducting construction workers' safety research. The authors identified thirty countries contributing most to the research. Figure 2.4 shows the collaboration network among the countries. The edge represents the collaboration between countries and the size of node represents the country's involvement in the research. Countries like USA, Canada, China, UK, Korea, Hong Kong, Australia, Germany, among others, had the major contribution in the construction workers' safety research. And, USA was the major collaborator with multiple countries.

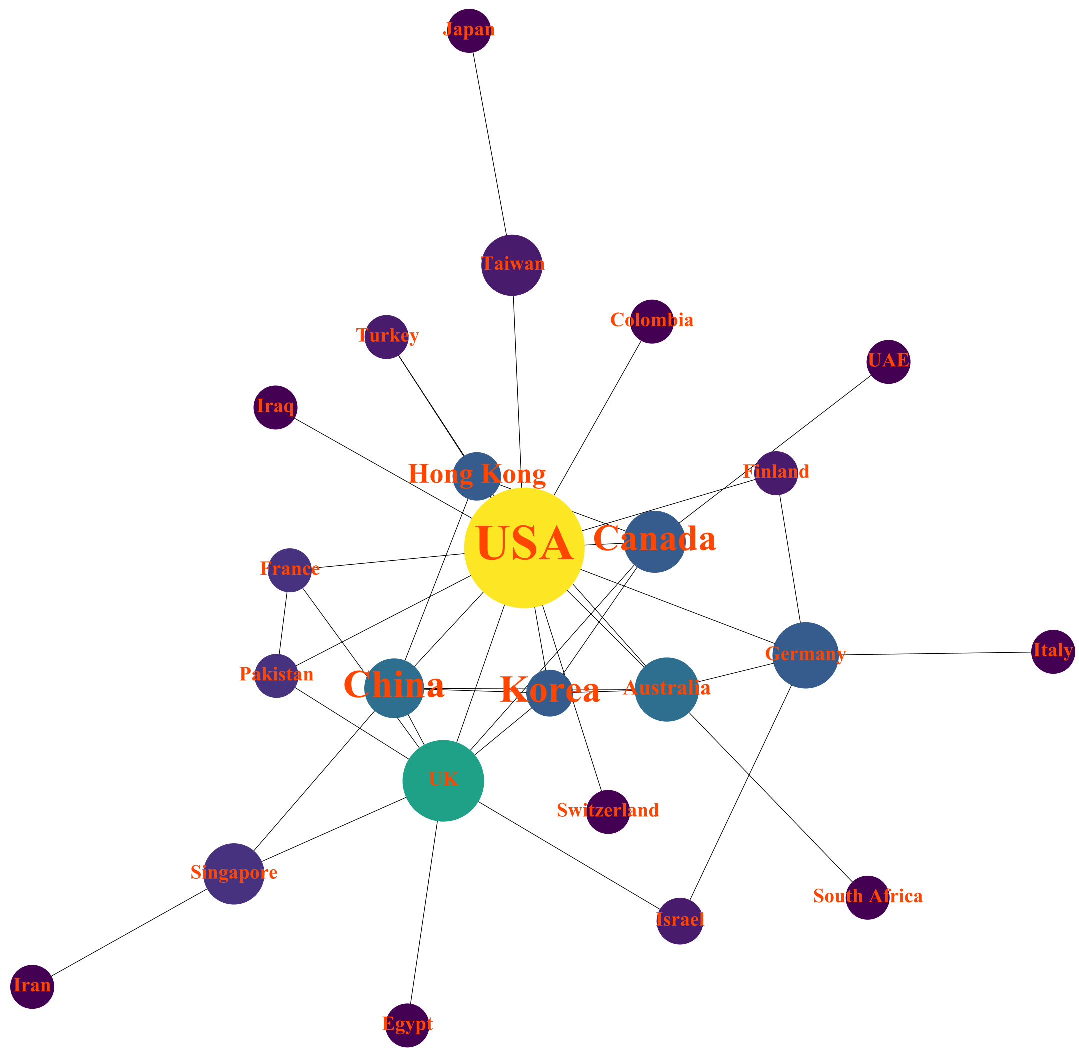

Fig. 2.4. Inter-country collaboration network

2.7.2 Technologies Aiding Construction Workers' Safety

The authors found forty-three different technology from the in-depth literature review of 276 journal papers, directly or indirectly involved in tracking the construction workers' safety. Figure 2.5 shows the chronological matrix of the different technology used in the published researches for the review period. The most popular technology among the researchers were computer vision, ultra-wideband (UWB), radio frequency identification (RFID), building information modeling (BIM), range camera, accelerometer, virtual reality (VR), inertial measurement unit (IMU), RTS, and augmented reality (AR), among others and were used more in the researches.

Some of the technology like lumbar motion monitor (LMS), magnetic head orientation tracker (MHOT), headset, and target alarm (TA) among others were only used once and were not preferred by any other researchers which could be due to various reasons like cost of technology, complexity, wear-ability, and accuracy among others. Similarly, there was an overall incremental trend regarding the use of technology throughout the reviewed period. After 2010, a more pronounced rise can be observed in the use of technology for tracking the construction workers. The total is different from the total number of papers because some research activities used multiple technology.

Technology	#		2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	Total
			Year																			
Technology	1	Computer Vision			1		1	1			1	1	2	5	3	3	1	7	13	12	16	67
	2	Ultra Wide Band								1	3	1	2	6	5	6	2	1	2			29
	3	Radio Frequency Identification System								1		2	4	1	4	4	1	1	4			22
	4	Building Information Model										1		2	1	3	6	6	8	7	5	39
	5	Range Camera								1	2	1	1		6	2	5	1	1	2	3	25
	6	Accelerometer												2			1	1	4	4	2	14
	7	Inertial Measurement Unit											1					1	5	4	1	12
	8	Virtual Reality			1	1			1	1		1			1	1	2	6	7	2	6	30
	9	Motion Sensor												1		2	1	2		3	1	10
	10	EEG Sensor																	2	2	3	7
	11	Robotic Total Station										1	1	2	1			2				7
	12	Augmented Reality									1	1			1	1	1	1		2	3	11
	13	Computer							2	1									2			5
	14	Game Engine													2		1	2	1			6
	15	Global Positioning System						1				1	1					2	4			9
	16	Laser Scanner										1	1	1			1	1			1	6
	17	Physiological Status Monitoring Device												1	2	2	1			1		7
	18	Wireless Network System										1	1			3			1	1	1	8
	19	Chirp Spread Spectrum																2	1	1		4
	20	Eye Tracking System																1		2	3	6
	21	Heart Rate Monitor						1												3		4
	22	Metabolic System Monitor			1										1		1		1			4
	23	Wearable Insole Pressure System																			4	4
	24	Bluetooth Proximity Sensor																	1	3	1	5
	25	ECG Sensor												1			1		1			3
	26	EMG Sensor																1		2		3
	27	Gyroscope															1	1		1	1	4
	28	Temperature Sensor															1			2		3
	29	Angle Sensor												1	1							2
	30	Geographic Information System			1									1								2
	31	Heat Stress Monitor													1				1			2
	32	Oxygen Sensor															1			1		2
	33	Alarm																			1	1
	34	Dynamometer																1				1
	35	Exoskeleton													1							1
	36	GSR Sensor																		1		1
	37	Headset						1														1
	38	Laser with Pan & Tilt Unit							1													1
	39	Lumber Motion Monitor					1															1
	40	Magnetic Field Sensor																		1		1
	41	Magnetic Head Orientation Tracker									1											1
	42	Photoplethysmogram Sensor																	1			1
	43	Unmanned Aerial Vehicle																			1	1
		Yearly Total	0	0	4	1	2	4	4	5	8	12	14	24	30	27	28	40	60	57	53	373

Fig. 2.5. Matrix representation of different technology used by published researches

Real-time location system (RTLS) based technology such as UWB, active RFID, and GPS were the most used technology to track the location and positioning of the workers. Also, researchers extensively used computer vision either to track the workers' safety directly or to visualize and verify the usability of other technology during analysis. The use of advanced environments like BIM, VR, and AR for visualization increased rapidly from 2010. Figure 2.6 shows the trend line of the use of BIM, VR, and AR in the visualization of construction workers' safety.

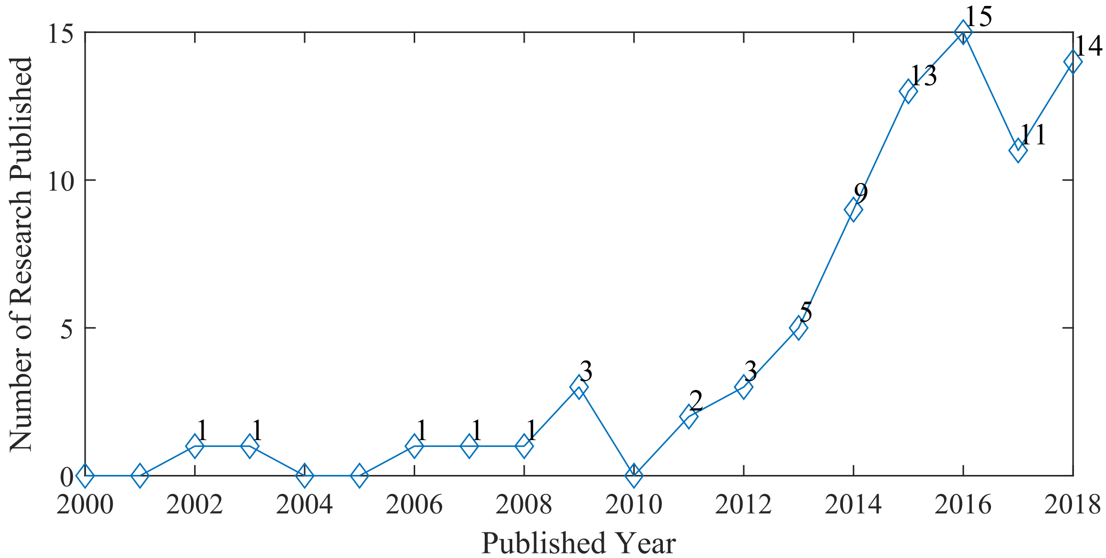

Fig. 2.6. Trend line for the use of BIM, VR, and AR in the visualization of construction workers' safety

2.7.3 Visual Mapping of Identified Factors and Tracking Technologies

The authors used the qualitative analysis software (NVIVO) and python networkx module, to derive a visual map for each factor showing the list of technology used to directly or indirectly track construction workers' safety. These visual maps made the task of finding the proper technology suitable for research or site environment easier. Figure 2.7 shows the visual map showing the list of technology used to, directly and indirectly, track the physiological factors of construction workers.

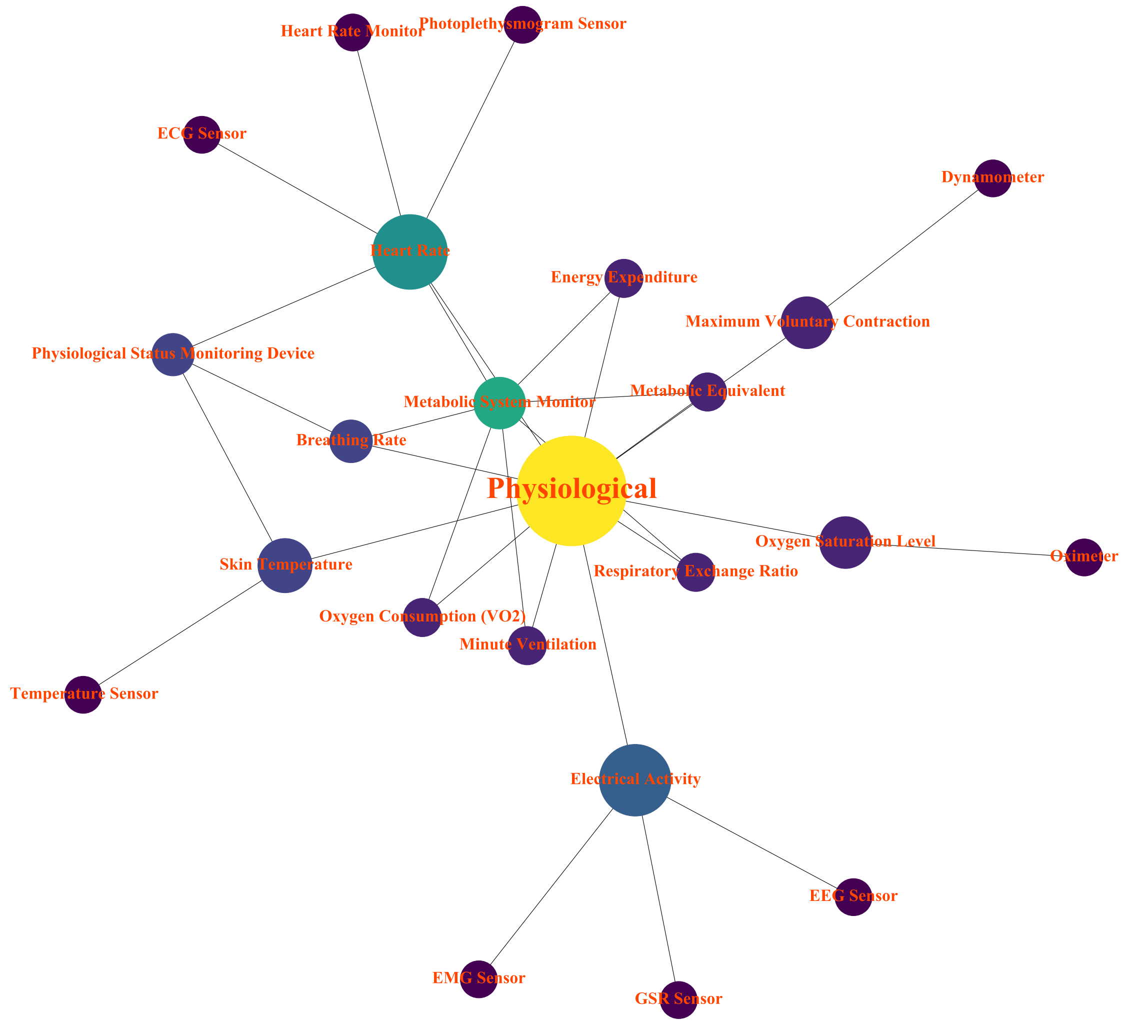

Fig. 2.7. Visual map for the list of technology used to track physiological factors of a construction worker

The authors further sub-divided the 2nd tier secondary (physiological) factor as, defined previously, into 3rd tier tertiary factors such as oxygen consumption, breathing rate, heart rate, electrical activity, respiratory exchange ratio, energy expenditure, and skin temperature among others. For each 3rd tier tertiary factors, the authors listed 4th tier technology such as metabolic system monitor (MMS), oximeter, PSM device, and temperature sensor among others. We can create similar maps for all other factors like location, psychological, postural, cognitive, and visualization among others.

From Figure 2.7, it can be noticed that the same technology could be used to track the multiple factors. Also, this could ease the task for researchers and construction personnel, to find a suitable technology for tracking multiple factors, by merely using these visual maps. Additionally, Figure 2.8, 2.9, and 2.10 shows the similar visual maps for physical, psychological, vigilance, and cognitive factors of construction workers. The physical factors include location, posture, motion, and vision. From Figure 2.8, it can be observed that majority of the research was focused on technologies tracking workers' location.

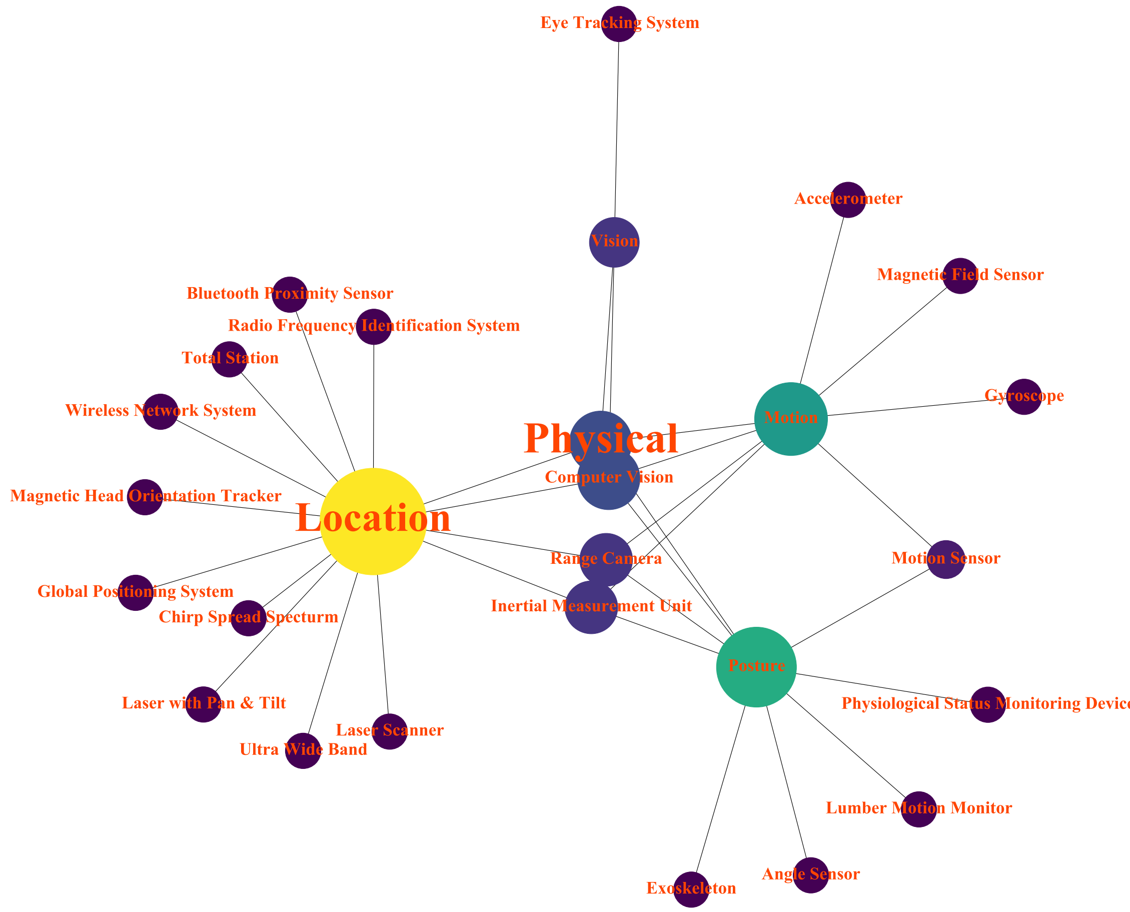

Fig. 2.8. Visual map for the list of technology used to track physical factors of a construction worker

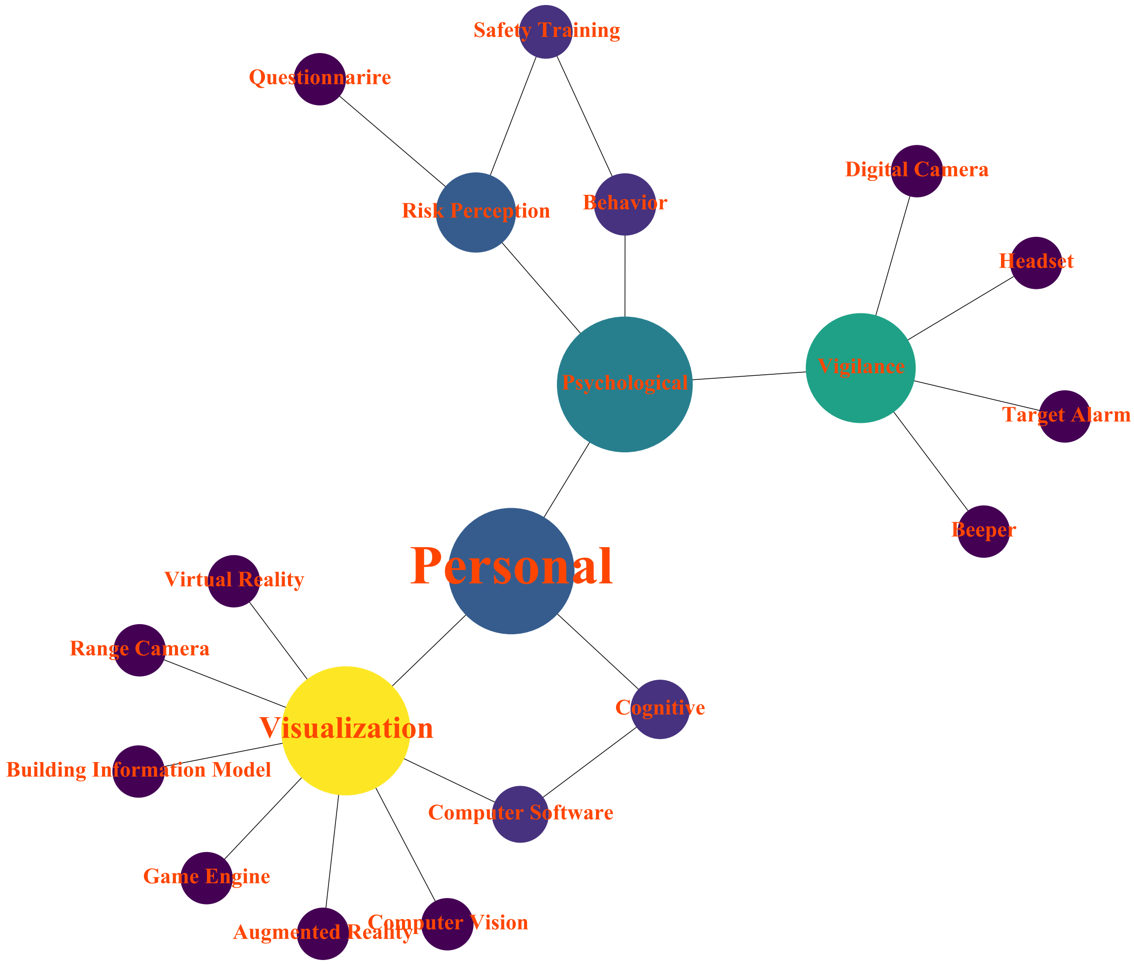

Fig. 2.9. Visual map for the list of technology used to track psychological, visualization, and cognitive factors of a construction worker

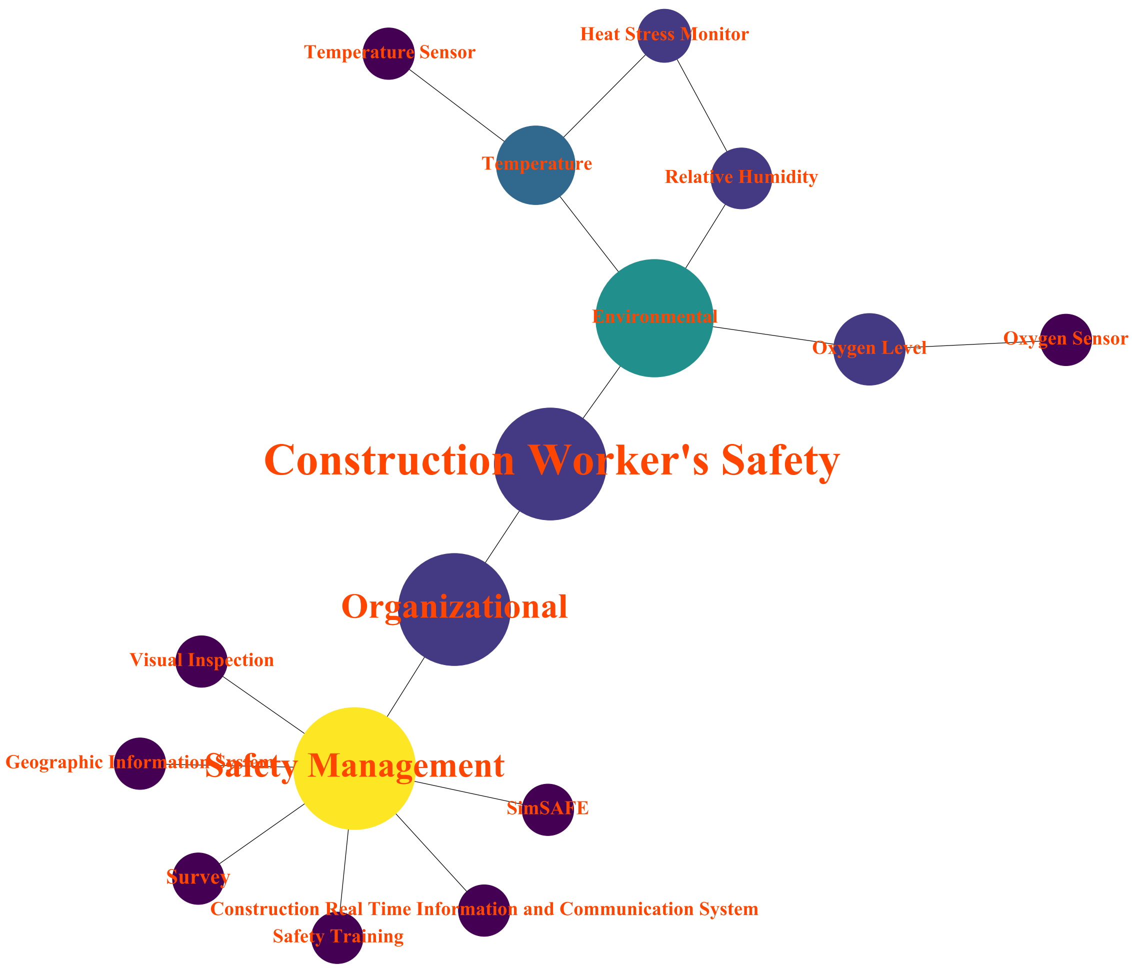

Fig. 2.10. Visual map for the list of technology used to track environmental and organizational factors of a construction worker

2.7.4 Tabular Index with Critical Information about the Technology

The authors created a tabular index from this review, which held all the critical information about the technology used to track different construction workers' safety factors, as shown in Tables 2.7 and 2.8. Table 2.7 shows the information like factors tracked, technology used, type of data, data transfer rate, range, accuracy, and task performed from all the reviewed research papers while Table 2.8 shows the related citations for information collected in Table 2.7. The authors obtained all the information included in the tabular index from the reviewed research papers itself. And the authors did not investigate any additional source to find more details about the technology. For example, there might be more advanced computer vision technology available in the market with better data transfer capacity. However, those pieces of information were excluded in this literature review. Moreover, if any specific information could not be obtained about technology, then the table was left empty rather than finding the information from other sources. The authors primarily focused on the technology used to track the personal factors of construction workers' safety, as stated in the scope of this chapter.

Similarly, not all the technology listed are used directly to track the construction workers' safety. Some of the technology are used either to indirectly track the construction workers' safety or as supporting technology such as laser scanner, RTS, etc. Also, some of the popular methodologies like questionnaires and surveys have been included in this indexing, although they were not real-time tracking technology, as they were found to be key methods for tracking construction workers' safety. For instance, [55] used depth sensor camera (direct hardware) to track the postural data (physical factor), and PSM device (direct hardware) to track heart rate (physiological data). Besides, computer vision (indirect hardware) was used to record the experiment for assisting in the analysis, and the gaming engine (software) was used to create an animation of lifting technique to help the subject visualize using a virtual environment (tools and environment).

Table 2.7. Tabular index of different technology used to track construction workers' safety factors

A[a]	**B**[b]	**C**[c]	**D**[d]	**E**[e]	**F**[f]	**G**[g]	**H**[h]
1	Environmental[i]						
1.1	Oxygen Level	Oxygen Sensor	Numeric	1/900Hz			Real-time update of oxygen level of confined space in a construction site
1.2	Relative Humidity	Heat Stress Monitor	Numeric	1/60Hz	38-95%, 60m	±5%	Measure and collect the relative humidity data
		Wireless Network System (WNS)	Numeric	3Hz	100m		Dynamic update of a humidity information of defined space
1.3	Temperature	Heat Stress Monitor	Numeric	1/60Hz	29.8-56.1 °C Up to 60m	±0.5°C	Measure and collect the temperature data
		Temperature Sensor	Numeric	1/900Hz			Real-time update of a temperature level of confined space in a construction site
		WNS	Numeric	3Hz	100m		Dynamic update of a temperature information of defined space
2	Organizational[i]						
2.1	Safety Management	Construction Real Time Information & Communication (CRTIC) System	Report				Relevant data stored in a centralized database with access for analysis to individual projects

Table 2.7. (Continued...)

A	B	C	D	E	F	G	H
		Geographical Information System (GIS)[j]	Spatial & Non-spatial				Develop a safety database of a project, construction sequence that helps hazard identification and analyzes spatial & non-spatial safety information
		Safety Training					Enhance the construction workers' safety performance
		SimSAFE					Enhance the construction workers' safety by monitoring schedule and its activity
		Survey					Enhance the construction workers' safety by asking safety related questionnaire
		Visual Inspection					Inspect the construction site to identify possible safety hazards
3	Personal						
3.1	Cognitive						
3.1.1	Electrical Activity	EEG Sensors	Numeric	220Hz to 250Hz			Measure the electrical activity of construction workers' brain to track workload stress
3.2	Physical						
3.2.1	Location	Bluetooth Proximity Sensor (BPS)	Numeric	0.7Hz	18.3m	0.53m	Real-time detection and storage of unsafe incidents through tracking construction resources
		Chirp Spread Spectrum (CSS)	Numeric	124Kbps to 2Mbps	1000m	±0.87m	Real-time locating tracking of the position of construction site workers using time-of-arrival, and WPAN

Table 2.7. (Continued...)

A	B	C	D	E	F	G	H
		Range Camera	Numeric	15.2Hz to 50Hz	0.8m to 7.5m		Track real-time positional, motion and postural data of construction workers
		Computer Vision	Numeric, Image	10Hz to 30Hz	300m	±1.05m	Track the location of construction workers
		GPS	Numeric	1Hz to 10Hz	1cm to 0.3m		Track the position of the construction workers
		IMU	Numeric	128Hz	0.43m to 1.44m		Track the location of the construction workers
		Laser Scanner[j]	Numeric				Scan and create a point cloud of a construction field
		Laser with Pan & Tilt[j]	Numeric				Acquire 3D coordinates of range points of various objects
		MHOT	Numeric				Track the workers' head orientation in a 3D space
		RFID	Numeric	100Hz		1.5m	Track the location of the construction workers
		RTS[j]	Numeric				Cross verify the coordinate data obtained from other technology
		UWB	Numeric	1Hz to 60Hz		0.3m	Track the location of the construction workers
		WNS	Numeric	250Kbps	100m	1m to 2m	Track the location of the construction workers
3.2.2	Motion	Accelerometer	Numeric	40Hz to 400Hz			Track the body movement of construction workers

Table 2.7. (Continued...)

A	B	C	D	E	F	G	H
		Computer Vision	Numeric, Image	5Hz to 120Hz			Track the body movement of construction workers
		Gyroscope	Numeric	51.2Hz to 800Hz			Track the body movement of construction workers
		IMU	Numeric	52Hz			Track the body movement of construction workers
		Magnetic Field Sensor	Numeric				Track the body direction of construction workers
		Motion Sensor	Numeric	100Hz to 2400Hz			Track the body movement of construction workers
		Range Camera	Numeric	30 Hz	0.8m to 4m		Track the body movement of construction workers
3.2.3	Posture	Angle Sensor	Numeric	103Hz		0.05°	Measure the bodily postural angle of construction workers
		Range Camera	Numeric				Measure the bodily postural angle of construction workers
		Computer Vision	Numeric, Image	25Hz			Track the posture of construction workers
		Exoskeleton	Numeric	100Hz			Measure the bodily postural angle of construction workers
		IMU	Numeric	10 Hz			Measure the bodily postural angle of construction workers

Table 2.7. (Continued...)

A	B	C	D	E	F	G	H
		LMS	Numeric	60Hz			Measure the positional data of the lumbar region of construction workers
		Motion Sensor	Numeric	100Hz to 2400Hz			Track the body posture of construction workers
		PSM Device	Numeric	25Hz to 50Hz			Measure the bodily postural angle of construction workers
		Wearable Insole Pressure System (WIPS)	Numeric	50 Hz			Track workers' posture based on raw foot planar pressure distribution data
3.2.4	Eye Fixation/ Vision	Computer Vision	Image	5Hz to 6.67Hz		95% to 99%	Track the construction workers by computer vision
		Eye Tracking System	Numeric	500Hz			Measure the eye movement data of construction workers
		Range Camera	Image				Track the construction workers using a range camera
3.3	Physiological						
3.3.1	Breathing Rate	MMS	Numeric	0.2Hz			Measure the breathing rate of construction workers
		PSM Device	Numeric	1Hz			Measure the breathing rate of construction workers
3.3.2	Electrical Activity						
3.3.2.1	Electroencephalogram (EEG)	EEG Sensor	Numeric	1Hz to 220Hz			Measure the electrical activity of construction workers' brain

Table 2.7. (Continued...)

A	B	C	D	E	F	G	H
3.3.2.2	Electromyography (EMG)	EMG Sensor	Numeric	12 Hz to 1500 Hz			Measure the electrical activity of construction workers' muscle
3.3.2.3	Galvanic Skin Response (GSR)	GSR Sensor	Numeric	1/60Hz			Measure the electrical resistance of construction workers' skin
3.3.3	Energy Expenditure	MMS	Numeric	1/5Hz			Measure the energy expenditure of construction workers
3.3.4	Heart Rate	Heart Rate Monitor	Numeric	1/60Hz to 1/15Hz			Measure the heart rate of construction workers
		Electrocar- diography (ECG) Sensor	Numeric	1Hz to 500Hz			Measure the electrical activity of construction workers' heart
		MMS	Numeric	1/5Hz			Measure the heart rate of construction workers
		Photo plethysmograph (PPG) Sensor	Numeric	1/60Hz			Measure the heart rate of construction workers
		PSM Device	Numeric	1Hz			Measure the heart rate of construction workers

Table 2.7. (Continued...)

A	**B**	**C**	**D**	**E**	**F**	**G**	**H**
3.3.5	Maximum Voluntary Contraction	Dynamometer	Numeric				Measure the strength of lumbar muscles of construction workers
3.3.6	Metabolic Equivalent	MMS	Numeric	1/5 Hz			Measure the ratio of working vs. resting metabolic rate of construction workers
3.3.7	Minute Ventilation	MMS	Numeric	1/5Hz			Measure the volume of gas inhaled or exhaled from construction workers' lungs
3.3.8	Oxygen Consumption	MMS	Numeric	1/5 Hz			Measure the oxygen consumption of construction workers
3.3.9	Oxygen Saturation	Oximeter	Numeric	0.5Hz			Measure the oxygen saturation level in arterial blood to indirectly quantify the blood circulation in the lower extremities of construction workers
3.3.10	Respiratory Exchange Ratio	MMS	Numeric	1/5Hz			Measure the ratio between the amount of CO2 produced in metabolism and O2 used by construction workers
3.3.11	Skin Temperature	PSM Device	Numeric				Measure the skin temperature of construction workers
		Temperature Sensor	Numeric	1/60Hz to 1Hz		0.01°C	Measure the skin temperature of construction workers

Table 2.7. (Continued...)

A	B	C	D	E	F	G	H
3.4	Psychological						
3.4.1	Risk Perception	Questionnaire	Numeric/ Subjective				Measure the level of risk perception level for the hazards encountered by construction workers
		VR	Virtual Site				Analyze the people's risk perception in a virtual construction site
3.4.2	Vigilance	Beeper	Sound				Produce an alarming sound when there is a hazard in the construction site
		Computer Vision	Image/ Video				Provide visual information to safety in-charge to identify the hazardous areas in the construction site
		Headset	Sound				Provide bidirectional communication to construction workers regarding any hazardous situation at the construction site
		Alarm	Sound				Produce an alarming sound when there is a hazard in the construction site
3.5	Visualization	AR	3D Image				Help construction personnel to visualize a construction site/ procedure by superimposing the computer-generated image on a user's real view
		BIM	3D Image				Provide the complete 3D visualization of the construction site or procedure to a construction personnel

Table 2.7. (Continued...)

A	B	C	D	E	F	G	H
		Computer					Provide a platform to create a safety monitoring automated flow chart
		Computer Vision	Image/ Video	1/10Hz to 1Hz			Visualize and verify the data obtained using other technology by visual comparison
		Game Engine	Virtual Site				Create the virtual construction environment for construction personnel to help in training or visualization
		Range Camera	3D image /Coordinate				Create a realistic 3D model that helps construction personnel in the visualization of a construction site
		VR	Virtual Site				Create a virtual construction environment for construction personnel to help in training or visualization
		Unmanned Aerial Vehicle (UAV)					Monitoring of potential safety hazards by UAVs

[a] SN
[b] Factors Tracked
[c] Technology
[d] Data Type
[e] Data Transfer Rate
[f] Range
[g] Accuracy

Table 2.8. Reference journal articles for different technology identified in Table 2.7

SN	Factors Tracked	Technology	Citation
1	Environmental [i]		
1.1	Oxygen Level	Oxygen Sensor	[56, 57]
1.2	Relative Humidity	Heat Stress Monitor	[58]
		WNS	[59]
1.3	Temperature	Heat Stress Monitor	[58, 60]
		Temperature Sensor	[56]
		WNS	[59]
2	Organizational[i]		
2.1	Safety Management	CRTIC System	[61]
		GIS[j]	[62, 63]
		Safety Training	[64–66]
		SimSAFE	[67]
		Survey	[68–77]
		Visual Inspection	[78]
3	Personal		
3.1	Cognitive		
3.1.1	Electrical Activity	EEG Sensors	[79–85]
3.2	Physical		
3.2.1	Location	BPS	[86–90]
		CSS	[74, 91–93]
		Range Camera	[24–29]
		Computer Vision	[16–19, 94–101]

[h]Task

[i]Since the primary focus was to identify personal factors, environmental and organizational factors listed above are incomplete.

[j]These technology are indirectly used to enhance the construction workers' safety tracking.

Table 2.8. (Continued...)

SN	Factors Tracked	Technology	Citation
		GPS	[92, 102–107]
		IMU	[104, 108–111]
		Laser Scanner[j]	[6, 112–116]
		Laser with Pan & Tilt[j]	[117]
		MHOT	[118]
		RFID	[86, 92, 104, 112, 113, 119–135]
		RTS[j]	[6, 18, 96, 98, 112, 113, 133]
		UWB	[6, 23, 96, 98, 103, 104, 136–157]
		WNS	[5, 103, 130, 131, 158, 159]
3.2.2	Motion	Accelerometer	[82, 160–170]
		Computer Vision	[21, 161, 171–176]
		Gyroscope	[162, 166, 167, 170]
		IMU	[164, 177, 178]
		Magnetic Field Sensor	[168]
		Motion Sensor	[108, 173, 178–182]
		Range Camera	[183–187]
3.2.3	Posture	Angle Sensor	[188, 189]
		Range Camera	[15, 20, 27, 190–198]
		Computer Vision	[173, 199, 200]
		Exoskeleton	[189]
		IMU	[201–205]
		LMS	[206]
		Motion Sensor	[20–23, 57, 173, 179]
		PSM Device	[146, 149, 157, 160, 169]
		WIPS	[199, 207–209]
3.2.4	Eye Fixation/ Vision	Computer Vision	[108, 111, 163, 166–168, 195, 200, 210–224]

Table 2.8. (Continued...)

SN	Factors Tracked	Technology	Citation
		Eye Tracking System	[225–228]
		Range Camera	[229]
3.3	Physiological		
3.3.1	Breathing Rate	MMS	[58, 60, 230]
		PSM Device	[160, 230]
3.3.2	Electrical Activity		
3.3.2.1	EEG	EEG Sensor	[79–85]
3.3.2.2	EMG	EMG Sensor	[21, 57, 181]
3.3.2.3	GSR	GSR Sensor	[231]
3.3.3	Energy Expenditure	MMS	[58]
3.3.4	Heart Rate	Heart Rate Monitor	[80, 231–233]
		ECG Sensor	[160, 230, 234]
		MMS	[58, 60, 230]
		PPG Sensor	[234]
		PSM Device	[146, 160, 169, 230]
3.3.5	Maximum Voluntary Contraction	Dynamometer	[181]
3.3.6	Metabolic Equivalent	MMS	[58]
3.3.7	Minute Ventilation	MMS	[58]
3.3.8	Oxygen Consumption	MMS	[58, 60, 232]
3.3.9	Oxygen Saturation	Oximeter	[57]
3.3.10	Respiratory Exchange Ratio	MMS	[58]
3.3.11	Skin Temperature	PSM Device	[160]

Table 2.8. (Continued...)

SN	Factors Tracked	Technology	Citation
		Temperature Sensor	[80, 231]
3.4	Psychological		
3.4.1	Risk Perception	Questionnaire	[68, 235–242]
		VR	[243, 244]
3.4.2	Vigilance	Beeper	[245]
		Computer Vision	[246]
		Headset	[102]
		Alarm	[245, 247]
3.5	Visualization	AR	[118, 168, 248–256]
		BIM	[59, 88, 90, 105, 115, 134, 156, 158, 197, 242, 249, 251, 257–282]
		Computer	[100, 117, 283, 284]
		Computer Vision	[6, 18, 23, 100, 102, 105, 146, 198, 208, 228, 250, 264, 284–291]
		Game Engine	[74, 91, 109, 251, 292, 293]
		Range Camera	[294, 295]
		VR	[193, 252, 253, 296–314]
		UAV	[280]

Figure 2.11 shows the visual map showing the construction workers' safety factors. Tables 2.7 and 2.8 show all the details of the technology used to track these factors. The number after the factor in Figure 2.11 locates its position in Tables 2.7 and 2.8 where all the necessary details like technology used, type of data, data transfer rate, citations, among others can be found. Tables 2.7, 2.8, and Figure 2.11 combined provide an insight to new researchers and construction practitioners for finding suitable technology that can be implemented in the construction site to reduce injuries.

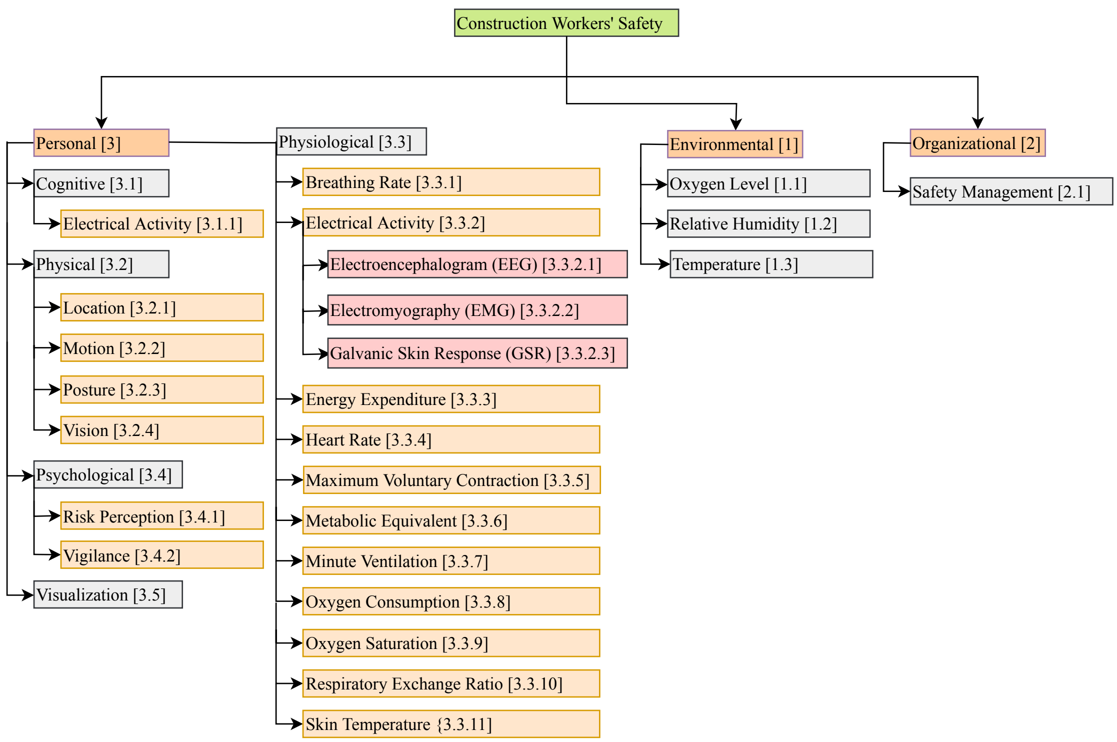

Fig. 2.11. Mapping of Real-Time Construction Safety Tracking Factors

2.7.5 Applicability to Legal Dispute Resolution

The authors identified some major technology which are applicable for monitoring the workers' safety reducing the risk of injury. As well, these technology are capable of collecting hard data which can be useful for dispute resolution in case an injury occur causing legal dispute. Table 2.9 displays the identified major workers' injury related disputes and list of applicable technology for dispute resolution.

Table 2.9. Identified workers' injury related disputes with applicable technology for its resolution

Disputes	Technology	Application	References
Liability of injury	Computer Vision	Collect visual data that helps in visualization of how an injury occurred and determination of liable party, if any	[315–318], *(Reese v. Triple D. Truss, LLC; Amant v. Pacific Power & Light; Frampton v. Dauphin Distribution Services Co.)*
Causation of injury	Computer Vision, Range Camera, IMU	Capture visual data or measure bodily postural data that can be used to identify the cause of injury	[31, 317, 319, 320], *(Purcell v. Visiting Nurses Found. Inc.; Molinar v. Larry Reetz Constr. Ltd.; Orth v. Stoebner Permann Const)*
Work-relation of injury	UWB, RFID System, BPS, CSS, Computer Vision	Track the worker's location which can help in determining whether the injury occurred in workplace or not	[30, 321], *(Orth v. Stoebner Permann Const; Rakestraw v. General Dynamics Land Systems Inc.)*
Severity of injury	Range Camera, PSM Device, IMU	Measure the bodily postural data that can be used to predict the severity of injury attributed to work	[30, 321–323], *(Orth v. Stoebner Permann Const; Parsons v. Workforce Safety & Ins. Fund)*
Working condition	Heat Stress Monitor, temperature sensor, oxygen sensor	Keep track of working condition related data such as relative humidity, temperature, wet/dry floor, among others, which can help in determining the injuries such as heat stroke, slip and fall, anoxia, hypoxia, among others	[324, 325], *(Callan v Structure Tone, Inc.; Gulf States Steel Co. v. Christison; Pedroza v. BRB)*

Continued on Next Page...

Table 2.9. (Continued...)

Disputes	Technology	Application	References
Negligence	Computer Vision	Captures the visual data that helps in identifying the negligent party responsible for injury	[325–327], *(Callan v Structure Tone, Inc.; Fraser v. Norman; Lee v. M&H Enters., Inc.)*

2.8 Major Technologies Tracking the Construction Workers' Safety

From the literature review, the authors identified major technologies implementable to track construction workers' safety. Some of these technologies include UWB, range camera, computer vision, IMU, RFID system, among others.

2.8.1 Ultra-Wide Band (UWB)

Ultra-wideband (UWB) is a communication technology that employs a wide range of effective signal bandwidth (typically greater than 25% of the center frequency) . UWB is usually used in short-range wireless applications and can carry high data with low power and little interference [328]. The use of UWB in the field of construction workers' safety was traced back to 2007. Twenty-three different research papers were found related to the tracking of construction workers' location using UWB for enhancing construction safety. Figure 2.12 shows the trend line of the use of UWB for enhancing construction workers' safety. The figure shows the typical trend of rise in use of technology to the peak and its fall after it gets outdated by new technology.

The UWB is used to track the location of construction workers in an indoor environment [157]. The UWB system consists of a set of central processing hub, several receiving antennas, CAT-5 shielded cable and active RFID tags (one of which is used as a calibration or reference tag) [137, 144, 157]. The receiver antennas are connected via shielded cables to the central processing hub. The UWB tags come in the form of a small badge (6.5 x 3.4 x 0.6 cm3), asset cube (2.9 x 2.9 x 2.9 cm3), or micro rectangular form (1.3 x 2.5 x 0.6 cm3) with a weight of each tag less than 12g [74]. The data rate of the radio frequency (RF) signal of each tag is fixed and can be up to 60 Hz, including 1, 15, and 30 Hz [144]. The average error of these tags was found to be about 0.3m [149]. [153] listed less error, work-ability in mid-sized indoor workspaces, small sized tags, real-time data recording and streaming, cost efficient, among others as the reasons for choosing UWB for a workers' tracking.

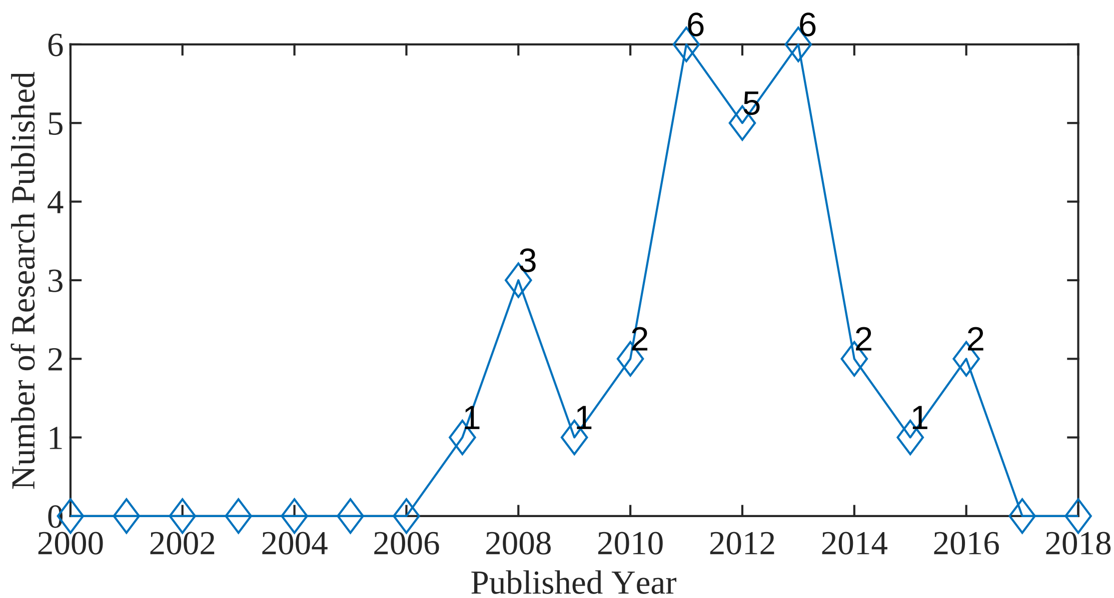

Fig. 2.12. Trend line of UWB use in construction workers' safety

2.8.2 Range Camera

Range camera is the technology used to produce a two-dimensional (2D) image showing the distance to points in a scene from a specific point. The range image has pixel values which can be converted into physical distance. The biggest and unique advantage of using a range camera is to track moving objects in real-time at high-frame update rates approximate to the television update rate [24]. Like the UWB technology, the use of range camera for construction workers' safety tracking was tracked back to 2007. Twenty-five different published research papers were found regarding the use of range camera. Depth sensor camera (Kinect) [29, 183, 184, 187, 329], 3D range video camera [24], 3D range image camera [26–28, 294], flash laser detection and ranging (LADAR) [25] were among the different types of range cameras used in the published research. Figure 2.13 shows the trend line of the use of UWB for enhancing construction workers' safety. The range camera was used to track the location, motion, and posture of the construction workers.

The most significant advantage of range camera sensors is the ability to collect dense point cloud range data in real-time of a larger field of view, safe and concise data acquisition, competitive prices, among others [24]. And, data noise resulting inaccuracies, non-optimal manufacturing of camera device, line-of-sight producing shadow effects, among others are some of the limitations of the range camera [24].

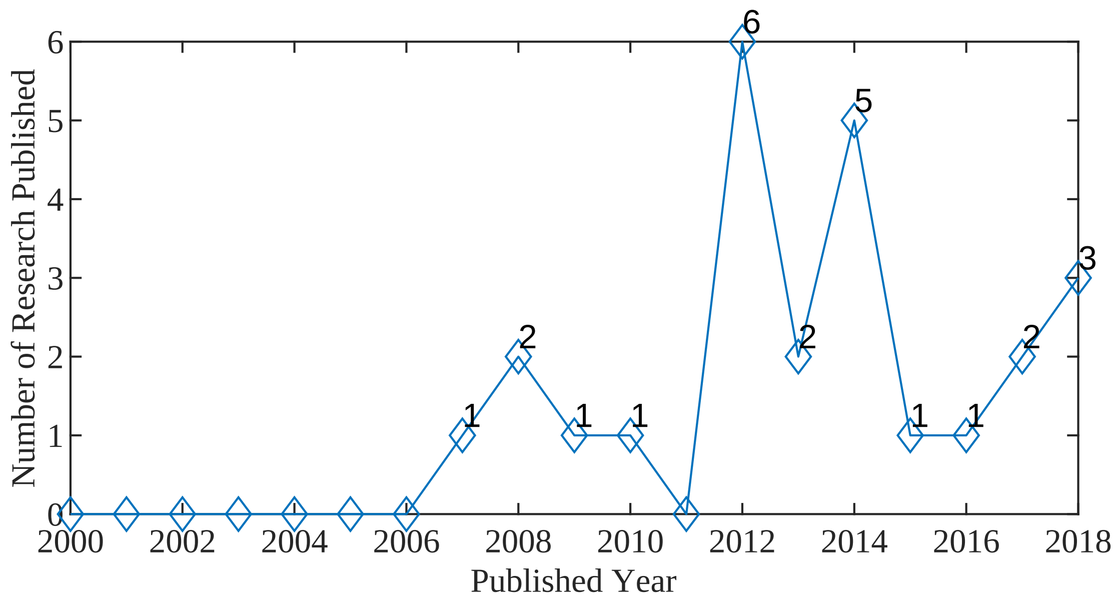

Fig. 2.13. Trend line of range camera use in tracking construction workers' safety

2.8.3 Computer Vision

The computer vision is concerned with the automatic extraction, analysis, and understanding of useful information from a single image or a sequence of images which involves the development of a theoretical and algorithmic basis to achieve automatic visual understanding [330]. Digital cameras and time-lapse photography which can capture stationary or visual images are categorized as computer vision. The digital camera is the camera which can capture the images and store them in digital memory. It is used to capture the stationary images as well as the visual motion. The data collection rate for computer vision technology varies from 5 Hz to 120 Hz depending upon the nature of data required and the quality of the technology used. The types of data collected from computer vision vary with the nature of the research such as numeric data, photographic image, and visual image. They were used directly as well as indirectly to track the construction workers' safety. [16–

19, 94, 95, 102, 172, 284] used the computer vision technology directly to track the location of the construction workers, [21, 161, 171–175] used it for tracking motion, [27, 173] for posture tracking, and [100, 108, 168, 172, 210, 212, 284] for visualization; whereas [82, 96, 98, 111, 118, 146, 163, 166, 250] used the computer vision technology indirectly to visualize and validate the use of other technologies for enhancing construction workers' safety. Sixty-seven different published papers used computer vision directly/ indirectly for tracking workers' safety. Figure 2.14 shows the trend line of the use of computer vision for tracking and enhancing construction workers' safety. It can be inferred from the figure that the use of computer vision is still rising and bears potential in tracking and enhancing the safety.

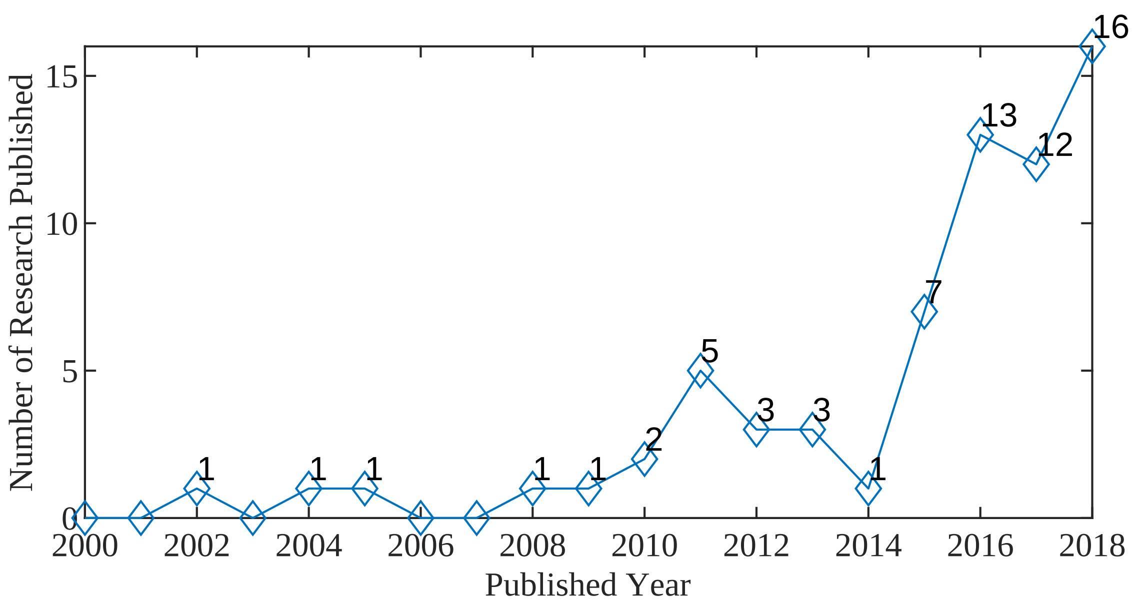

Fig. 2.14. Trend line of computer vision use in tracking construction workers' safety

2.8.4 Inertial Measurement Unit (IMU)

The inertial measurement unit (IMU) is defined as a device that uses measurement systems such as gyroscopes and accelerometers to estimate the relative position (x, y, z), orientation (roll, pitch, yaw), velocity, and acceleration of a moving object with respect to an inertial frame [331]. The data collected from the IMU sensors attached to construction workers' bodies are used to analyze the workers' bodily response. It is used to track personal factors such as location, motion, and posture of construction workers. [108–111] used the IMU for construction workers' location tracking, [110, 164, 177] for motion tracking, and [202–204] for posture tracking. Twelve different published papers used IMU for tracking construction workers' safety. The use of IMU for workers' safety research was found to be started from 2010 (1 no.) which increased to 5 nos. in 2016. The data transfer rate of IMU varied and was found to be varying from 10 Hz to 128 Hz in different published researches.

2.8.5 Radio Frequency Identification (RFID) System

The radio frequency identification (RFID) is a form of wireless communication that allows for the automated remote identification of objects [332]. The major components of an RFID system are tags or transponders that are affixed to objects of interests and readers or interrogators that communicate remotely with the tags to enable identification [332]. Better range, no need for a line of sight, multiple tags readability, reliability among others are the significant advantages of RFID [332].

2.9 Conclusion and Limitations

A detailed tabular index was created that contained the critical information (the type of data, data transfer rate, range, accuracy, the task performed, and citations) of different technologies used to track different construction workers' factors. Additionally, some visual maps were created showing the major technologies validated by researchers to track construction workers' safety. Academic researchers can use this index to get an overview of different technologies proven to be useful for tracking and enhancing construction workers' safety. Also, construction professionals can use the index to find suitable technology and its methodology relevant to ensuring workers' safety as per site requirements.

Among the identified personal, organizational, and environmental factors tracking the construction workers' safety, the authors found that the researchers prioritized tracking personal factors (physical, psychological, physiological, and visualization). The location tracking of construction workers implementing different technologies was of key interest to the researchers to enhance safety. Also, the authors found the rise in the research validating the applicability of computer vision in tracking construction workers' safety.

Additionally, the authors found an overall increase in the use of technology for enhancing and tracking construction workers' safety every year. The findings from the literature review indicate that new technologies have the potential to capture real-time data and assist in minimizing accidents as well as resolving disputes after accidents. It needs to be acknowledged that privacy and accountability, that comes with the implementation of technology, have not been addressed in this chapter. Although there might be several other latest technologies that can be implemented to track construction workers' safety, only the technologies that are already available and validated in construction site by researchers, have been introduced.

Construction work-related injuries have always been a major challenge to the construction industry resulting in loss of life, workers' disability, schedule delay, increased cost, compensation claims, and legal disputes, among others. While legal affairs and dispute mitigation have been traditionally focused on contracts and human involvements, this chapter shows a new trend that can change the way legal issues are dealt with in the future. First, the tabular index and visual map generated from the literature review aid in enhancing site safety by providing a catalog for the construction personnel to get the required information regarding the selection of suitable technology that can be implemented in a construction site. Second, in case of injury, the authors identified the list of potential technologies that can be implemented to collect real-time data that can assist in pinpointing the cause of injury and play a key role in dispute resolution, if any.

From this literature review, the authors identified several technologies that researchers used for tracking the construction workers' safety. Also, many construction workers' safety-related factors were identified. All this information was coded in the text using the qualitative analysis software, NVIVO. With the current advancement in technology, an algorithm can be created using machine learning (ML) and natural language processing (NLP) to automatically generate all the required information for each technology from the pool of relevant research papers. Also, a similar algorithm can be developed to create a similar visual map for any data of interest.

Not all workers might feel comfortable being tracked and monitored while working due to the privacy issue. Similarly, in case of any injuries, the ownership of the data can be another issue. And with the datafication comes the risk of a potential data breach. Further research is needed to address all these issues which are not considered in the scope of this literature review.

2.10 Data Availability Statement

Data generated or analyzed during the study are available from the corresponding author by request.

2.11 List of Cases

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CHAPTER 3

OBJECTIVE AND SCOPE

The literature review described in Chapter 2 highlights the importance of ergonomic safety of construction workers. Several researchers identified MSDs such as neck disorder, shoulder disorder, wrist/hand disorder, lower back disorder, and knee disorder, among others, as a major problem in construction workers. This necessitates the development of a control system to maximize the safety level and thrive for higher safety benchmark in construction projects. This study aims to investigate the existence of the *safety frontier*, on a construction site. From literature review, we also identified several factors affecting the construction workers' behavior causing safety inefficiencies. The framework includes the identification of the *system inefficiencies* and *operational inefficiencies* from real construction site to define *sustainable safety* and *observed safety*. The framework focuses on repetitive labor-intensive operations and considers both kinetic and kinematic aspect of labor safety. The following hypothesis will be tested to fulfill this aim:

1. There exists a theoretical maximum level of safety, *safety frontier* for a given construction task.

2. The theoretical maximum level of safety, *safety frontier* can be determined using the proposed methodology.

3. A safety control system can be developed by identification and removal of *system inefficiencies* and *operational inefficiencies* to obtain *sustainable safety.*

The scope of this study is limited to lower back safety as we identified lower back related MSDs to be the most common issue among construction workers. Furthermore, among numerous repetitive labor-intensive activities occurring in a construction site, we only selected manual material handling and metal plate folding activities due to the availability of real construction site data. From the literature review, we identified several technologies that could be implemented to track human skeletal. We chose depth sensing camera, *Kinect* to track postural data for this study because of its several features such as economic, availability, ability to track multiple workers at a time, robustness, and accuracy, among others. Also, several researchers already validated the applicability of *Kinect* for skeletal tracking in construction site.

CHAPTER 4

COMPUTATION OF SAFETY FRONTIER

Sensor-based computational approach to prevent back injuries in construction workers[a]

Sudip SUBEDI[1], Nipesh PRADHANANGA[2]

Abstract

Repetitive labor-intensive tasks are common in civil construction projects. Construction workers are prone to getting into musculoskeletal disorders-related injuries while performing such activities. The research proposes a novel approach to identify the theoretical maximum attainable level of safety, *safety frontier*, for a given construction task that can be achieved in perfect conditions under good management. The chapter outlines the method and the framework components and provides demonstration through a real construction-lab-based case study. The case study includes computation of *safety frontier* for lifting and setting down tasks. For this, we propose to use a depth sensor camera (Kinect) for workers' postural data collection while performing the task. With the postural data as an input feature, all the unique actions are identified for each movement frame using a random forest classifier model. Also, we propose to develop a moment prediction model to predict

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the lower back moment exerted in each movement frame. The lower back moment is computed using inverse kinematics and inverse dynamic in *OpenSim* for the training data set. Then, we implement a random forest regression algorithm to create a moment prediction model with postural data and velocity as input features. Finally, the safe work posture, *safety frontier* is computed, combining the unique actions exerting minimum lower back moment. The computed *safety frontier* can potentially help the safety managers to improve their safety strategies by providing a higher safety benchmark for monitoring their construction site.

Keywords: Safety frontier, Musculoskeletal disorder, Construction workers' safety, Random forest classifier, Random forest regression, OpenSim

4.1 Introduction

Construction researchers and industrialists are working hand-in-hand to enhance the overall safety of the construction site [1, 2]. In the past few decades, there has been a significant improvement in construction safety [3–8]. Researchers have done several studies and implemented them to improve the construction methodology [9], equipment safety [4, 10–12], and workers' safety [6, 13–15]. Also, researchers have identified numerous technologies, such as inertial measurement unit (IMU) [16, 17], computer vision [18–20], and depth sensor camera [21–24] among others, to ensure the safety of materials, equipment, and workers in the construction field. Besides, safety regulation agencies, such as the Occupational Safety and Health Administration (OSHA), continuously monitor workplace safety. These improvements have significantly reduced the injury rate occurring on a construction site [25].

Despite this, the construction industry is still considered a high-risk industry for work-related musculoskeletal disorders (MSDs) [26]. CDC [27] defined MSDs as, “soft tissue injuries caused by sudden or sustained exposure to repetitive motion, force, vibration, or awkward positions”. MSDs are common among construction workers performing repetitive labor-intensive activities such as masonry work, reinforcement bar fabrication & installation, concrete work, tile work, drywall installation, among others [17]. These activities are physically demanding in nature, exposing construction workers to high force exertion, awkward & unsafe body posture (such as bending, twisting, and kneeling), heavy lifting, repetitive motions, and vibration [28, 29]. MSDs affect the muscles, tendons, ligaments, joints, peripheral nerves, and supporting blood vessels in the body [30] and include back injuries, tendinitis, degenerative disc disease, and white finger disease. Furthermore, the dynamic nature of the construction site makes it difficult to monitor the workers' ergonomic safety manually [31]. It underlines the necessity for developing an automated control system to monitor, identify, and reduce the postural hazards contributing to MSDs among construction workers performing repetitive labor-intensive activities.

Researchers have already labeled MSDs as crucial health issues among construction workers performing repetitive labor-intensive activities [32–34]. They have identified several MSDs related risk factors among construction workers such as overexertion, awkward body postures, pressure pinch points, excessive vibration, bending and twisting, and working in static positions, among others [26, 34, 35]. Umer et al. [36] found that more than 50% of the construction workers suffer from lower back MSDs symptoms worldwide from the literature review. Inyang et al. [37] identified bodily reaction and exertion injuries as the second-highest cause of lost-time claims (LTC) surpassed only by falls within 2006-2010. Labor-intensive activities require workers to stay in the same or an awkward posture for an extended time, increasing the risk of MSDs [38]. The major MSDs for construction workers include neck disorder, wrist/hand disorder, lower back disorder, shoulder disorder, and knee disorder [32].

Similarly, a survey among the construction workers revealed the back, knee, and shoulder as the body regions with the highest prevalence of MSDs [33]. Ray and Teizer [39] identified overexertion and unsafe posture as the leading cause of MSDs among construction workers performing repetitive labor-intensive activities such as lifting, pushing, pulling, and carrying. Moreover, researchers proposed several MSDs exposure assessment techniques such as self-assessment [40–44], observational techniques [31, 43, 45–47], and instrument-based techniques [36, 41, 48–51]. Previous studies have also recommended some preventive solutions to reduce MSDs exposure such as providing safety training [39, 52], monitoring workers' postural behavior [53–55], implementing wearable-sensor-based real-time motion warning system [17], among others.

Past studies are focused on assessing and monitoring workers' postural behavior to assess MSDs-related injuries. However, few or no studies have identified the possible safest way to perform a given activity. Moreover, the current safety monitoring system depends upon the guidelines provided by regulating agencies such as OSHA. The OSHA standard interpretation 1926.760(a) states that *"OSHA standards set minimum safety and health requirements; they do not prohibit employers from adopting more stringent requirements"* [56], further highlighting the need for the identification of a higher safety benchmark.

Despite the existing safety standards, the cost of MSDs in the US is about $45-54 billion a year [57, 58]. Although the exact cost of MSDs has not been estimated for the construction industry, researchers found that more than 50% of construction workers suffer from symptoms of low back pain and MSDs annually around the globe [59]. Moreover, the average cost of MSDs is estimated at around $15K per injury [60]. Not all MSDs are caused by failure to abide by the safety standards. Repetitive labor-intensive activities have a significant risk of MSDs-related injuries even while following the safety standards [61]. Some of the reasons include the need for doing the same motion repeatedly, performing motions constantly without breaks, maintaining an awkward posture while performing the activity, and staying in the same posture for a long time [61]. Repetitive activities require performing multiple tasks involving the same muscles and tissues, leading to fatigue and exertion [62]. It further strengthens the need to improve the safety behavior above and beyond the safety standards to reduce the risk of MSDs-related injuries.

4.2 Research Background

MSDs are a crucial health problem among construction workers [63]. It substantially impacts the workers' quality of life and has a substantial economic burden related to compensation, medical expenses, lost wages, and reduced productivity, among others [63, 64]. The physically demanding nature of construction activities often results workers' exhaustion at the end of the day [63]. Yan et al. [17] found lower back injuries a severe issue among the rebar fabricating and installing workers in in-situ concrete work. Similarly, Goldsheyder et al. [35] found that about 77% of workers suffered from at least one MSDs, and lower back pain was the most frequently experienced MSDs among concrete workers. Crane operators and painters have a higher risk of neck disorders, while roofers and floorers are prone to MSDs in the lower back and lower extremities [26]. Likewise, rebar workers are vulnerable to lower back MSDs as they need to bend forward in a stooping or squatting posture frequently to tie reinforcement bars [36].

Moreover, drywall installers reported a high rate of the lower back, hand, waist, and shoulder-related MSDs due to overexertion from heavy manual materials handling tasks during drywall installation [65]. It warrants MSDs as a significant issue among construction workers performing repetitive labor-intensive activities. For all construction trades, the lower back injury was the most common type of MSDs; thus, the chapter's central focus.

4.2.1 Assessment of MSDs among Construction Workers

Researchers have carried out several studies exploring manual methods and the applicability of technology to assess the risk of MSDs mentioned in Section 4.1 among construction workers. The postural behavior of workers plays a governing role in the occurrence of MSDs. Kee and Karwowski [47] classified the postural classification methods into two categories depending upon the methods used for quantifying the postural stresses, instrument-based and observational techniques. As the latter does not require any equipment and does not interfere with the workers during observation, it is widely employed [47]. Also, possible implementation of technology such as computer vision [66], inertial measurement unit (IMU) [17], and electromyogram (EMG) [36], among others have already been explored.

Observational Methods for Assessing MSDs

The observational methods include Ovako working posture analysis system (OWAS) [45], rapid upper limb assessment (RULA) [67], rapid entire body assessment (REBA) [46], loading on the upper body assessment (LUBA) [47], task recording and analysis on computer (TRAC) [68], posture, activity, tools & handling (PATH) method

[31, 69], postural workload evaluation system (PLES) [70] as well as subjective questionnaires [34].

Ovako Working Posture Analysis System (OWAS) OWAS [45] is used to identify poor working postures. It is widely used in several industries for postural analysis, including the construction industry [71]. The system includes the observational technique for evaluating the work postures and a set of criteria for the redesign of working methods and places [45]. Despite being inexpensive and practical, OWAS still lacks precision and is time-consuming as it relies solely on manual observation. We can overcome this by implementing the recent computer vision techniques showing great potential for automated and real-time ergonomic analysis in construction.

Rapid Upper Limb Assessment (RULA) RULA [67] is a surveying method for investigating the exposure of workers to risk factors associated with work-related upper limb disorders. It provides a rapid assessment of the loads on the musculoskeletal system of workers to assess the possible exposure to upper limb disorders. It uses the information of different body postures and scoring tables to evaluate exposure to the risk factors such as the number of movements, static muscle work, force, work postures, and time worked without a break. Also, this system is manual, making it time-consuming and lacks precision. Manghisi et al. [72] has validated the use of a depth sensor camera (*Kinect V2*) for automated and real-time RULA assessment overcoming the shortcomings of the manual method. Haggag et al. [73] coupled the depth sensor camera (*Kinect V2*) with the RULA method for ergonomic assessment and identified joint occlusion as a significant challenge for using *Kinect V2*.

Rapid Entire Body Assessment (REBA) REBA [46] is a system aimed to develop a postural analysis system sensitive to musculoskeletal risks in a variety of task, divide the body into segments to be coded individually with reference to movement planes, provide a scoring system for muscle activity, give an action level with an indication of urgency, and require minimal equipment - pen and paper method. REBA is a subjective method for ergonomic assessment lacking detail and precision [74]. Also, REBA provides equal weight to factors such as twisting, lateral bending, and abduction regardless to what degree they exists (5° vs 25° twisting) [74, 75]. The inconsistency in reliability of ergonomic assessment among inter-rater and intra-rater over longer period is another limitation of REBA [76].

Loading on the Upper Body Assessment (LUBA) The LUBA [47] method computes the composite index of perceived discomfort, expressed as numerical ratio scores for a set of joint motions (including the hand, arm, neck, and back) and the corresponding data for maximum holding time in static postures. Each postural class is assigned a relative discomfort score. The ratio discomfort score makes it easy to quantitatively evaluate varying postural stresses and compare them across different postures. Thus a postural classification scheme, based on consideration of perceived discomfort and static holding times, can be used to assess postural stresses and prevent posture-related musculoskeletal disorders [47, 77]. The advantages of the method includes simple procedure, physiological data based scoring, and numerical output easing the decision-making compared to qualitative output [77]. However, as the LUBA method does not consider the factor of movement frequency, high-risk tasks are not well-identified [78].

Occupational Repetitive Action (OCRA) Method The OCRA [79, 80] method analyzes the workers' exposure to tasks featuring various upper limb risk factors. It evaluates the main collective factors such as excessive use of force, action frequency, inadequate recovery period, and awkward postures, among others, based on their respective duration. The OCRA index is the ratio between the number of technical actions carried out to complete the work and the number of recommended technical actions. The method involves manual observation by experienced technical specialists. The main disadvantages of OCRA includes the time required to compute all considered factors, especially the counting of the technical actions to estimate the frequency factor, and intra- and inter-subject assessment variability [81].

Instrument-based Methods for Assessing MSDs

Most of the previously mentioned methods are manual and time-consuming with less precision. Nevertheless, researchers have also done several studies to assess the risk of MSDs among construction workers by implementing technologies such as computer vision [66], inertial measurement unit (IMU) [17], electromyogram (EMG) [36], and depth sensor camera [51, 82], among others.

Computer Vision The construction industry has widely implemented computer vision in construction safety improvement studies, including the MSDs. Yu et al. [83] used it for recording RGB video to calculate joint capacity based on a joint capacity prediction equation using a computer vision algorithm. Similarly, Ohya et al. [84] used it for worker tracking, posture estimation, and behavior recognition using multiple video cameras. Additionally, Seo et al. [50] used it for kinematic measurement and evaluation while performing tasks to identify the fundamental causes of excessive physical demands. Some of the limitations of computer vision includes inability to accurately track 3D motion estimate due to severe vision obstructions, and need to measure the mass of materials and tools being used prior to working limiting the applicability in real construction projects [85].

Inertial Measurement Unit (IMU) The inertial measurement unit (IMU) sensors can measure real-time acceleration, angular velocity, and heading in 3D. It provides non-invasive, long-term, and ubiquitous tracking of body postures and movements [49]. Several researchers have validated the use of IMU for body posture and motion tracking to assess MSDs in workers [17, 49, 86]. Researchers have also identified some limitations for implementing IMU, such as the requirement of accessories (belts, straps), the possibility of detachment of sensors, workers' discomfort, and inconveniences, among others [87].

Depth Sensor Camera Researchers have validated the effectiveness of the depth sensor camera, such as the *Microsoft Kinect*, in tracking 3D human posture in real-time [50, 88]. Diego-Mas and Alcaide-Marzal [89] validated the use of a depth sensor camera for assessing the postures at work. Low precision, when the tracked subject is not facing the sensor or when a body part is occluded, is its main challenge [89]. We can overcome these challenges by using multiple depth sensors [90, 91] and stochastic filters [92–94].

Despite all the aforestated efforts, many workers are still suffering from MSDs [34]. The reason is that construction workers are dispersed randomly in a construction site with only a handful of safety personnel to monitor the overall site safety. Furthermore, it is difficult for a handful of safety personnel to monitor the construction workers individually and perceive the potential postural risks, necessitating an automated control system to monitor the construction workers' activity. Besides, safety-related risk perception is subjective [6], and safety personnel uses the minimum guidelines provided by safety regulatory agencies such as OSHA to monitor the workers [56]. Despite several quantitative MSDs exposure assessment techniques, few or no studies focused on quantitative measurement of the maximum level of safety that can be achieved (hereafter called "*maximum achievable level of safety*") in a construction site. So, there is a need for identifying a higher safety benchmark that can act as a guideline for monitoring workers' safety behavior rather than just fulfilling the safety standards. For this, we proposed to use the frontier approach to define the maximum attainable level of safety. The presented method analyzes different instances of the repetitive labor-intensive activity separately, identifies the involved unique actions, breaks it down to several movements, identifies the safest movements for each unique actions, and then combines them together to get the safe work procedure.

The frontier approach principally differs from existing studies. First, the proposed model collects data from the same worker for multiple instances of the same task and identifies the safest procedure based on the worker's performance to get the individualized safe work procedure. Second, several workers' individual safe work procedures are analyzed together to compute the general safe work procedure. It provides construction workers a unique opportunity to learn from themselves and their co-workers' performance. Moreover, the computed general safe work procedure allows the safety personnel and workers to identify and aim for the maximum possible level of safety instead of assessing compliance with the regulatory safety requirements. Furthermore, this approach provides a peer learning platform for the workers to learn about the safe work procedure.

4.3 Frontier Approach

4.3.1 Motivation

In 1991, Joyner [95] worked on optimizing human performance to predict the minimum marathon running time and proposed it to be 1:57:58. The world record then was 2:06:50 (Ethiopia's Belayneh Dinsamo at the 1988 Rotterdam Marathon, Netherland) [96], which was nearly 9 minutes more than Joyner predicted. After 28 years, the athlete Eliud Kipchoge set a new record by finishing the marathon in a record time of 1:59:40 [97]. Instead of trying to beat the existing world record, athletes got a higher benchmark to attain and improve running skills, encouraging them to break the two-hour mark for completing the marathon.

We can implement a similar concept to improve the construction workers' safety. Similar to Joyner [95] approach, if we identify the safe work procedure providing the theoretical maximum achievable level of safety for any given activity, then we can implement it as a higher index for construction workers' safety monitoring. Moreover, we can educate, train, and encourage workers to aim for the higher index instead of maintaining minimum safety standards.

4.3.2 Frontier in Construction Industry

The frontier approach has been widely used in the production field [98–102]. The *production frontier* is defined as the maximum output obtained from a given set of inputs [103, 104] in which the cost function acts as an input parameter, and the profit function acts as an output parameter. The lower cost function and the higher profit function mean the higher *production frontier* [104]. Son and Rojas [105] introduced the terminology *productivity frontier* in the construction domain and defined it as "the theoretical maximum productivity that could be achieved under perfect conditions." Time and motion study was a basis for the estimation of *productivity frontier* [106]. Time and motion studies [107] are generally conducted to collect and analyze the site data [108]. Time and motion studies determine the actual time required to accomplish a specific task [107] by observing the performance of well-trained workers [109].

Mani [110] adopted a concept of inverse mean-variance optimization, hierarchical analysis, and probability distribution theory to yield a robust calculation of the productivity frontier. According to inverse mean-variance optimization, the lower one moves in a structured hierarchy, the more variability one sees within the contributing components [110]. Higher variability is beneficial because it helps to identify the shortest theoretical duration, which means the highest productivity when time is a measurable metric.

4.3.3 Proposed Safety Frontier Approach

Based on the frontier concept, the study proposes four different levels of safety dynamics: (i) *Safety Standard*, (ii) *Observed Safety*, (iii) *Safety Frontier*, and (iv) *Sustainable Safety*. We defined the safety dynamics as "the process of assessing different levels of workers' safety existing in a changing construction environment." The following sub-sections describe each component to provide a general idea of the proposed safety dynamics. However, the scope of the chapter is only limited to the computation of the *safety frontier*.

Safety Standard

Safety standard is the minimum level of safety required by regulatory agencies such as OSHA, EU-OSHA, or the construction company itself, for a given task and field conditions. The OSHA monitors the safety practice in the US. It has the right to inspect or investigate the matter of compliance with safety and health standards. The OSHA may choose to issue citations and financial penalties to the employer for violating specific OSHA standards or regulations.

Observed Safety

The *observed safety* is the actual level of safety observed in the construction site, which can be above or below the *safety standard*. The injury risk increases when the *observed safety* is below the *safety standard*. The regulatory agencies and the site safety manager continuously monitor the construction site to ensure the *observed safety* is above the *safety standard*. Manual or real-time sensor data might be required to measure and record observed safety, depending upon the factor to be examined. Researchers have identified technologies such as ultra-wideband (UWB) [111], IMU [17], computer vision [83], depth sensor camera [51, 82], and manual observation techniques such as OCRA [79], RULA [67], REBA [46], among others, for real-time monitoring of observed safety.

Safety Frontier

Safety frontier is a novel concept and we defined it as "*the theoretical maximum attainable level of safety while performing any construction task under perfect condition*" [112]. *Perfect condition* is an ideal state where all factors affecting construction workers' safety are at their most favorable levels, such as good weather, highly motivated and trained workers with flawless artisanship, an ergonomically safe working posture or poses of workers, optimal safe utilization of materials and equipment, no interference from other trades, no design errors, no equipment failures, no fatigue, no injury, no loss of life, and precise understanding of the design intent, among others.

Because of several inefficiencies inherent to the construction process, perfect conditions are virtually unachievable in the construction site. The inefficiencies in a construction site can be summarized into two categories, *system inefficiencies* and *operational inefficiencies* [110, 112]. Mani [110] has provided the detailed methodology to identify and compute the *system* and *operational inefficiencies* for construction productivity frontier. We will implement a similar approach to identify the inefficiencies, which is beyond the scope of the chapter.

System Inefficiencies *System inefficiencies* imply the loss in the level of safety due to factors that are not under the control of a project manager, such as environmental conditions (high humidity, cold or hot temperatures), workers' health, absenteeism driven by health or family issues, interference from other trades, design errors, behavior and intention of workers, and unsafe or uncertain conditions due to mechanical failures of equipment among others [112]. Based upon the characteristics of activity or task, the number and type of factors causing the *system inefficiencies* vary. For instance, the influencing factors for a manual lifting task can be working behavior and health conditions of that worker, disturbances by other people on the way during hauling, hot or cold temperature, and high humidity.

Operational Inefficiencies *Operational inefficiencies* refer to the loss in the level of safety due to factors that are under the control of a project manager, such as poor sequencing of activities, inadequate and improper or unsafe utilization of equipment or tools, excessive overtime, untrained or unskilled workers, poor lighting conditions, the mismatch between skills and task complexity, and carelessness of workers, among others [112]. For a manual lifting task, if the worker does not know how to properly (ergonomically safely) lift and haul the object and if that worker does not care about the working procedure, then these factors can play a significant role in operational inefficiencies. These inefficiencies can be minimized by providing training on time.

Sustainable Safety

Sustainable safety is defined as the highest level of safety that can be achieved and sustained under good management and typical site conditions [112]. Good management is considered as the best acceptable level of proficiency in the project team. Typical field conditions are project site circumstances as per the construction industry standard, excluding adverse events such as natural disasters and labor-union conflicts.

Upper Limit of Sustainable Safety The *safety frontier* is the theoretical maximum level of safety which is virtually impossible to achieve due to underlying inefficiencies in the construction process. If we add the *system inefficiencies* to the *safety frontier*, we get the upper limit of safety that can actually be achieved and sustained in a real construction site (hereinafter referred to as the *upper limit of sustainable safety*).

Lower Limit of Sustainable Safety The *observed safety* has higher probability of underlying inefficiencies, both *system* and *operational.* If we remove the *operational inefficiencies*, we get the lower limit of safety that can actually be achieved and sustained in a real construction site (hereinafter referred to as the *lower limit of sustainable safety*).

The safety dynamics components can be better represented by a conceptual radar chart shown in Figure 4.1. The radial lines represent the factors that affect the workers' safety on a construction site. These factors can be categorized into personal, organizational, regulatory, and environmental factors.

Personal Factors Personal factors are related to an individual that can influence how they act and behave, such as attitude, motivation, and ability to perform a task. Subedi and Pradhananga [113, 114] categorized personal factors into different sub-factors; physical (location, motion, posture, vision), psychological (risk perception, vigilance), physiological (breathing rate, electrical activity, heart rate, skin temperature, maximum voluntary contraction, among others), and visualization.

Environmental Factors These factors relate to site conditions such as tidiness, relative humidity, oxygen level, and temperature, among others [114].

Organizational Factors These factor relate to safety management, group interactions, safety policy, and trade union involvement, among others [114, 115].

Regulatory Factors These relate to safety regulations such as fall protection requirements, proper scaffolding, safety net, regular safety training, and provision of personnel protective equipment, among others.

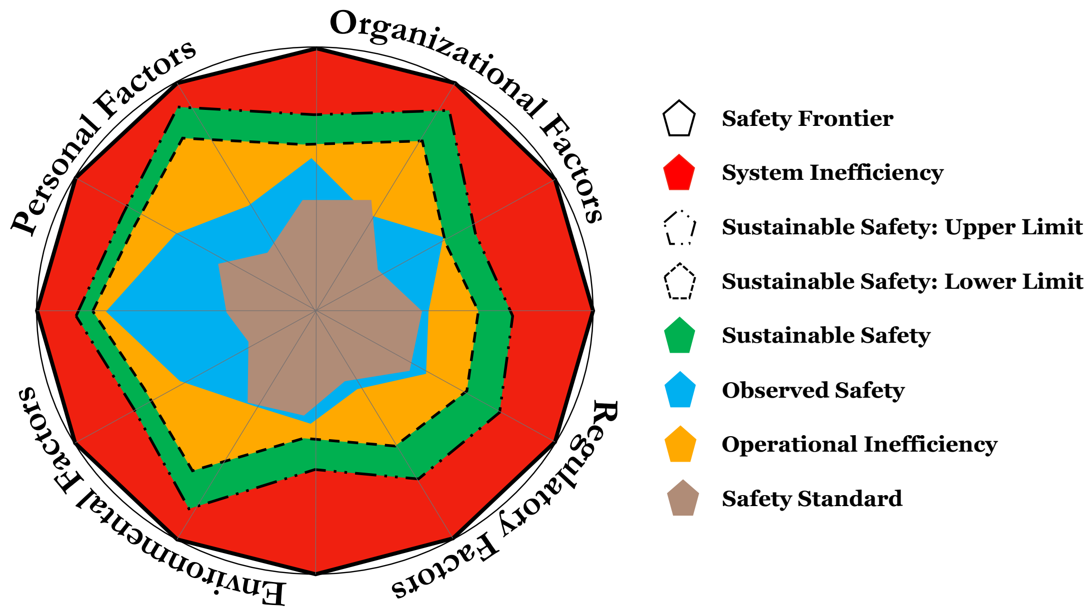

Fig. 4.1. Conceptual radar chart with safety dynamics components for various factors [112]

We can determine the current safety level by manually observing the site or by real-time data collection for each factor. The outermost solid line represents the *safety frontier* in Figure 4.1. If we add the *system inefficiencies*, represented by the red shaded region, we will get the *upper limit of sustainable safety*, represented by the dashed-dot-dot line in the figure. Similarly, the blue shaded region represents the *observed safety*, above or below the *safety standard* represented by the brown shaded region in the figure. The brown region crossing the blue region represents the possible hazardous situation or an injury. The *observed safety* has *operational inefficiencies* which can be removed under good management. If we remove the *operational inefficiencies*, represented by the orange shaded region in the figure, from the *observed safety*, then we will get the *lower limit of sustainable safety* represented by the dashed line in the figure. Any safety behavior between the upper and lower limit of *sustainable safety*, represented by the green shaded region in the figure, is *sustainable safety*. For the chosen set of factors, Figure 4.1 will give the safety status and will also provide insight into the areas needing improvement at a glance. Figure 4.2 shows the proposed framework for computation of aforestated *safety frontier* and *sustainable safety*. As mentioned earlier, the chapter focuses only on identifying the *safety frontier*.

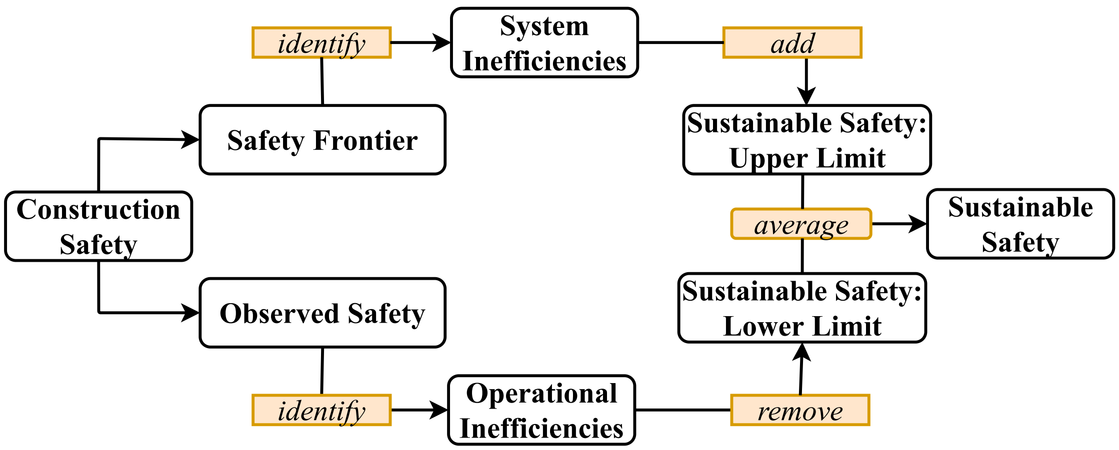

Fig. 4.2. Framework to develop the safety control system

4.4 Objective and Scope

The overall objective of the research is to develop a control system (refer to Figure 4.2) that can identify the theoretical maximum achievable level of safety, *safety frontier*, incorporate existing *inefficiencies*, and compute the *sustainable safety* that can be achieved and sustained in a construction site. However, the chapter's scope is limited to developing and demonstrating the prototype system to compute the *safety frontier*.

4.5 Methodology

This chapter proposed the frontier approach for developing a prototype system for achieving *safety frontier* for repetitive labor-intensive tasks. First, we extracted the postural data while performing a repetitive labor-intensive task using a depth sensor camera. Then, we implemented an inverse dynamics principle to compute the moment exerted on the joints. We used the computed moment and corresponding postural data to develop prediction models to classify the movements into different unique actions involved in the tasks, and predict the moment exerted on joints.

The scope of the chapter incorporates proposing the concept of *safety frontier* approach and validating it via a case study, not validating the accuracy of the implemented machine learning algorithm, efficiency and accuracy of implemented technology, or the system's applicability to monitor the onsite workers' safety. Figure 4.3 shows the details of the proposed methodology.

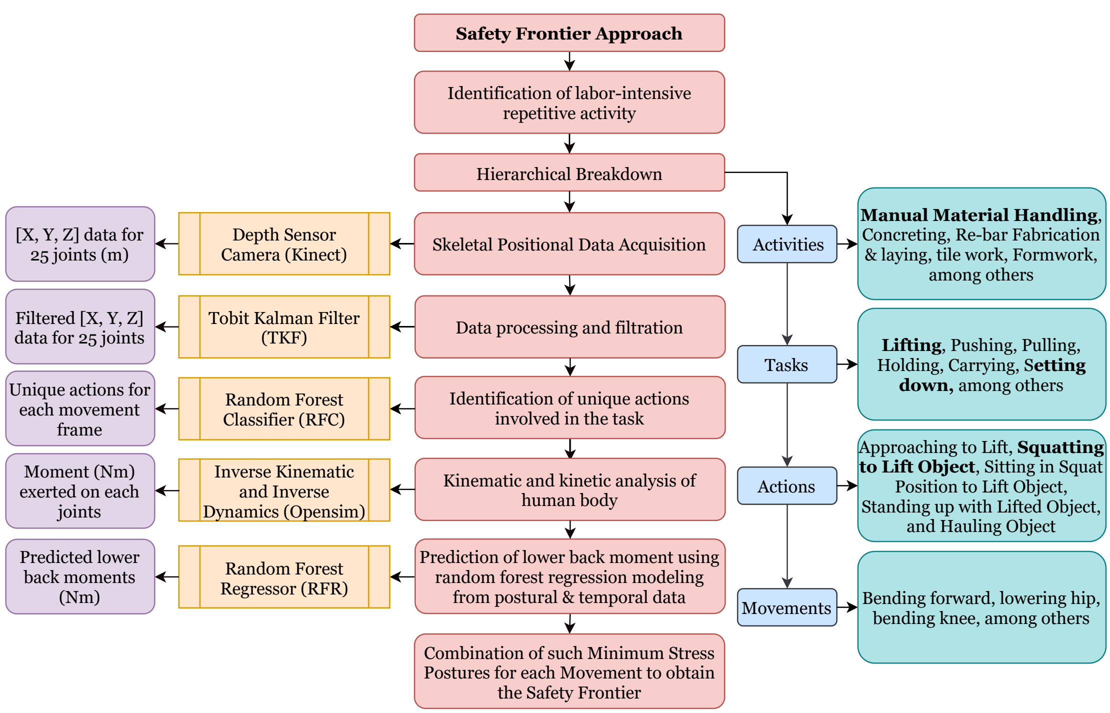

Fig. 4.3. Methodology to define *safety frontier*

4.5.1 Identification of Labor-Intensive Repetitive Activity

Despite the availability of advanced equipment, methodology, and tools & plants, most of the construction activities are still labor-intensive and repetitive. Reinforcement bar fabrication & placement, concreting work, masonry work, and tile work are some of the labor-intensive repetitive activities occurring at the construction site. Among these, we chose the manual material handling activity (lifting and setting down tasks) for the scope of this chapter.

- **An Activity:** An activity is the collection of tasks representing the specific unit of work with spatial limits and/or dimensions [116]. Masonry work, reinforcement bar fabrication & installation, tile work, formwork, manual material handling, and concreting work, among others, are some of the activities on the construction site.
- **A Task:** A task is the lowest recognizable work-related characteristic. A combination of integrated tasks makes up an activity [117]. For a manual material handling activity, lifting, pushing, pulling, holding, carrying, and setting down, among others, are some of the tasks involved.
- **An Action:** An action is a motion that performs a single element of a task. A combination of integrated actions makes up a task. For a lifting task, approaching the object to be lifted, standing erect close to the object, squatting to lift, staying in a squat position to lift, and squatting up with the lifted object, among others, are some of the actions involved.
- **A Movement:** A movement is the lowest level of the construction operational taxonomy that corresponds to the divisible gestures of the body performing an action. For squatting to lift action, bending forward, lowering hip, and bending knee, among others, are some of the movements involved.

4.5.2 Skeletal Positional Data Acquisition

For the complete hierarchical breakdown of activity, we need to identify involved movements. In general, these movements can be identified by existing methods, such as direct manual observation [118], recorded video observation [119], and physiological measurements (accelerometers [120], motion sensors [121], lumbar motion monitor [122], depth sensor camera [82], computer vision [123]), among others. Among these methods, the physiological measurement methods provide higher accuracy and quantitative data. However, each method has its limitations, such as associated cost, comfort, invasiveness, robustness, and adaptability in the site environment, among others..

We chose a depth sensor camera (*Xbox One Kinect v2.0 Sensor for Windows SDK*) for the skeletal position data acquisition due to its features such as non-invasive, low cost, robustness, ability to track multiple workers, and adaptability in the site environment, among others. It can track the skeletal positional data of construction workers while performing the task in the real field. Figure 4.4 shows the major joints in the human body, joints detected by the depth sensor camera, and good & bad lifting postures [82].

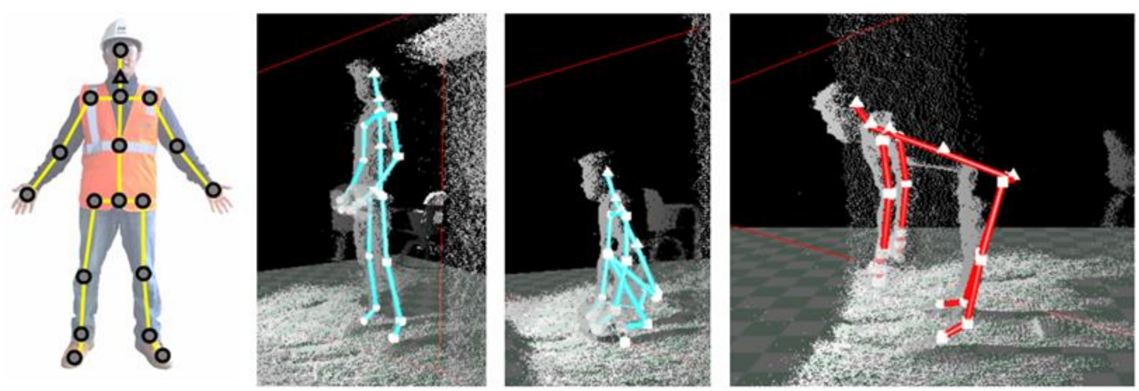

Fig. 4.4. (Left to right) Joints in the human body, joints detected by *Kinect* camera, good lifting posture, bad lifting posture in red

The skeletal data collected from the depth sensor camera generates noise because of self-occlusion, limited range, and lack of accuracy in fast movements [124]. The lifted object and the workers' body parts themselves can also create further occlusion. These occlusions distort the skeletal positional data by shifting the joints unreasonably. So, before further analysis, the collected data needs to be smoothed using stochastic filters such as moving average filter [125], Kalman filter (KF) [92], Savitzky-Golay filter (SGF) [93], Tobit-Kalman filter (TKF) [94], among others. We used TKF by taking joints' speed restrictions into account, as proposed by Loumponias et al. [124].

4.5.3 Data Processing and Filtration using TKF Model

Using the TKF model, the unknown state vector $\boldsymbol{x_k} \in \Re^n$ of a discrete time-varying system with censored measurement is governed by the equation 4.1 [94, 124]:

$$
\begin{aligned}
& x_k = Ax_{k-1} + w_{k-1}, \\
& y_k^* = Hx_k + v_k, \\
& y_k = \begin{cases} y_k^*, & T_l < y_k^* < T_u \\ T_l, & y_k^* < T_l \\ T_u, & y_k^* > T_u \end{cases}
\end{aligned}
\tag{4.1}
$$

where $\boldsymbol{x_k} \in \Re^{nx1}$ is the unknown state vector, $\boldsymbol{y_k^*} \in \Re^n$ is the uncensored measurement, $\boldsymbol{A} \in \Re^{nxn}$ is the state transition matrix, and $\boldsymbol{H} \in \Re^{nxn}$ is the measurement transition matrix. $\boldsymbol{w_k \sim N(0, Q_k)}$ and $\boldsymbol{v_k \sim N(0, R_k)}$ are the state and measurement Gaussian noise with zero mean and co-variance $\boldsymbol{Q_k} \in \Re^{nxn}$ and $\boldsymbol{R_k = \sigma^2} \in \Re^{nxn}$. Equation 4.1 represents the standard Kalman filter with added Tobit censored measurements, where $\boldsymbol{y_k} \in \Re^n$ is the censored measurement vector, $\boldsymbol{T_u} \in \Re^n$ and $\boldsymbol{T_l} \in \Re^n$ are upper and lower threshold vector.

The TKF model includes the predict stage and the update stage as defined by Bethany [94]:

The Predict Stage:

$$\hat{x}_k^- = A\hat{x}_{k-1}, \tag{4.2}$$

$$P_k^- = AP_{k-1}A^T + Q \tag{4.3}$$

where, $\hat{\boldsymbol{x}}_{\boldsymbol{k}}^-$ is the a priori state estimate at step $\boldsymbol{k}$ by assuming knowledge of the process history prior to step $\boldsymbol{k}$, $\hat{\boldsymbol{x}}_{\boldsymbol{k}}$ is the a posteriori state estimate at step $\boldsymbol{k}$ by assuming that the measurement $\boldsymbol{y_k}$ is given, $\boldsymbol{P_k^-}$ and $\boldsymbol{P_{k-1}}$ are the covariance matrices of the errors of the a priori and a posteriori state estimates, respectively.

The Update Stage:

$$R_1 = P_k^- H^T P_{un,k}, \tag{4.4}$$

$$R_2 = P_{un,k} H P_k^- H^T P_{un,k} + R_k^*, \tag{4.5}$$

$$K_k = R_1 R_2^{-1}, \tag{4.6}$$

$$\hat{x}_k = \hat{x}_k^- + K_k(y_k - E(y_k|\hat{x}_k^-)), \tag{4.7}$$

$$P_k = (I - K_k P_{un,k} H)P_k^- \tag{4.8}$$

where, $\boldsymbol{R_1}$ is the cross covariance, $\boldsymbol{H}$ is the observation matrix, $\boldsymbol{E(y_k|\hat{x}_k^-)}$ is the expected value of the measurement when censored and uncensored measurements are included, $\boldsymbol{P_{un,k}}$ is the probability of a measurement to be uncensored, $\boldsymbol{R_2}$ is the a priori measurement error covariance, $\boldsymbol{R_k^*}$ is the covariance matrix of the measurement, $\boldsymbol{K_k}$ is the Kalman gain.

$$E(y_k|\hat{x}_k^-) = P_{un,k}\left(H\hat{x}_k^- + R^{\frac{1}{2}} l_k\right) + P_{min,k}T_l + P_{max,k}T_u \tag{4.9}$$

$$P_{un,k} = diag \begin{bmatrix} \Phi\left(\dfrac{T_{u,1} - h_1\hat{x}^-_{k,1}}{\sigma_1}\right) - \Phi\left(\dfrac{T_{l,1} - h_1\hat{x}^-_{k,1}}{\sigma_1}\right) \\ \dots \\ \Phi\left(\dfrac{T_{u,m} - h_m\hat{x}^-_{k,m}}{\sigma_m}\right) - \Phi\left(\dfrac{T_{l,m} - h_m\hat{x}^-_{k,m}}{\sigma_m}\right) \end{bmatrix} \tag{4.10}$$

$$R^*_k = R\left(I + P^{-1}_{un,k} diag(c_k) - diag(l_k)^2\right) \tag{4.11}$$

where, the parameter $\boldsymbol{c_k}$ and $\boldsymbol{l_k}$ are given by

$$c_k = diag \begin{bmatrix} \dfrac{T_{l,1} - h_1\hat{x}^-_{k,1}}{\sigma_1}\phi\left(\dfrac{T_{l,1} - h_1\hat{x}^-_{k,1}}{\sigma_1}\right) - \dfrac{T_{u,1} - h_1\hat{x}^-_{k,1}}{\sigma_1}\phi\left(\dfrac{T_{u,1} - h_1\hat{x}^-_{k,1}}{\sigma_1}\right) \\ \dots \\ \dfrac{T_{l,m} - h_m\hat{x}^-_{k,m}}{\sigma_m}\phi\left(\dfrac{T_{l,m} - h_m\hat{x}^-_{k,m}}{\sigma_m}\right) - \dfrac{T_{u,m} - h_m\hat{x}^-_{k,m}}{\sigma_m}\phi\left(\dfrac{T_{u,m} - h_m\hat{x}^-_{k,m}}{\sigma_m}\right) \end{bmatrix}$$

$$l_k = P^{-1}_{un,k} \begin{bmatrix} \phi\left(\dfrac{T_{u,1} - h_1\hat{x}^-_{k,1}}{\sigma_1}\right) - \phi\left(\dfrac{T_{l,1} - h_1\hat{x}^-_{k,1}}{\sigma_1}\right) \\ \dots \\ \phi\left(\dfrac{T_{u,m} - h_m\hat{x}^-_{k,m}}{\sigma_m}\right) - \phi\left(\dfrac{T_{l,m} - h_m\hat{x}^-_{k,m}}{\sigma_m}\right) \end{bmatrix}$$

4.5.4 Action Identification Using Machine Learning

For the determination of the safety frontier, the identification of the unique actions involved is the most. Furthermore, several movements define unique actions. For instance, we can categorize the lifting and setting down tasks into five different unique actions based on the involved movement listed in Table 4.1.

Table 4.1. List of unique actions involved in lifting (L1-L5) and setting down (S1-S5) tasks

Actions involved in lifting and setting down tasks	**ID**
Approaching the object to be lifted	L1
Squatting down to lift the object	L2
Staying in squat position to lift the object	L3
Squatting up with lifted object	L4
Standing in an erect position with the lifted object	L5
Approaching the place to set down the lifted object	S1
Squatting down with the lifted object	S2
Staying in squat position to set down the lifted object	S3
Squatting up after setting down the lifted object	S4
Standing in an erect position	S5

The actions can be identified manually by observing each movement frame, which is time-consuming and virtually impossible to carry out in real-time. So we adopted a classification algorithm to make the process fast, reliable, and automated. Several researchers have already validated the use of classification models such as deep neural networks [126], decision trees [127], K-nearest neighbor [128], naive-Bayes [129], support vector machine [130], random forest [131], among others, for gait classification. Ray and Teizer [39] applied the classification algorithm to predict human posture using the *Kinect* feature extraction method. We chose the random forest model for action identification based on each movement frame. A random forest comprises unpruned decision trees and is often used with extensive training data having many input features [132]. For this study, the input features included positional data of 25 joints from the *Kinect* and their computed velocity resulting in 150 total features.

4.5.5 Kinematic and Kinetic Analysis of Human Motion

We can use the inverse kinematic principle to compute the motion data (joint angles and/or translations) from the skeletal positional data collected from the *Kinect*. Rotation of the joints can be computed using an equation 4.12.

$$R(\alpha, \beta, \gamma) = \begin{bmatrix} cos\alpha cos\beta & cos\alpha sin\beta sin\gamma - sin\alpha cos\gamma & cos\alpha sin\beta cos\gamma - sin\alpha sin\gamma \\ sin\alpha sin\beta & sin\alpha sin\beta sin\gamma - cos\alpha cos\gamma & sin\alpha sin\beta cos\gamma - cos\alpha sin\gamma \\ -sin\beta & cos\beta sin\gamma & sin\beta cos\gamma \end{bmatrix} \tag{4.12}$$

where $\boldsymbol{R}$ is the resultant rotation, $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, $\boldsymbol{\gamma}$ are the rotations about x, y, and z axis respectively

Similarly, we can compute relative forces at intersegmental joints on a human body using an inverse dynamic procedure [133]. The human skeleton forms a rigid body system in which Newton's equation of motion can be applied to distribute forces through the body and analyze the stress at all joints due to a load, shown in equations 4.13 and 4.14 proposed by Zhang and Hsiang [133].

$$F_p = \dot{P} - F_D - W \tag{4.13}$$

$$T_p = \dot{H} - T_D - L_D x F_D - W x d_i \tag{4.14}$$

where, $\boldsymbol{P}$ is the momentum of the segment, $\boldsymbol{H}$ is an angular momentum of the segment, $\boldsymbol{F_D}$ and $\boldsymbol{T_D}$ are the force and torque from the distal joint, $\boldsymbol{F_P}$ and $\boldsymbol{T_P}$ are the force and torque from the proximal joint, $\boldsymbol{L_D}$ is the segment length, $\boldsymbol{d_i}$ is the length from CG to the proximal joint, $\boldsymbol{W}$ is the gravity.

For realistic kinematic and kinetic motion analysis, we proposed to use a freely available open-source software system, *OpenSim* [134], that estimates the force and the moment exerted on human body joints due to changes in the velocity and direction of the motion [121].

Kinematic and Kinetic Analysis in OpenSim

OpenSim lets users develop musculoskeletal models and create dynamic simulations of movement. *OpenSim* is supported by the National Institutes of Health (NIH). For this research, we used the full-body lumbar spine (FBLS) model proposed by Raabe and Chaudhari [135]. The model consists of 21 segments, 30 degrees of freedom, and the five lumbar vertebrae that are modeled as individual bodies, each connected by a 6 degree of freedom joint [135].

Using the *Kinect* positional and temporal data, we scaled the model and performed the inverse kinematics (IK) analysis to obtain the generalized coordinate trajectories (joint angles and/or translations) in *OpenSim*. The IK analyzes each time frame of the *Kinect* data and identifies the best pose of the model that minimizes the sum of weighted squared errors of markers and/or coordinates, which is solved by using equation 4.15.

$$\min_{\mathbf{q}} \left[\sum_{i \in markers} w_i \parallel x_i^{exp} - x_i(q) \parallel^2 + \sum_{j \in unprscbcrds} \omega_j (q_j^{exp} - q_j)^2 \right] \tag{4.15}$$

where $\boldsymbol{q}$ is the vector of generalized coordinates of model, $\boldsymbol{x_i^{exp}}$ is the experimental position of marker i, $\boldsymbol{x_i(q)}$ is the position of corresponding marker on the model, $\boldsymbol{q_j^{exp}}$ is the experimental value for coordinate j, and $\boldsymbol{w}$ is the weight associated with the marker.

Using the result from the IK, we performed the inverse dynamics (ID) analysis for each movement frame to compute the force and moment exerted on human body joints. Equation 4.16 represents the equation of motion for a multibody system.

$$\underbrace{\mathbf{M}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{C}(\mathbf{q}, \dot{\mathbf{q}}) + \mathbf{G}(\mathbf{q})}_{knowns} = \underbrace{\tau}_{unknowns} \tag{4.16}$$

where $\boldsymbol{q}, \dot{\boldsymbol{q}}, \ddot{\boldsymbol{q}} \in \Re^N$ are the vectors of generalized positions, velocities, and accelerations, respectively; $\boldsymbol{N}$ is the number of degrees of freedom; $\boldsymbol{M}(\boldsymbol{q}) \in \Re^{NxN}$ is the system mass matrix; $\boldsymbol{C}(\boldsymbol{q}, \dot{\boldsymbol{q}}) \in \Re^N$ is the vector of Coriolis and centrifugal forces; $\boldsymbol{G}(\boldsymbol{q}) \in \Re^N$ is the vector of gravitational forces; and $\boldsymbol{G}(\boldsymbol{q}) \in \Re^N$ is the vector of unknown generalized forces.

Researchers have identified lower back pain as a major MSDs among construction workers [17, 136]. Thus, we prioritized the lower back-related MSDs in the dissertation. From the *OpenSim*, we computed the moment developed in different lower back muscles: erector spinae (ES), internal obliques (IO), external obliques (EO), psoas major (PS), quadratus lumborum (QL), multifidus (MF), iliocostalis lumborum (IL), and the latissimus dorsi (LD). We identified the PS and LD as the major muscles with higher moment exerted when performing the lifting and setting down tasks. Furthermore, we found that the moment exerted on PS_L1_VB muscle (referred to as "lower back moment" onward) represented the lifting behavior significantly and was used for further analysis. Researchers have identified the involvement of psoas major muscle during upright standing, forward bending, and lifting [137]. Also, these are major actions involved in manual material handling activity. In addition, to accelerate and automate the whole process, we used the random forest regression algorithm for developing a prediction model to predict the moment exerted on the lower back with positional data from *Kinect*, joint velocity, and predicted movements as the input features.

4.5.6 Identification of Movements involved in a Safe Work Procedure

The safe work procedure involves the identification of unique actions exerting a minimum lower back moment. After isolating an individual task, we can perform a micromotion analysis to segregate groups of movements involved in each unique action. Then we can add the lower back moment induced in each movement frame for the segregated groups to get the cumulative moment for each unique action. Furthermore, we can identify all the unique actions exerting minimum cumulative lower back moment from the pool of all tasks. Finally, we can define the safe work procedure as the combination of segregated movements causing these unique actions, which serves as the *safety frontier* for the lifting and setting down tasks.

4.6 Case Study: Lifting and Setting Down Tasks

We conducted several experiments in a laboratory setup (both indoor and outdoor) using the proposed methodology. To demonstrate the applicability of the proposed methodology, we selected an outdoor environment as it represented the actual construction site conditions such as environmental noise, varying lighting conditions, among others. We collected data outside the university's construction laboratory. Additionally, we collected more data in an indoor controlled environment to train a prediction model using supervised machine learning algorithm.

4.6.1 Subject Selection

We recruited three healthy graduate students (mean age 28.5 $\pm$ 1.5 years and mean weight 159.5 $\pm$ 8.1 lbs) as subjects for this research. Participation in the research was voluntary, with no provision of compensation. We asked each subject to perform 32 "lifting object" and 32 "setting down object" tasks sequentially. The subjects had to perform all lifts continuously with no significant break in between. The weight of the object to be lifted was minimal (less than 10 lbs).

4.6.2 Equipment Setup

To get accurate positional data, the positioning of the *Kinect* was paramount. We placed the *Kinect* at an approximate distance of 2m in front of the subject. The optimal tracking range of *Kinect* is 1m - 3m [138]. We positioned the video camera perpendicular to the *Kinect* to record the task performance for manual verification of collected data. Figure 4.5 shows the typical setup for the data collection.

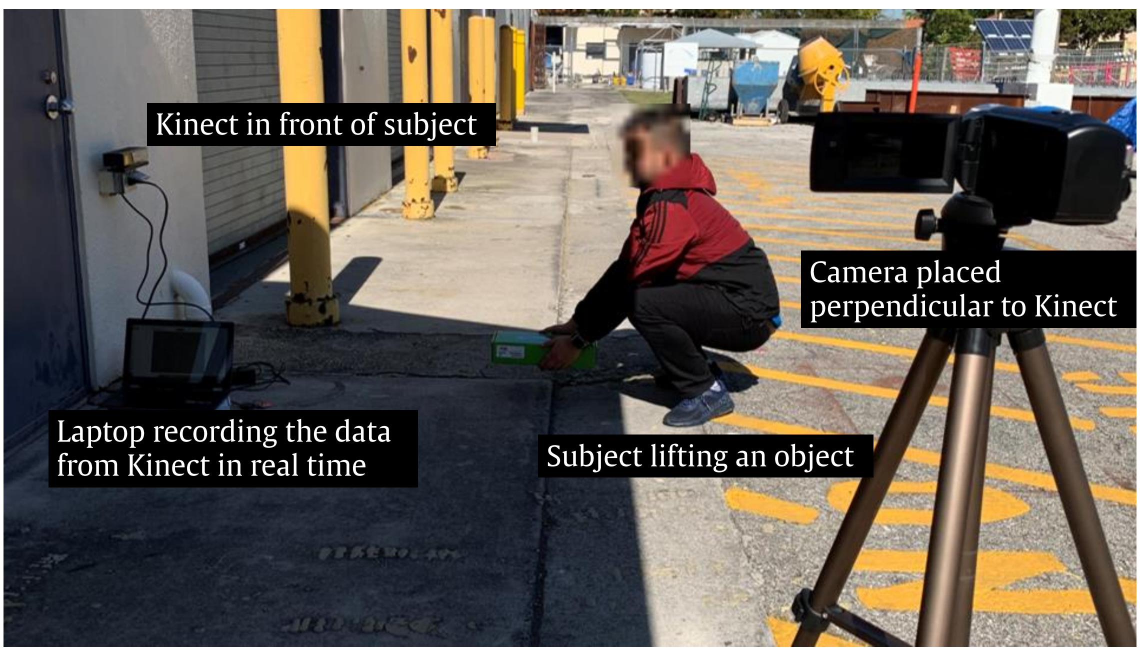

Fig. 4.5. Typical equipment setup for data collection

This study included two tasks, lifting an object and setting down the lifted object. We asked subjects to perform 32 lifting and 32 setting down the object tasks continuously with minimal breaks in between. The subjects were free to leave the experiment at any time without providing any reason whatsoever. The frequency of the data collection was 30Hz. Each subject took approximately 5 minutes to complete the tasks.

4.6.3 Data Analysis

Data Filtration using TKF Model

To denoise the joints' coordinates (X, Y, Z) obtained from the *Kinect*, we implemented the TKF model. We defined the transition matrix (**A**) and observation matrix (**H**) as I_3, an identity matrix.

We assumed the noise covariance (Q) in the order of 0.002 m^2 and measurement covariance (R) in the order of 0.01 m^2 as proposed by Loumponias et al. [124]. Then we defined the covariance matrix of the noise and measurement process as:

$$\mathbf{Q} = 0.002 I_3 \qquad \mathbf{R} = 0.01 I_3$$

We constructed the TKF model with threshold vectors $\mathbf{T}_l$ and $\mathbf{T}_u$ for the spatial coordinates $[x,\ y,\ z]$ as proposed by Loumponias et al. [124].

$$\mathbf{T_{u,k}} = (\hat{x}_{k-1} + 0.31, \hat{y}_{k-1} + 0.18, \hat{z}_{k-1} + 0.31)$$

$$\mathbf{T_{l,k}} = (\hat{x}_{k-1} - 0.31, \hat{y}_{k-1} - 0.18, \hat{z}_{k-1} - 0.31)$$

Figure 4.6 shows the spatial coordinates for the spine base obtained from the *Kinect* and filtered coordinates after using TKF. We can observe that the applied filter doesn't over-smooth the *Kinect* data and corrects the noise significantly.

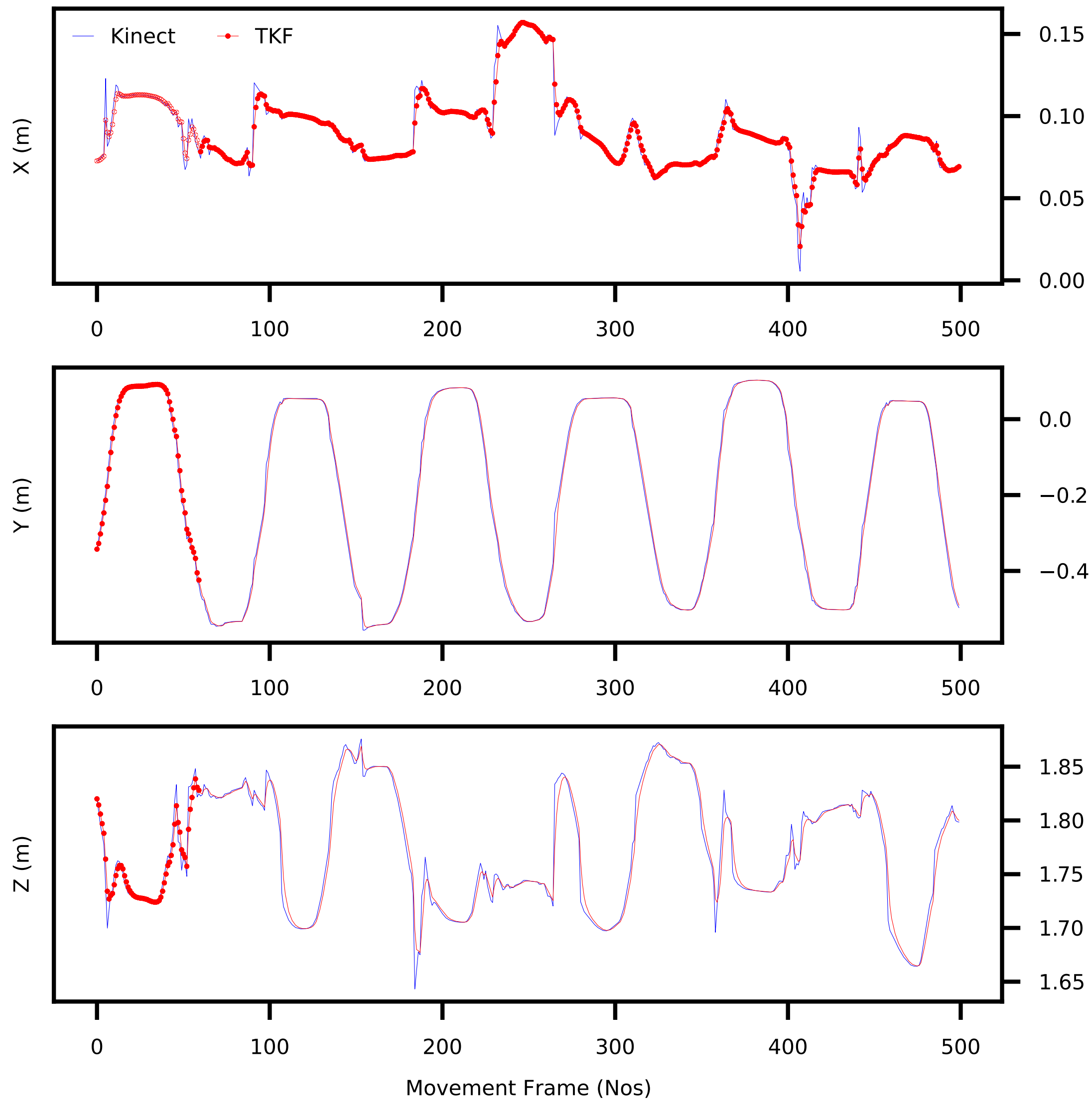

Fig. 4.6. Spatial coordinates of spine base obtained from *Kinect* before and after applying TKF

Action Identification using Machine Learning

We collected additional lifting and setting down task data in a similar setup for prediction model training purposes. The training data had seven lifting tasks and six setting down tasks with 6966 movement frames. We manually labeled each movement frame into different actions provided in Table 4.1 by running the motion in *OpenSim*. From the temporal and spatial data collected from the *Kinect*, we computed the velocity [V_x, V_y, V_z] for all 25 joints. We used the spatial coordinates (75 variables) and velocity (75 variables) as an input variable to train and predict the action involved in each movement frame. Out of the 6966 movement frames, we separated the last chunk of 966 frames (13.9%) for independent model testing. Out of the remaining 6000 frames, we randomly chose 3600 frames (60%) for model training, 1200 frames (20%) for model validation, and 1200 frames (20%) for model testing.

We implemented random forest classifier (RFC) algorithm with 5-fold cross-validation for model fitting. For hyperparameter tuning, we varied *n_estimators*, *max_features*, and *max_depth* parameters as shown in the Table 4.2. *n_estimators (n_e)* represents the number of trees in the forest, *max_features (m_f)* represents number of features to consider when looking for the best split, and *max_depth (m_d)* represents the maximum depth of the tree. Forty-eight different models were created with 5-fold cross-validation totaling 240 fits in total.

Table 4.2. Varied parameters for hyperparameter tuning of RFC model

Parameter	**Variations**
n_e	[50, 100, 150, 200]
m_f	['sqrt', 0.1, 0.5]
m_d	[20, 50, 100, None]

Out of 48 models, we selected three best model with higher accuracy and further checked the model with validation and test data. Table 4.3 shows the details of the selected models. Based on the performance, we used the model with $n\_e = 200$, $m\_f =$ 'sqrt', and $m\_d = 100$ as the prediction model for further analysis.

Table 4.3. Accuracy (A), Precision (P), Recall (R) and F1-score of selected models

n_e	*m_f*	*m_d*	**A**	**P**	**R**	**F1**
Train data (3600 frames)						
50	'sqrt'	20	0.984	0.984	0.984	0.984
100	0.1	None	0.983	0.983	0.983	0.983
200	'sqrt'	100	0.985	0.985	0.985	0.985
Validation data (1200 frames)						
50	'sqrt'	20	0.984	0.984	0.984	0.984
100	0.1	None	0.983	0.983	0.983	0.983
200	'sqrt'	100	0.985	0.985	0.985	0.985
Test data (1200 frames)						
50	'sqrt'	20	0.985	0.985	0.985	0.985
100	0.1	None	0.984	0.984	0.984	0.984
200	'sqrt'	100	0.985	0.985	0.985	0.985
Unused Test data (996 frames)						
50	'sqrt'	20	0.919	0.928	0.919	0.92
100	0.1	None	0.941	0.946	0.941	0.941
200	'sqrt'	100	0.943	0.947	0.943	0.943

Using the prediction model, we predicted the unique actions for all three subjects using their movement data collected from the *Kinect*. We manually classified all the movement frames (8784 frames) of subject_1 and crosschecked with the model prediction for further authentication of the model. The prediction score of the model was [0.926 (A), 0.927 (P), 0.926 (R), 0.925 (F1)]. It further validated the applicability of the prediction model for action classification.

Kinematic and Kinetic Analysis of Lifting and Setting Down Action

With the temporal and spatial data from the *Kinect*, we placed the 25 joint markers in the FBLS model representing the joints tracked. Then we scaled the model and performed kinematic and kinetic analysis. Then we performed the muscle and joint reaction analysis to compute the moment and force exerted on each joint. Figure 4.7 shows the moment exerted in two lower back psoas major muscles (PS_L1_VB_right and PS_L1_VB_left). Researchers have shown that the psoas major was active during standing, forward bending, and lifting [137, 139, 140]. These are the major movements involved in the lifting and setting down action. For further analysis, we chose the moment exerted on PS_L1_VB_r muscle as the "lower back moment."

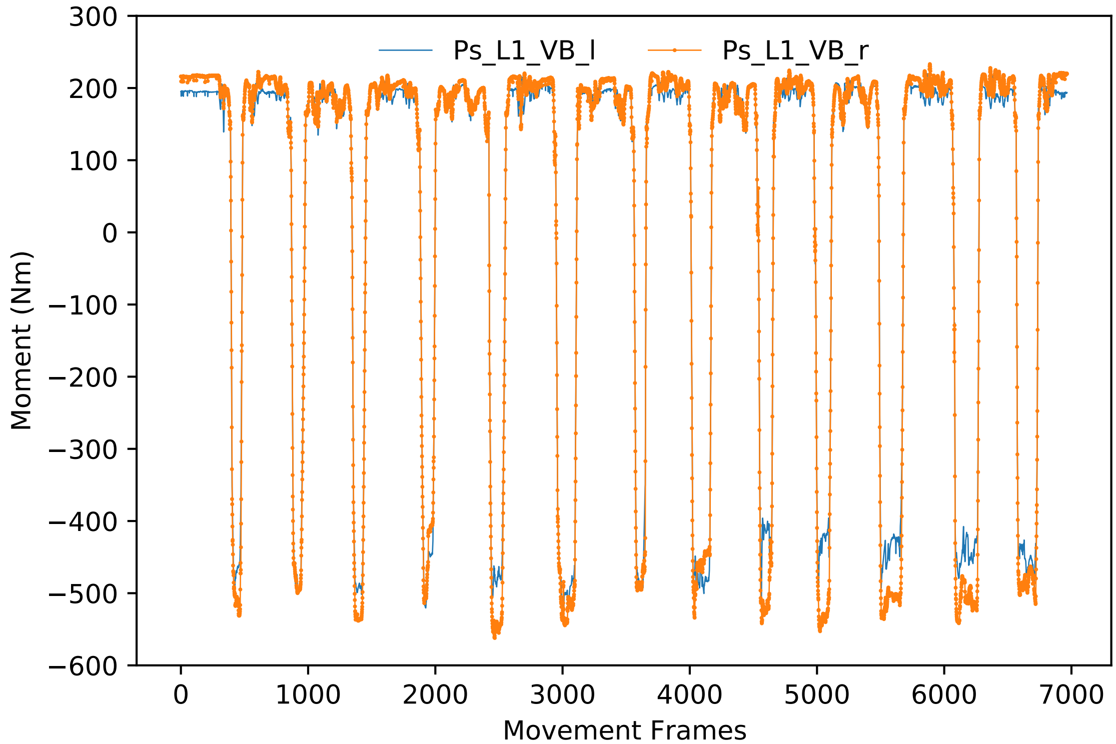

Fig. 4.7. Moment exerted on major lower back muscles (PS_L1_VB_right and PS_L1_VB_left)

With the moment computed from the *OpenSim* on the additional data as a target, we used the random forest regression (RFR) algorithm with 5-fold cross-validation to fit the model to predict the moment with 151 input features, including identified action as an additional input variable to that of RFC algorithm. We split the total 6966 movement frames as discussed earlier in Section 4.6.3. For hyperparameter tuning, we varied *n_estimators*, *max_features*, and *max_depth* parameters as shown in the Table 4.4. Forty-eight different models were created with 5-fold cross-validation totaling 240 fits in total.

Table 4.4. Varied parameters for hyperparameter tuning of RFR model

Parameter	**Variations**
n_e	[50, 100, 150, 200]
m_f	['sqrt', 0.1, 0.5]
m_d	[50, 100, 150, None]

Out of 48 models, we selected three best model with higher accuracy and further checked the model with validation and test data. Table 4.5 shows the details of the selected models. Based on the performance, we used the model with $n\_e = 100$, $m\_f = 0.5$, and $m\_d = 200$ as the prediction model for further analysis. Figure 4.8 shows the lower back moment computed from *OpenSim* and predicted by the RFR model for the independent 966 frames.

Table 4.5. Accuracy (A) and root mean square error (RMSE) (Nm) of selected models

$\boldsymbol{n\_e}$	$\boldsymbol{m\_f}$	$\boldsymbol{m\_d}$	**A**	**RMSE**
Validation data (1200 frames)				
200	0.1	200	0.999	9.618
Test data (1200 frames)				
200	0.1	200	0.999	10.644
Unused Test data (996 frames)				
200	0.1	200	0.999	9.053

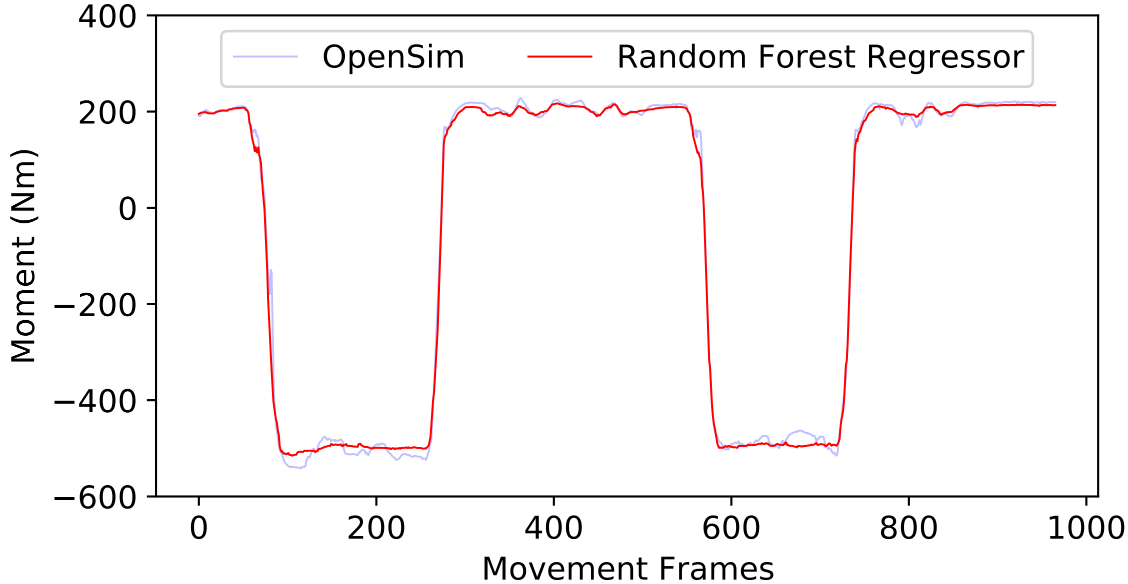

Fig. 4.8. RFR predicted lower back moment for lifting and setting down actions

Using the prediction model, we predicted the lower back moment for all three subjects using their movement data collected from the *Kinect*, computed velocity [V_x, V_y, V_z], and the predicted actions for each frame as input variables. Figure 4.9 shows the predicted lower back moment for all three subjects for consecutive lifting and setting down actions. We can notice the variation of actions in lifting and setting down techniques among the subjects. Subject_1 performed three lifting & three setting down tasks, while Subject_2 performed four lifting & four setting down tasks, and Subject_3 performed six lifting & six setting down tasks within the same number of movement frames.

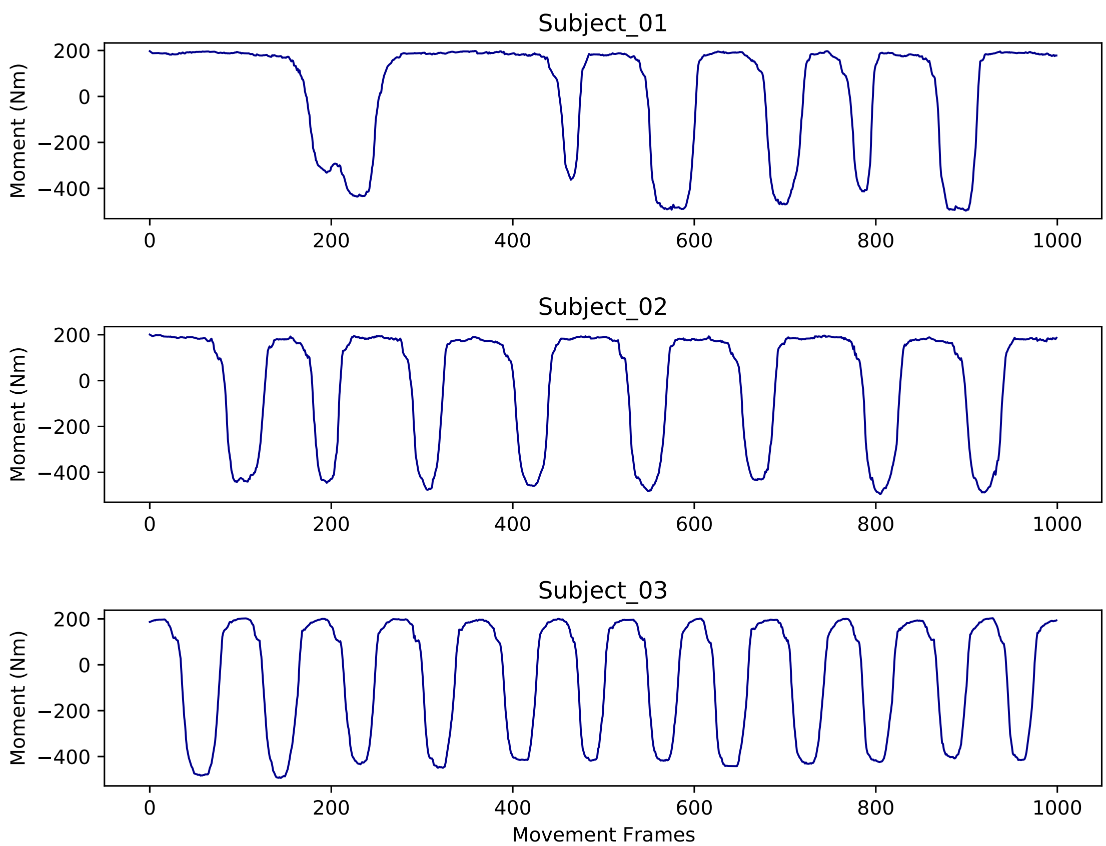

Fig. 4.9. RFR predicted lower back moment for lifting and setting down tasks for all 3 subjects

Identification of Movements involved in a Safe Work Procedure

After predicting the lower back moment, we computed the cumulative moment of all the movements involved in each unique action. For the scope of this chapter, we combined the unique actions with the minimum cumulative lower back moment to get the safe work procedure, which serves as the *individual safety frontier* for lifting and setting down tasks. Figure 4.10 shows the cumulative lower back moment for all the lifting and setting down tasks and the computed *individual safety frontier* for each subject based on their performance. Each line represents the single instance of the task performed and the highlighted thicker line represented the computed *individual safety frontier*. We can observe the variation in the lower back moment among the subjects while repetitively performing the lifting and setting down tasks.

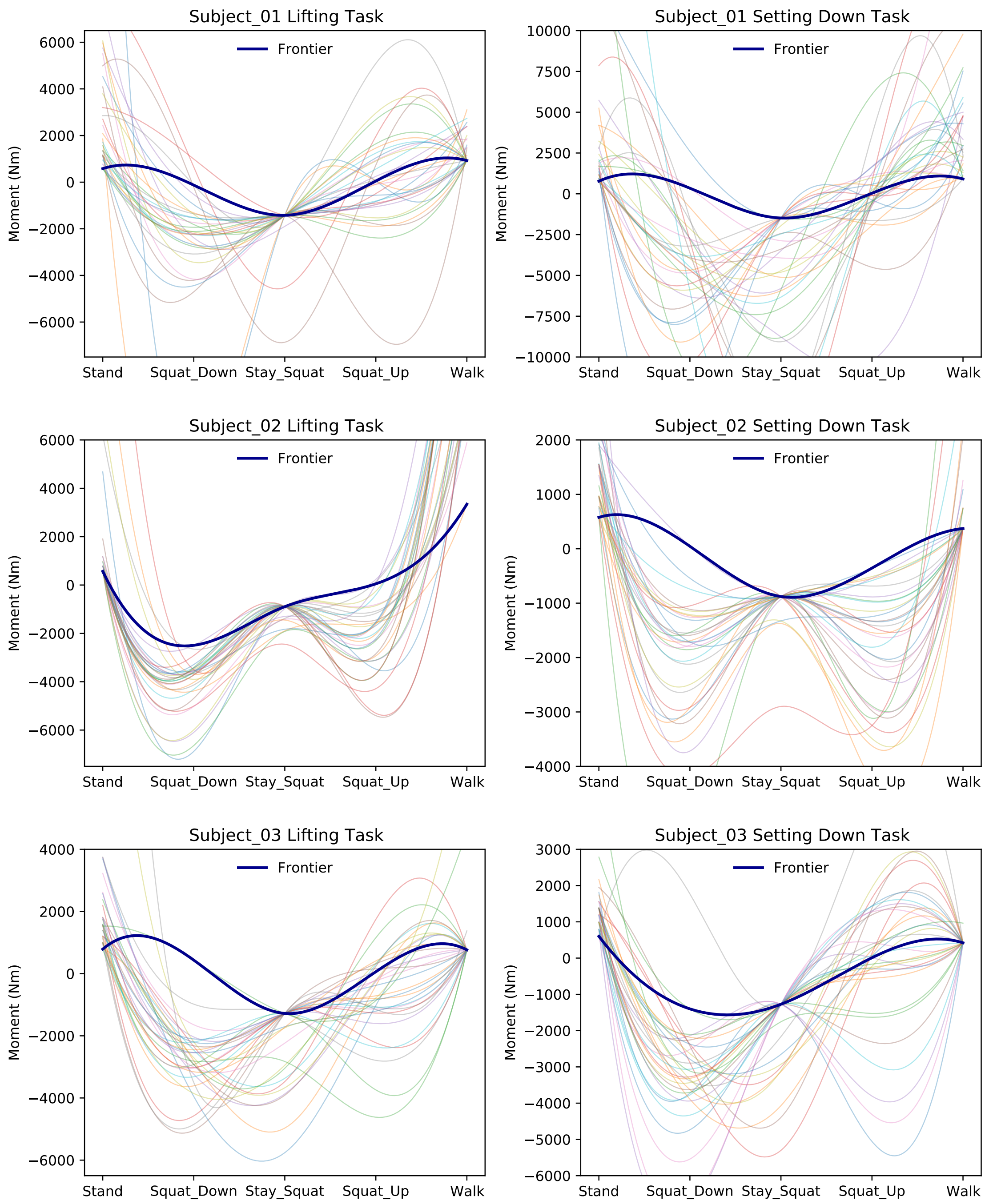

Fig. 4.10. Cumulative lower back moment for all the performed tasks and the identified frontier for all subjects

Furthermore, we utilized the *individual safety frontiers* for subjects of similar physique and stature to compute the *overall safety frontier* for the lifting and setting down tasks. Table 4.6 shows the cumulative lower back moment for actions involved in *individual safety frontiers* for all the subjects and the *overall safety frontier* for the lifting and setting down tasks. We used the absolute minimum value of the lower back moment to determine the *individual* and *overall safety frontier*. The highlighted values for each action in Table 4.6 represents the minimum cumulative lower back moment to compute the *overall safety frontier* for lifting and setting down tasks.

Table 4.6. Cumulative lower back moment (Nm) for actions involved in individual frontiers for all the subjects and the overall safety frontier

Action	Subject_01	Subject_02	Subject_03
Lifting Task			
L1	581.10	**564.24**	788.74
L2	**-126.44**	-2494.56	435.15
L3	-1423.15	**-892.94**	-1280.55
L4	49.35	**48.88**	62.20
L5	924.94	3342.47	**765.19**
Setting Down Task			
S1	773.61	**576.74**	600.06
S2	344.61	**45.45**	-1401.09
S3	-1484.80	**-878.74**	-1273.36
S4	39.82	-355.62	**10.27**
S5	909.96	**372.07**	421.00

Figure 4.11 shows the cumulative lower back moment for all three *individual safety frontiers* and the *overall safety frontier* for the lifting and setting down tasks. Then, we identified all the movement frames involved in these actions to obtain the postural data for the identified *overall safety frontier* and the lower back moment exerted in each movement frame. The identified *safety frontier* can serve as a higher index for safety monitoring of activities involving lifting and setting down tasks.

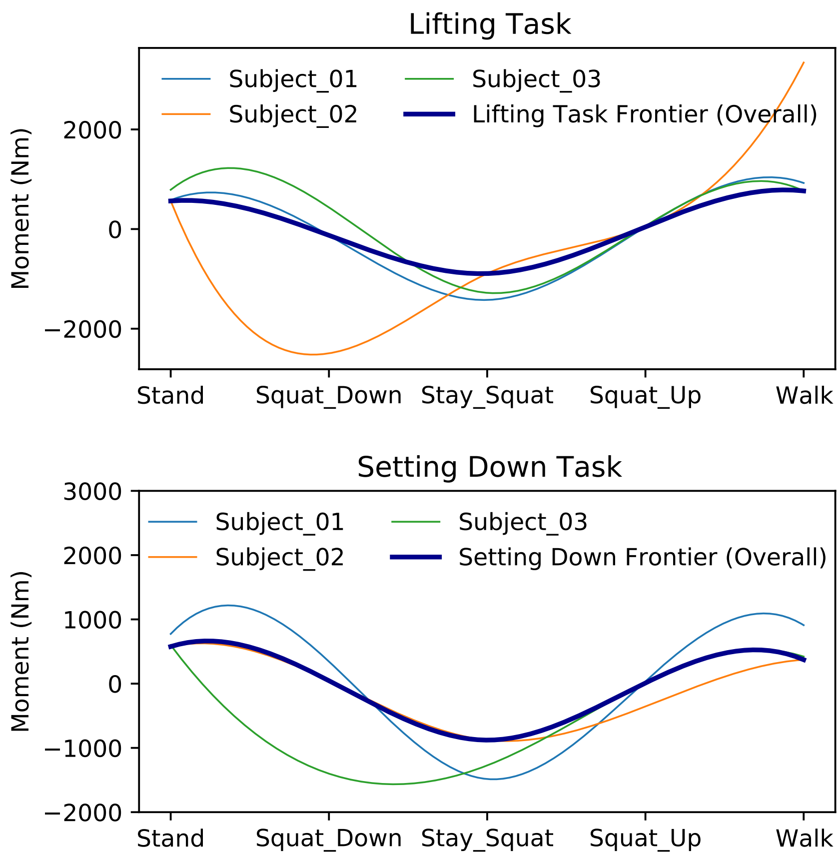

Fig. 4.11. Cumulative lower back moment representing unique actions involved in lifting and setting down task for individual and overall safety frontier

Moreover, Figure 4.12 shows the strip plot for the absolute value of cumulative lower back moment for all three subjects for the lifting task. If we join the points representing minimum cumulative moment for all unique actions of each subject then we get the *individual safety frontiers*. Furthermore, if we identify the unique actions with minimum cumulative moments from *individual safety frontiers* then we get the *overall safety frontier*.

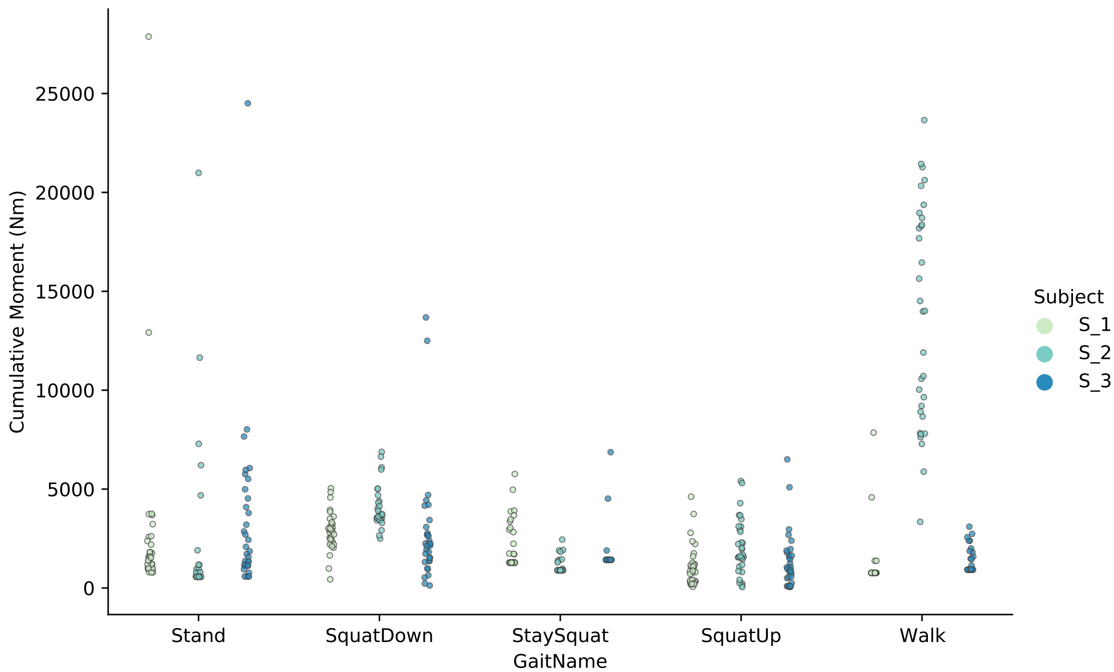

Fig. 4.12. Absolute cumulative lower back moment for all unique actions involved in lifting task

4.7 Discussion and Limitations

4.7.1 Discussion

Chapter 4 proposed the *safety frontier* approach to identify the maximum achievable level of safety for repetitive labor-intensive construction activities. We conducted a case study in a construction lab environment to validate the proposed *safety frontier* approach for lifting and setting down tasks. The case study demonstrated the applicability of the proposed system to identify the maximum achievable level of safety for various repetitive labor-intensive activities such as concreting, re-bar fabrication & installation, housekeeping, drywall installation, masonry work, tile laying, manual material handling, among others. Compared to the past studies related to MSDs exposure assessment, the following subsections describe the chapter's contribution.

Computation of *Safety Frontier*

The past studies focus on assessing the workers' MSDs exposure and implementing different observational and instrumental techniques to reduce the risk of MSDs. However, there is little or no research targeted towards identifying "how safely can a worker perform an activity?". The chapter provides the method to individually identify the worker's maximum achievable level of safety, *safety frontier* using recent posture tracking technology. We implemented depth-sensing technology (*Kinect*) for postural data extraction, but any other posture tracking technology such as motion sensors, inertial measurement units, accelerometers, among others, can be used.

The kinematic and kinetic analysis of human body ergonomic was the key to computation of *safety frontier*. We implemented random forest classification ML model to identify the unique actions involved in the lifting and setting down tasks. The implemented algorithm predicted the unique actions with high accuracy of 95% (Table 4.3). The computation of stress, induced in critical joints, with real-time data is computationally demanding [141–143]. We demonstrated the applicability of the random forest regression ML model to predict the stress developed in the lower back while performing the lifting and setting down tasks. The implemented algorithm predicted the lower back moment with high accuracy (Accuracy: 0.999 and RMSE: 9.053 Nm, Table 4.5).

Availability of Higher Index for Safety Monitoring

Recently, the construction industry relies upon the safety guidelines provided by safety regulating agencies such as OSHA to monitor the workers' safety. However, the safety guidelines only provide the minimum safety requirement [56]. We can implement the *safety frontier* computed from the study as the higher safety benchmark for the onsite monitoring of construction activities, reducing the risk of getting into MSDs.

Self-learning Opportunity for Construction Workers

Mok et al. [144] defined self-learning as "a process whereby the learner participates actively in the learning process, including planning, goal setting, progress monitoring, selecting learning strategies, and controlling the environment for learning." Widaningsih et al. [145] emphasized the importance of self-learning among construction workers. The identified *individual safety frontier* (Figure 4.8) provides a self-learning opportunity to construction workers from multiple instances of the repetitive labor-intensive activity performed in the construction site. Referring to Figure 4.8, we can observe that the construction worker might be separately performing involved unique actions safely in different instances. The *individual safety frontier* is based on the individual worker's performance and should be achievable in every repetition in similar working conditions.

Peer Learning Opportunity among Construction Workers

Peer learning is the key to training new workers and improving the performance of the existing workers in construction work [146]. The method presented in the chapter can play a vital role in improving peer learning among construction workers. As explained in Section 4.6.3, we can compare the *individual safety frontiers* to compute the *overall safety frontier* for the activity (refer to Table 4.6 and Figure 4.11). Moreover, training the workers using a virtual reality (VR) environment has gained some attention in the construction domain [147–150]. Using the postural data, we can animate the *safety frontier* and workers' performance, assist workers to visualize "how they performed the activity versus how they should have performed" in a virtual environment, and provide personalized training based on their requirements [82]. Furthermore, one worker might be performing one unique action safely while another worker might be performing another unique action safely (Figure 4.10 and Figure 4.11). By combining the *individual safety frontiers* to compute the *overall safety frontier*, the workers get a platform to learn from each other visualizing the safe work procedure using a VR environment, which researchers validate as an effective way to train workers [151].

4.7.2 Implications and Potential Applications

The presented research framework provides practical applications to both researchers and industrialists in the construction domain. First, the computed *safety frontier* provides a higher index to industrialists for monitoring the safety performance of construction workers. It also provides a platform for training the workers in virtual environment. Second, apart from construction industry, the proposed method can be beneficial to other industries such as warehouses, supermarkets, mechanic workshops, movers, housecleaning, among others; where repetitive labor-intensive activities are common. Third, the researchers can implement the presented method to explore the safety of other major joints such as knees and shoulders. Although the framework was demonstrated for lifting and setting down tasks, the methodology can be implemented to compute the *safety frontier* for any repetitive labor-intensive activities. Moreover, with the availability of more robust technologies to track postural data in future, the *Kinect* implemented in the research can be easily replaced with minimal change in methodology. Thus, there is a great potential for the implementation of *safety frontier* approach to identify maximum achievable level of safety for any repetitive labor-intensive activities.

4.7.3 Limitations

Despite the contributions mentioned above, the study still has several limitations.

- Although we chose *Kinect* due to its low cost and acceptable accuracy & reliability, it has certain limitations such as self-occlusion, limited range, among others. Despite using TKF to reduce the noise, the data had some errors affecting the machine learning algorithm to predict the unique actions and lower back moment for each movement frame. We collected additional postural data in a controlled indoor environment and used it to train and validate the prediction model to resolve this issue. We can introduce robust technologies, such as motion sensor system [121], computer vision [152, 153], and IMU [17], to get accurate data that will boost the prediction model score and the reliability of the proposed system.

- For the demonstration of the proposed model, we chose manual material handling activity (lifting and setting down task) for a case study. As we identified the lower back injury as one of the major MSDs from the literature review, we further limited the scope of this chapter to the computation of the lower back *safety frontier*. To compute the *safety frontier*, we identified the movements involved in the unique actions exerting minimum stress to the lower back. We can implement a similar approach to get a more robust *safety frontier* by considering multiple joints, such as knees and shoulders. To validate the robustness of the system, we need to include different construction activities in the experiment.

- For the case study, we collected the skeletal data outside the construction laboratory in a controlled environment. More data needs to be collected from real construction sites to robustify the proposed model. And the number of participants in the study needs to be increased as well to ensure the robustness of the system.

4.8 Conclusion and Future Work

MSDs have been a genuine concern for repetitive labor-intensive construction activities. Although the safety guidelines provided by regulating agency, such as OSHA, has reduced the fatal and non-fatal injuries in construction sites, the workers are still suffering from MSDs. Similarly, the real-time monitoring of individual workers performing such activities has been a massive challenge to construction safety personnel. It necessitated developing a better system that can identify the safest possible way of doing any task and monitor the workers' performance individually in real-time.

To address it, we proposed the frontier approach to develop a prototype model to identify the *safety frontier* for any construction activity with the implementation of recent depth-sensing technology (*Kinect*) for postural data extraction and machine learning for automation and real-time monitoring. The *safety frontier* is a novel concept and represents the maximum attainable level of safety that is virtually impossible to sustain in a real construction site. Nevertheless, it can play a pivotal role in improving construction workers' safety by providing a better safety index to monitor the workers' performance in real-time automatically.

Future research should incorporate a broader range of construction workers with different skill levels, experience, and demographic factors to robustify the proposed model. Moreover, future studies should focus on computing the *safety frontier* for various repetitive labor-intensive construction activities. Furthermore, identifying safety factors causing *system* and *operational* inefficiencies plays a vital role in completing the safety control system proposed in section 4.3 (Figure 4.2). For this, the questionnaire survey can be conducted with construction experts. In addition, comprehensive studies need to be performed to incorporate the existing *inefficiencies* to the *safety frontier* and compute the *sustainable safety* that can be achieved and sustained in a construction site. However, just identifying the *safety frontier* and *sustainable safety* does not serve the purpose. The workers need to be educated about how they are performing versus how they should perform the task. For this, future work should explore the applicability of a need-based personalized learning environment for construction workers performing repetitive labor-intensive construction activities in a VR environment. The authors have already started the initial work in this respect [82].

Furthermore, the applicability of the proposed framework needs to be tested and validated in a real construction site. We acknowledge the limitations of depth sensor camera (*Kinect*) such as self-occlusion, tracking range, and occlusion by co-workers for its applicability in a real construction site. However, the scope of the chapter is to introduce and demonstrate a novel *safety frontier* approach. More robust technologies such as computer vision, optical fiber sensors, goniometer, strain sensors, and inertial measurement unit can be implemented in the future to improve the computed *safety frontier*. Moreover, researchers have validated the applicability of computer vision in tracking workers' postural behaviors & estimating bio-mechanical workload and its suitability to the complex and diversified nature of construction activities [154]. Future work should explore the applicability of the *safety frontier* approach in a construction site using more robust technologies.

Safety frontier is a safety optimization problem similar to productivity frontier [106] and time-cost optimization [155] approach in construction. The cost of monitoring and training workers increases with the increase in the safety level. However, the expenses related to workers' compensation claims, decreased productivity, and cost of training new workers decreases with increased safety level. So, the future work should consider all interrelated construction dimensions and find a solution to ensure optimum cost, time, quality, and safety.

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4.10 Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this research.

4.11 Bibliography

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CHAPTER 5

COMPUTATION OF SYSTEM & OPERATIONAL INEFFICIENCIES AND SUSTAINABLE SAFETY

Identification of System and Operational Inefficiencies affecting Construction Worker's Safety

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Abstract

The construction industrialists and researchers have given uttermost priority to laborers' safety. Yet laborers are suffering from fatal and non-fatal injuries. There are several factors causing the inefficiencies in the safety behavior of construction laborers. These inefficiencies can be categorized as *system inefficiencies* and *operational inefficiencies*. *System inefficiencies* imply the loss in level of safety due to factors that are not under the control of a project manager. And, *operational inefficiencies* imply the loss in level of safety due to factors that are under the control of a project manager. To identify the safe work procedure that can be achieved and sustained in a construction site (defined as *sustainable safety*), the identification of these inefficiencies is the most. The chapter proposes a methodology to identify and incorporate the inefficiencies to the actual safety behavior to improve overall safety performance. For this, the research implements questionnaire survey approach to categorize the safety factors into *system* and *operational inefficiencies*. As well, the

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significance of each factor to overall safety performance is identified from the survey. Then the inefficiency risk indices are computed and incorporated to the actual performance to identify the sustainable safety.

5.1 Introduction

The dynamic nature of construction makes it vulnerable to accidents. The risk of fatal and nonfatal injuries are relatively higher in the construction industry compared to other sectors [1]. As per the 2019 report from the Bureau of Labor Statistics US, the rate of injury and illness per 100 full-time laborers in construction is 2.8 [2]. Moreover, the construction industry accounts for nearly 10% of the workforce but 20-40% of occupational fatal injuries [3, 4]. [5] identified different factors such as lack of knowledge or training, lack of supervision, lack of tools and skills to carry out the task safely, judgmental error, carelessness, lack of controlled working environment, and laborers' unsafe behavior, among others, as a reason for construction workplace injuries. [6] identified several factors influencing the safety performance in the construction industry, including laborers' attitude, company size, safety policy, project coordination, economic pressure, management training, and safety culture, among others. [7] identified construction activities with high physical demands as another factor for causing fatigue and exhaustion, resulting in decreased productivity and motivation, inattentiveness, poor judgment and quality work, low job satisfaction, and more injuries. [8] conducted extensive literature to identify several factors affecting laborers' safety: laborers' attitude, posture, work location, laborers' physiological health, and environmental condition, among others.

Construction researchers and industrialists are working hand-in-hand to enhance the overall safety of the construction site [9]. The access to the advanced technology and improved methodology has significantly reduced laborers' based physical works as well as the hazards associated [10, 11]. Despite all the efforts, the construction industry is still suffering from accidents and occupational injuries. The laborers are still subjected to the repetitive labor-intensive construction activities requiring heavy lifting and unsafe work postures for a longer duration [12, 13]. Past studies have associated repetitive exposure to heavy lifting and unsafe work postures to musculoskeletal disorders (MSDs) related injuries [14]. [15] defined MSDs as soft-tissue injuries caused by sudden or sustained exposure to repetitive motion, force, vibration, and awkward positions. MSDs occur due to the slow exposure of laborers to unsafe or awkward positions over a long period and are difficult to monitor manually in a construction site [11]. Also, regulating agencies such as occupational health and safety administration (OSHA) provides laborers minimum safety guidelines, which might not be sufficient to prevent construction injuries [16]. It necessitates developing a monitoring system that can automatically identify the maximum achievable level of safety and provide a higher safety index to monitor laborers' safety behavior. For this we proposed a frontier approach to identify *safety frontier* in Chapter 4. And to achieve the *safety frontier*, the existing *system* and *operational inefficiencies* need to be identified and removed from the *observed safety* [16–18].

For identification and removal of existing inefficiencies, first we need to obtain different safety factors that causes inefficiencies. Second, we need to segregate safety factors that are under the management' control from the ones that are not. For this we proposed a questionnaire survey approach to capture responses from construction experts. Third, we need to be able to quantify the safety risk associated with each factor. For this we implemented the qualitative factor modeling (QFM) approach developed by [19] to compute *system risk index* ($\boldsymbol{R_{si}}$) and *operational risk index* ($\boldsymbol{R_{oi}}$).

5.2 Safety Dynamics: Theoretical Background

Prior diving into methodology, it is crucial to understand the overall safety dynamics. The fundamental concept of this research framework is developed based upon productivity dynamics described by [17–20]. Based on the *safety frontier* concept proposed in Chapter 4, the study implements four different levels of safety dynamics: (i) *Safety Standard*, (ii) *Observed Safety*, (iii) *Safety Frontier*, and (iv) *Sustainable Safety*. *Safety standard* is the minimum level of safety required by regulatory agencies such as occupational health and safety administration (OSHA), European-OSHA, or the construction company itself, for a given task and field conditions. The *observed safety* is the actual level of safety observed in the construction site, which can be above or below the *safety standard*. *Safety frontier* is the theoretical maximum attainable level of safety while performing any construction task under *perfect condition*. Chapter 4 provides the methodology to compute the *safety frontier* for any repetitive labor-intensive activity. *Perfect condition* is an ideal state where all factors affecting construction laborers' safety are at their most favorable levels, such as good weather, highly motivated and trained laborers with flawless artisanship, an ergonomically safe working posture or poses of laborers, optimal safe utilization of materials and equipment, no interference from other trades, no design errors, no equipment failures, no fatigue, no injury, no loss of life, and precise understanding of the design intent, among others. *Sustainable safety* is defined as the highest level of safety that can be achieved and sustained under good management and typical site conditions. Good management is considered as the best acceptable level of proficiency in the project team. Typical field conditions are project site circumstances as per the construction industry standard, excluding adverse events such as natural disaster and labor-union conflicts. Because of several inefficiencies inherent to the construction process, perfect conditions are virtually unachievable in the construction site. The inefficiencies in a construction site can be summarized into two categories, *system inefficiencies* and *operational inefficiencies* [16, 18, 21].

5.2.1 Inefficiencies in Construction Safety

The study of inefficiencies is not new in construction. The construction domain research is focused more towards identifying and reducing production inefficiencies by improving quality, costs, and schedule [17, 22–24]. The fundamental concept of this research framework is developed based upon productivity dynamics described by [17], [20], and [25]. They introduced a method of computing *optimal productivity* of an activity using *productivity frontier* and *actual productivity.* They showed that the optimal productivity that can be achieved for a construction activity is less than the theoretical maximum productivity (*productivity frontier*) due to the *system inefficiencies* and more than the observed productivity (*actual productivity*) due to the existence of *operational inefficiencies.* We used a similar concept to define *system inefficiencies* and *operational inefficiencies* [16] existing in the construction laborers' safety. Equation 5.1 shows the total safety-related inefficiencies inherent in a construction activity similar to productivity inefficiencies proposed by [19]. And, Equation 5.2 shows the theoretical relationship between the aforementioned inefficiencies and different levels of safety dynamics.

$$\Delta_{\mathrm{i}} = \Delta_{\mathrm{si}} + \Delta_{\mathrm{oi}} \tag{5.1}$$

$$SS = SF + \Delta_{\mathrm{si}} = OS - \Delta_{\mathrm{oi}} \tag{5.2}$$

where, Δ_{i}, Δ_{si}, and Δ_{oi} are *total, system*, and *operational inefficiencies*, SS is *sustainable safety*, SF is *safety frontier*, and OS is *observed safety*.

[8] has identified several safety factors that causes safety inefficiencies. And it is virtually impossible to incorporate all these safety factors while computing inefficiency indices due to computational limitation. So, we used a top-down approach to estimate the upper limit of sustainable safety and a bottom-up approach to estimate the lower limit of sustainable safety proposed by [19] for productivity domain. Figure 5.1 shows the relationship between the aforementioned inefficiencies and different levels of safety dynamics. δ_{si} and δ_{oi} represent estimated *system* and *operational inefficiencies* in the figure 5.1 respectively.

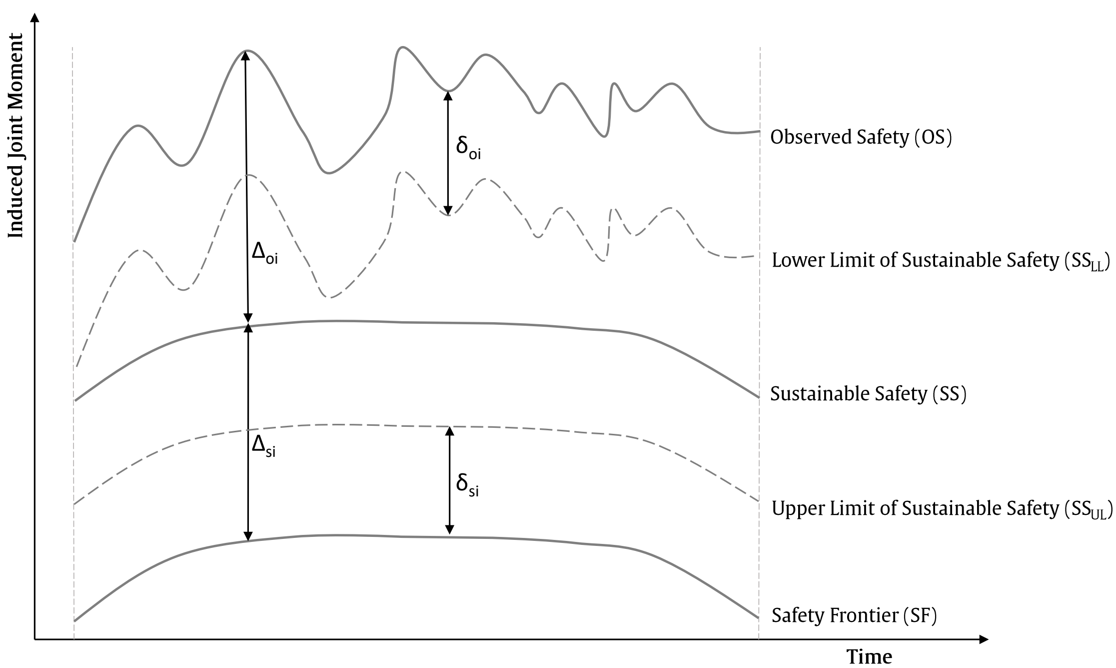

Fig. 5.1. Safety dynamics with different safety levels for any given activity

We implemented a qualitative analysis approach to estimate *operational* and *system inefficiencies*. Researchers have proposed several methods and models to qualitatively measure the construction productivity [26–31]. We implemented the qualitative factor model (QFM) to evaluate estimated *operational* (δ_{si}) and *system* (δ_{si}) *inefficiencies*. The QFM is a probabilistic approach that uses severity scoring technique [32]. We implemented the QFM approach proposed by [32] to compute estimated *inefficiencies*.

System Inefficiencies

We defined *system inefficiencies* as the loss in the level of safety due to factors that are not under the control of a project manager, such as environmental conditions (high humidity, cold or hot temperatures), laborers' health & attitude, absenteeism driven by health or family issues, interference from other trades, design errors, behavior and intention of laborers, and unsafe or uncertain conditions due to mechanical failures of equipment among others. Based upon the characteristics of activity or task, the number and type of factors causing the *system inefficiencies* vary. For instance, the influencing factors for a manual lifting task can be working behavior and health conditions of that laborer, disturbances by other people on the way during hauling, hot or cold temperature, and high humidity.

The *safety frontier* is the theoretical maximum level of safety which is virtually impossible to achieve due to underlying inefficiencies in the construction process. If we add the estimated *system inefficiencies* (δ_{si}) to the *safety frontier*, we get the upper limit of safety that can actually be achieved and sustained in a real construction site, referred as *upper limit of sustainable safety* (SS_{UL}) as shown in Equation 5.3.

$$SS_{\mathrm{UL}} = SF + \delta_{\mathrm{si}} \tag{5.3}$$

Using the QFM approach, estimated *system inefficiencies* can be computed using Equation 5.4.

$$\delta_{\mathrm{si}} = (SS_{\mathrm{UL}} - SF) * R_{\mathrm{si}} \tag{5.4}$$

where, $\boldsymbol{R_{si}}$ is the risk index of factors causing *system inefficiencies* given by Equation 5.5.

$$R_{\mathrm{si}} = \frac{\sum_{i=1}^{m} S_i P_i \epsilon_i}{\sum_{j=1}^{m+n} S_j \epsilon_j} \tag{5.5}$$

where, $\boldsymbol{S_i}$ & $\boldsymbol{S_j}$ are severity scores of safety factors $\boldsymbol{i}$ & $\boldsymbol{j}$ respectively, $\boldsymbol{P_i}$ is the probability of occurrence of a factor $\boldsymbol{i}$, $\boldsymbol{\epsilon_i}$ & $\boldsymbol{\epsilon_j}$ are existence indicator of safety factors $\boldsymbol{i}$ & $\boldsymbol{j}$ (0 = not present, 1 = present), and $\boldsymbol{m}$ & $\boldsymbol{n}$ are the number of factors causing *system* & *operational inefficiencies* respectively.

Operational Inefficiencies

We defined *operational inefficiencies* as the loss in the level of safety due to factors that are under the control of a project manager, such as poor sequencing of activities, inadequate and improper or unsafe utilization of equipment or tools, excessive overtime, untrained or unskilled laborers, poor lighting conditions, the mismatch between skills and task complexity, and carelessness of laborers, among others. For a manual lifting task, if the laborer does not know how to properly (ergonomically safely) lift and haul the object and if that laborer does not care about the working procedure, then these factors can play a significant role in causing *operational inefficiencies.* These inefficiencies can be minimized by providing training on time.

The *observed safety (OS)* has higher probability of underlying inefficiencies, both *system* and *operational.* If we remove the estimated *operational inefficiencies* (δ_{oi}), we get the lower limit of safety that can actually be achieved and sustained in a real construction site, referred as *lower limit of sustainable safety (SS_{LL})*, as shown in

Equation 5.6.

$$SS_{\mathrm{LL}} = OS - \delta_{\mathrm{oi}} \tag{5.6}$$

Using the QFM approach, the estimated *operational inefficiencies* can be computed using Equation 5.7.

$$\delta_{\mathrm{oi}} = (OS - SS_{\mathrm{LL}}) * R_{\mathrm{oi}} \tag{5.7}$$

where, $\boldsymbol{R_{oi}}$ is the risk index of factors causing *operational inefficiencies* given by Equation 5.8.

$$R_{\mathrm{oi}} = \frac{\sum_{i=1}^{n} S_i P_i \epsilon_i}{\sum_{j=1}^{m+n} S_j \epsilon_j} \tag{5.8}$$

The summation of the risk due to *system inefficiencies* ($\boldsymbol{R_{si}}$) and *operational inefficiencies* ($\boldsymbol{R_{oi}}$) represents the total risk ($\boldsymbol{R_i}$) involved in the activity and is given by Equation 5.9.

$$RR_i = R_{oi} + R_{si} = \frac{\sum_{i=1}^{m+n} S_i P_i \epsilon_i}{\sum_{i=1}^{m+n} S_i \epsilon_i} \leq 1 \tag{5.9}$$

Using Equations 5.1-5.9, we can compute the *upper* and *lower limits of sustainable safety*. The detailed derivation of equations 5.10 and 5.11 is presented in Appendix A.

$$S_{\mathrm{UL}} = \frac{R_{si}(1 - R_{oi})}{(1 - R_{si}R_{oi})} OS + \frac{(1 - R_{si})}{(1 - R_{si}R_{oi})} SF \tag{5.10}$$

$$S_{\mathrm{LL}} = \frac{(1 - R_{oi})}{(1 - R_{si}R_{oi})} OS + \frac{R_{oi}(1 - R_{si})}{(1 - R_{si}R_{oi})} SF \tag{5.11}$$

5.3 Objective and Scope

Figure 4.2 shows the proposed overall research framework for computation of aforestated *safety frontier* and *sustainable safety*. The chapter's scope is limited to identifying factors affecting safety while performing labor-intensive repetitive tasks and calculating risk indices for *system* and *operational inefficiencies* (refer to Figure 4.2). We used the experimental data collected in Chapter 4 to compute the *upper* and *lower level of sustainable safety*.

To understand the effect of inefficiencies in the laborers' safety performance, the chapter aims to fulfill the following objectives:

- identify the major factors affecting the laborers' safety
- categorize identified factors into *system* and *operational inefficiencies*
- compute risk indices associated with identified safety factors causing *system* and *operational inefficiencies*
- compute the *upper* and *lower level of sustainable safety*

5.4 Methodology

5.4.1 Research Design

The chapter focuses on identifying the *system* and *operational inefficiencies*, computing inefficiency risk indices, and calculating *sustainable safety*. We have adopted both qualitative and quantitative research approach. First, a qualitative literature review was conducted to identify factors affecting laborers' safety. Second, a quantitative survey was designed to compute the severity of the selected factors. Figure 5.2 shows the research methodology implemented for the identification and categorization of safety factors into *system* and *operational inefficiencies*.

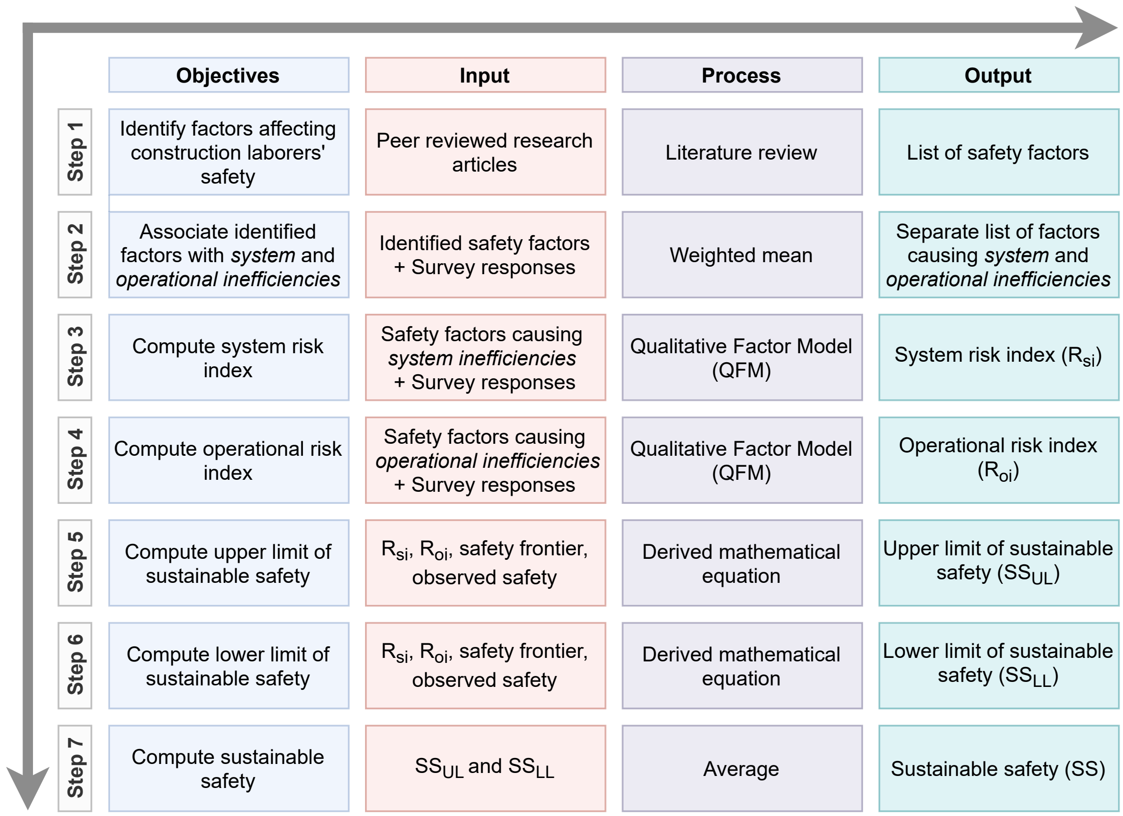

Fig. 5.2. Methodology to compute *system* and *operational inefficiencies*

5.4.2 Identification of Factors Affecting Construction Laborers' Safety

We conducted an extensive literature review to identify factors affecting construction laborers' safety from research articles published in reputed journal publications [8]. For the study, we prioritized factors associated with labor-intensive repetitive activities. Table 5.1 shows the list of factors identified from the review of published research articles.

Table 5.1. List of safety factors with corresponding literature references

Factors	Code	References
Age	AGE	[1, 4, 5, 33, 34]
Work Experience	LWE	[4, 5, 33–35]
Workers' safety training	LWST	[1, 4, 5, 33–35]
Workers' safety attitude	PWSA	[4, 5, 33, 35]
Education level	PEL	[1, 4, 33, 34, 36]
Physical health condition	PPHC	[4]
Emotion (Psychological health condition)	PPSC	[4]
Workers' judgment ability	PWJA	[4, 33]
Drug abuse	DA	[37]
Heart rate	LHHA	[7]
Oxygen uptake	LOU	[7]
Tidy site	US	[1, 5]
Planned and organized site	UPUS	[1, 5]
Weather	BW	[4, 33]
Noise	HN	[4]
High/Low temperature	HLT	[19]
High Humidity	HH	[19]
Availability of safety equipment	USE	[4, 5, 33]
Supervisor's safety behavior	PSSB	[4, 5, 35, 36]
Coworkers' safety behavior	PCSB	[4, 5, 33, 35, 36]
Workload	WO	[4, 7, 36]
Accident History	HAH	[1, 33, 34]
Time pressure	HTP	[4, 33, 36]
Working duration	LWD	[36, 38]
Provision of PPE	LPPE	[5]
Poor equipment	PE	[6]
Safety regulation	LSR	[4]
Availability of site safety personnel	USSP	[4, 5, 33]

5.4.3 Questionnaire Survey

Questionnaire Design

Based on the above identified factors affecting laborers' safety, we designed a set of questionnaire to measure the severity and probability of occurrence of those factors. The questionnaire comprised of two sections: (1) Section A: Respondent's background (job location, job designation, total experience, and construction site experience), and (2) Section B: Safety factors causing *system* and *operational inefficiencies* in construction sites. We used the information from Section A to perform the statistical comparison of response based on job location, designation, and experience. Section B was sub-divided into three sub-sections; Sub-section B.1: Inefficiency type (Can the factor be controlled by management team?) on a 3 point likert scale (1 = Yes, 0 = Maybe, -1 = No), Sub-section B.2: Severity (the severity of factors on laborers' safety) on a 6 point likert scale (0 = No effect, 1 = Very Low, 2 = Low, 3 = Moderate, 4 = High, 5 = Very High), and Sub-section B.3: Probability (what is the probability of the factor causing injury?) on a percentage (0 - 100%). A summary of the blank survey form is attached in Appendix B for reference.

Sample Size and Distribution Method

The population of the survey focused on construction sites at two locations, Nepal and USA. The reason behind selecting two different location was to perform the statistical comparison of safety dynamics between developing versus developed country. The respondents of the study focused on safety managers, construction managers, and resident engineers who are responsible for monitoring the laborers' safety in a construction site. Based on the minimum 20% to 30% questionnaire response rate of similar construction safety-related survey [6, 39], we circulated the questionnaire electronically to 738 respondents via different methods; personal email (476), company group email (154) and social media (LinkedIn (65) and Facebook (43)).

[40] pointed out the recommended minimum sample size of 100 respondents for the survey data to be suitable factor analysis. Moreover, the sample size of 150 respondents is deemed adequate for confirmatory factor analysis (CFA) [41, 42]. However, [43] suggested that the sample size with 51 more cases than the number

of variables to be sufficient for further analysis. Furthermore, [44] suggested that the sample size requirement depends upon the strength of the factors and the items. If the factor have more than three items with loadings of 0.60 or higher, then the sample size becomes irrelevant [44].

5.4.4 Statistical Analysis

Prior to categorizing the factors into system and operational inefficiencies, we performed the descriptive statistical analysis to explore the data, and find the correlation, covariance, and reliability of the survey data. To validate the reliability of the survey data for factor analysis, we performed the Bartlett's Test of Sphericity and Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO Test). Bartletts's test is used to evaluate if the determinant value is statistically different from zero [45]. Small values (<0.05) of the significance level indicate the applicability of factor analysis with the data. Similarly, the KMO test is a statistical measure that indicates the proportion of variance in the variables caused by the underlying factors. The value ranges from 0 to 1 and high value indicates the applicability of factor analysis with the data. [45] interpreted the KMO value as: $\geq 0.8 \sim$ good, 0.6 - 0.8 $\sim$ OK, and $\leq 0.6 \sim$ Not OK.

Factor analysis has been abundantly used to analyze the survey data [46–48]. It is a useful tool for investigating variable relationships for qualitative data. We explored the data using parallel analysis (PA), exploratory factor analysis (EFA) [48], and principal component analysis (PCA) [49, 50] methods.

5.4.5 Computation of Risk Indices for System and Operational Inefficiencies

We categorized the factors identified in section 5.4.2 into two categories, (i) factors causing *system inefficiencies* (FSI) and (ii) factors causing *operational inefficiencies* (FOI). For this, we used responses for sub-section B.1 from questionnaire explained in the section 5.4.3. We used the weighted mean to categorize factors based on the total year of construction experience.

After categorizing the factors, we computed the *system risk index* ($\boldsymbol{R_{si}}$) and *operational risk index* ($\boldsymbol{R_{oi}}$). For this, we implemented the QFM approach developed by [32] as explained in section 5.2.1.

5.5 Data Analysis

5.5.1 Descriptive Statistical Analysis

We received a total of 64 responses via Qualtrics XM with a response rate of 8%. The survey contained three main section as mentioned in section 5.4.3. Figure 5.3-5.5 shows the response distribution for 26 safety factors for inefficiency (Facet plot), severity (Violin plot), and probability (Violin plot) scores respectively. Table 5.2 shows the means, standard deviations, medians, standard deviations, skewness, kurtosis, and standard error for inefficiency and severity score of each safety factor. From Figure 5.3-5.5 and Table 5.2, we can observe that the data is negatively-skewed with a longer tail on the left side of the distribution.

Table 5.2. List of safety attributes with corresponding literature references

Code	Mean		Std. Dev.		Median		Skewness		Kurtosis		Std. Error	
	Inf	**Sev**	**Inf**	**Sev**	**Inf**	**Sev**	**Inf**	**Sev**	**Inf**	**Sev**	**Inf**	**Sev**
AGE	0.36	3.30	0.84	1.06	1.00	3.00	-0.73	-0.52	-1.21	0.60	0.11	0.14
LWE	0.71	3.91	0.49	0.94	1.00	4.00	-1.36	-0.60	0.76	0.04	0.07	0.13
LWST	0.95	4.05	0.30	1.10	1.00	4.00	-5.62	-1.22	31.96	0.94	0.04	0.15
PWSA	0.34	4.16	0.72	0.85	0.00	4.00	-0.58	-1.18	-0.94	2.00	0.10	0.11
PEL	0.14	3.04	0.84	1.04	0.00	3.00	-0.27	-0.07	-1.56	-0.65	0.11	0.14
PPHC	0.14	3.66	0.82	1.12	0.00	4.00	-0.26	-0.86	-1.49	0.95	0.11	0.15
PPSC	-0.02	3.70	0.77	0.99	0.00	4.00	0.03	-0.82	-1.36	0.33	0.10	0.13
PWJA	0.11	3.86	0.82	0.92	0.00	4.00	-0.19	-0.54	-1.53	0.07	0.11	0.12
DA	0.09	4.29	0.86	1.11	0.00	5.00	-0.17	-1.67	-1.65	2.04	0.11	0.15
US	0.84	3.75	0.46	1.10	1.00	4.00	-2.82	-1.20	7.28	1.59	0.06	0.15
PPUS	0.89	4.13	0.41	0.92	1.00	4.00	-3.80	-1.08	13.63	1.11	0.06	0.12
BW	-0.30	3.36	0.78	1.10	-0.50	3.00	0.57	-0.24	-1.18	-0.68	0.10	0.15
HN	0.32	3.16	0.66	0.99	0.00	3.00	-0.44	0.13	-0.82	-0.40	0.09	0.13
HLT	-0.25	3.30	0.77	0.93	0.00	3.00	0.44	0.04	-1.22	-0.46	0.10	0.12
HH	-0.41	2.93	0.78	0.99	-1.00	3.00	0.83	-0.30	-0.89	0.59	0.10	0.13
USE	0.93	4.34	0.37	0.86	1.00	4.00	-4.87	-2.38	22.12	9.25	0.05	0.11
LPPE	0.98	4.25	0.13	0.84	1.00	4.00	-7.09	-1.21	49.11	2.07	0.02	0.11
PSSB	0.73	4.00	0.56	0.97	1.00	4.00	-1.90	-1.28	2.59	3.07	0.07	0.13
PCSB	0.50	4.02	0.60	0.96	1.00	4.00	-0.73	-1.36	-0.50	3.40	0.08	0.13
WO	0.80	3.96	0.44	0.89	1.00	4.00	-2.08	-1.43	3.62	4.71	0.06	0.12
HAH	0.38	3.54	0.80	1.33	1.00	4.00	-0.75	-0.98	-1.05	0.20	0.11	0.18
HTP	0.68	3.82	0.58	1.05	1.00	4.00	-1.55	-1.14	1.36	1.62	0.08	0.14
LWD	0.75	3.89	0.51	0.76	1.00	4.00	-1.88	-0.08	2.68	-0.75	0.07	0.10
PE	0.88	4.13	0.38	0.99	1.00	4.00	-3.10	-0.90	9.52	0.15	0.05	0.13
LSR	0.82	4.00	0.47	0.81	1.00	4.00	-2.58	-0.40	5.98	-0.50	0.06	0.11
USSP	0.93	3.88	0.26	0.76	1.00	4.00	-3.24	-0.03	8.65	-0.83	0.03	0.10

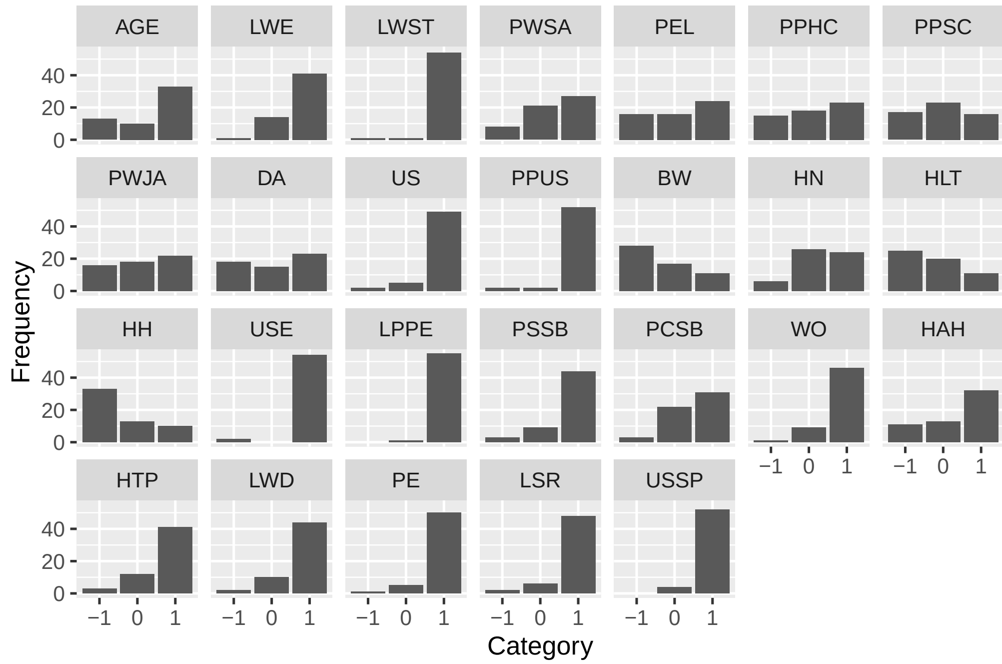

Fig. 5.3. Facet plot for inefficiency score response distribution of safety factors

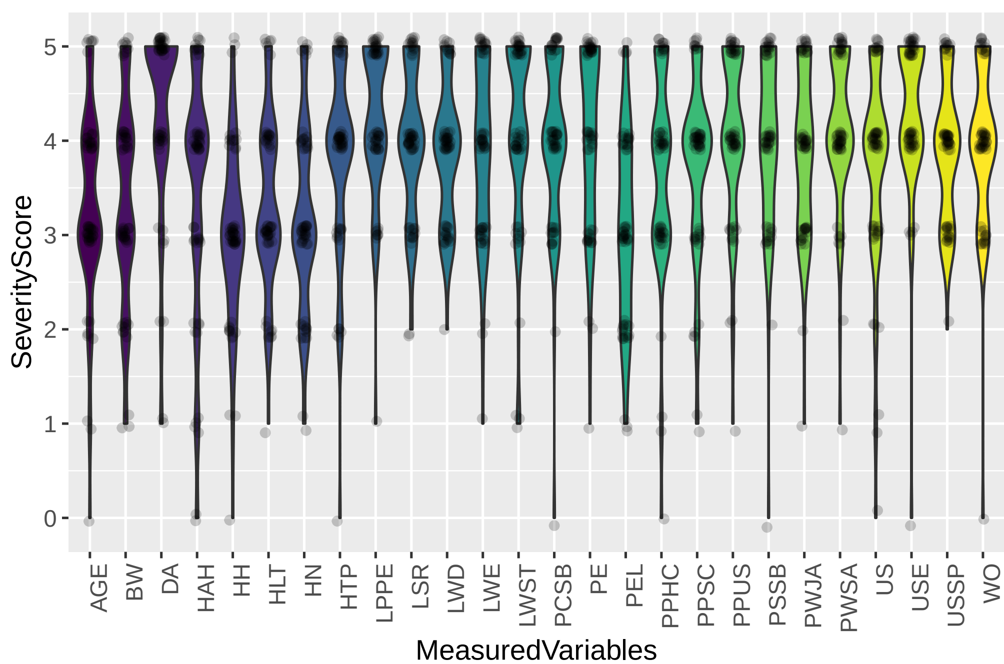

Fig. 5.4. Violin plot for severity score response distribution of safety factors

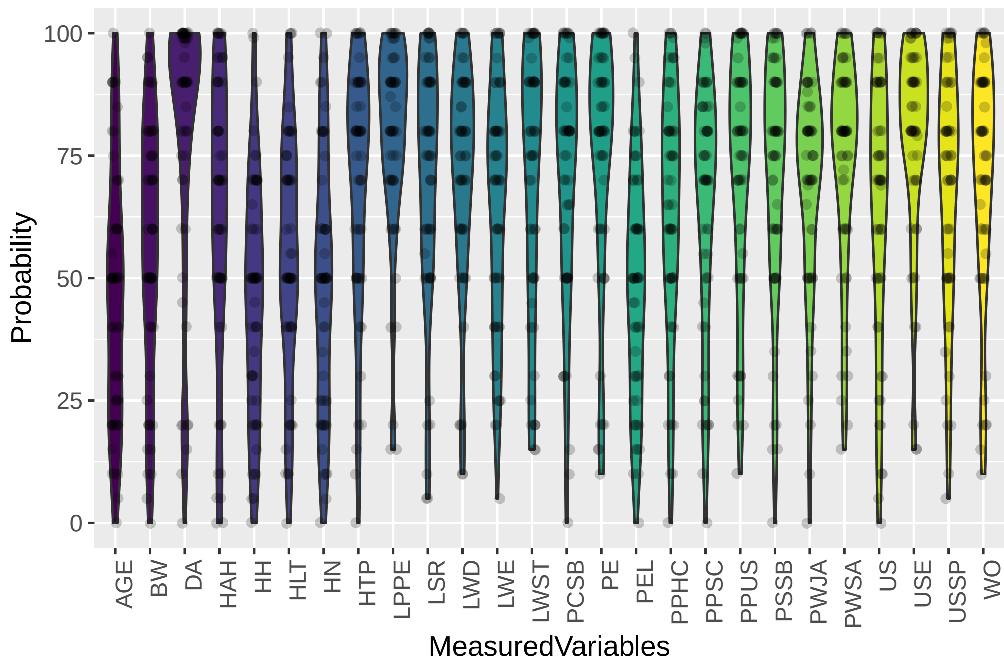

Fig. 5.5. Violin plot for probability score response distribution of safety factors

Moreover, we performed the Shapiro-Wilk normality test to check the normality of the data, as shown in Table 5.3. The low value of $\boldsymbol{W}$ and $\boldsymbol{p}$ from the Saphiro-Wilk normality test shows that the data for all three sections are not normally distributed. However the factor analysis does not assume data to be normal [48].

Table 5.3. Saphiro-Wilk normality test for inefficiencies, severity, and probability response

Data Type	W	p-value	Distribution
Inefficiency	0.116	2.2e-16	Not normally distributed
Severity	0.418	1.48e-13	Not normally distributed
Probability	0.499	1.96e-12	Not normally distributed

Additionally, we performed the Cronbach's alpha (α), KMO measure of sampling adequacy (MSA), and Bartlett's test to check the reliability, adequacy, and suitability of data for factor analysis, respectively as shown in Table 5.4.

Table 5.4. Cronbach's Alpha test for inefficiencies, severity, and probability response

Data Type	α - value	KMO	Bartlett's Test		
			χ^2	p-value	df
Inefficiency	0.821	0.60	721.96	3.41e-32	325
Severity	0.903	0.73	900.27	1.70e-55	325
Probability	0.956	0.85	1356.92	5.92e-126	325

The Cronbach's alpha (α) is the measurement of internal consistency of data. The α values above 0.8 are considered robust and above 0.9 as excellent for research studies [51]. The α values for inefficiency, severity, and probability are above 0.8 validating the reliability of data.

The minimum acceptable KMO value for sample adequacy is 0.6 [45]. The inefficiency data just meets the sample adequacy requirement. The KMO value for severity is OK and that of probability is good. Although, the higher KMO value is preferred, the survey data is adequate enough to perform factor analysis.

The null hypothesis of Bartlett's test states that the observed correlation matrix is equal to the identity matrix, suggesting that the observed matrix is not suitable for PCA or factor analysis [45]. Since the p-value for all three data type is ≈ 0, there is enough evidence to reject null hypothesis. This means that the data is suitable for PCA or factor analysis.

5.5.2 Parallel Analysis

Parallel Analysis (PA) is a Monte-Carlo simulation technique to determine the number of components to retain in PCA and factor analysis [52]. PA method is based on the generation of random variables, to determine the number of factors to retain. It compares the observed eigenvalues extracted from the correlation matrix to be analyzed with those obtained from uncorrelated normal variables [52, 53].

When the eigenvalues from the random data are larger than the eigenvalues from the PA, then those eigenvalues can be neglected as random noise. Table 5.5 shows observed eigenvalues, 95^{th} percentile random eigenvalues and mean of the random data eigenvalues for inefficiencies, severity, and probability. From Table 5.5, we can see that the inefficiency data are represented by 2 factors, severity by 4 factors, and probability by 3 factors.

Table 5.5. Observed eigenvalues from PA and 95^{th} percentile and mean eigenvalues from random data

Nfactor	**ReducedEig**			**RandEigM**	**RandEig95**
	Inf	**Sev**	**Prob**		
1	**5.06**	**8.09**	**12.64**	2.05	2.34
2	**3.46**	**2.51**	**2.13**	1.76	2.01
3	1.60	**1.94**	**1.80**	1.54	1.78
4	1.51	**1.66**	1.13	1.37	1.52
5	1.20	1.18	0.94	1.19	1.33
6	1.09	0.95	0.81	1.05	1.18

5.5.3 Exploratory Factor Analysis

EFA is a multivariate statistical model that attempts to discover the smallest number of latent constructs or factors that can parsimoniously explain the covariation of a relatively large set of observed variable [54]. [55] described the factors as "an unobservable variable that influences more than one observed measure and that accounts for the correlations among these observed measures." EFA is a data-driven approach with no initial hypothesis in regard to the number of latent factors or to the pattern of relationships between the common factors and the indicators (i.e., the factor loadings) [55]. The EFA for n ($\leq$ m) latent constructs can be algebraically represented by equation 5.12.

$$
\begin{aligned}
X_1 &= u_{11}CF_1 + u_{12}CF_2 + ... + u_{1n}CF_n + e_1 \\
X_2 &= u_{21}CF_1 + u_{22}CF_2 + ... + u_{2n}CF_n + e_2 \\
&: \\
&: \\
X_m &= u_{m1}CF_1 + u_{m2}CF_2 + ... + u_{mn}CF_n + e_m
\end{aligned}
\tag{5.12}
$$

where, $\boldsymbol{X_i}$ is i^{th} measured variable, $\boldsymbol{CF_j}$ is j^{th} latent variable, $\boldsymbol{u_{ij}}$ is the weight of j^{th} latent variable associated with the i^{th} measured variable, and $\boldsymbol{e_i}$ is the unique factor of i^{th} measured variable.

We performed the EFA with severity data to determine the underlying dimensions of 26 safety factors. Since the datatype was ordinal and the data was not normally distributed, we implemented the polychoric analysis method for EFA. Table 5.6 shows 26 latent factors, eigenvalues, variance, and cumulative variance. The EFA yielded 7 latent factors with eigenvalues more than 1 compared to 4 factors suggested by PA. The extracted 7 latent variables for EFA accounted for 84.2% of total variance. The Tucker Lewis Index (TLI) of factoring reliability is 0.94 indicating a good fit. The root mean square error of approximation (RMSEA) value for the EFA was 0.037 [0.000, 0.075, 90% confidence]. The chi-square value was 65.83 with 184 degree of freedom with probability < 0.18. Figure 5.6 shows the scree plot for the EFA model.

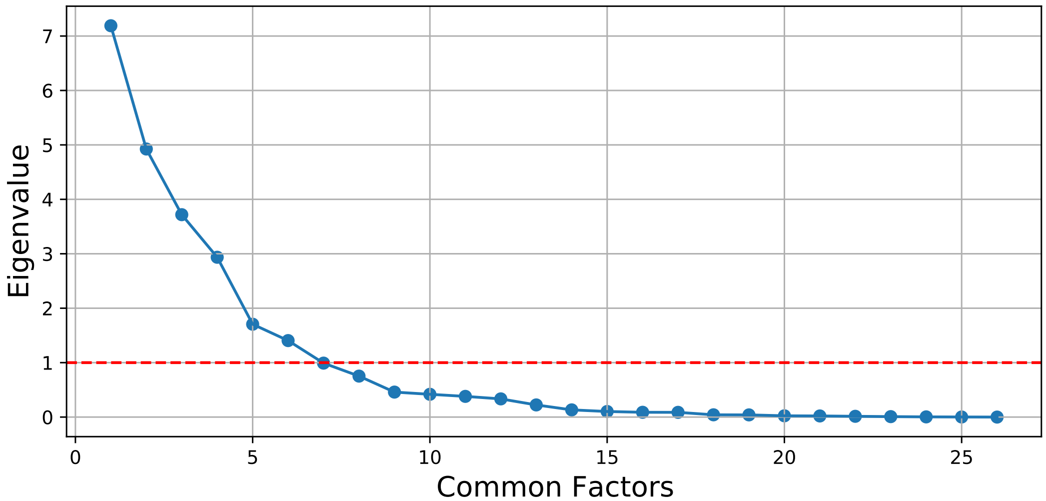

Fig. 5.6. Scree plot for selected EFA model

Table 5.6. Exploratory factory analysis eigenvalues for 26 factors

Factor	EigVal	Variance	CumVar	Factor	EigVal	Variance	CumVar
1	**7.189**	**0.277**	**0.277**	14	0.132	0.005	0.983
2	**4.925**	**0.189**	**0.466**	15	0.102	0.004	0.987
3	**3.718**	**0.143**	**0.609**	16	0.088	0.003	0.991
4	**2.936**	**0.113**	**0.722**	17	0.087	0.002	0.994
5	**1.706**	**0.066**	**0.787**	18	0.042	0.002	0.996
6	**1.405**	**0.054**	**0.842**	19	0.040	0.001	0.997
7	0.991	0.038	0.880	20	0.023	0.001	0.998
8	0.753	0.029	0.909	21	0.021	0.001	0.999
9	0.459	0.018	0.926	22	0.014	0.000	0.999
10	0.418	0.016	0.942	23	0.008	0.000	1.000
11	0.380	0.015	0.957	24	0.004	0.000	1.000
12	0.334	0.013	0.970	25	0.002	0.000	1.000
13	0.223	0.009	0.978	26	0.000	0.000	1.000

Table 5.7 shows the loadings of each safety factor for 6 latent factors, communalities of 26 safety factors (h^2), extracted common factors, and their Cronbach's α-value. The Cronbach's α-value ranging [0.74, 0.88] $<$ 0.70 (minimum acceptable value [51]), indicates acceptable internal consistency of extracted common factors. Based on the influencing factor loadings of each safety factor on latent variables, the following labels were assigned to extracted latent variables:

- Latent Factor 1 (EFA_1) accounted for 32% of the total variance. It included five safety factors, lack of PPE, unavailability of safety equipment, poor supervisors' safety behavior, poor coworkers' safety behavior, and poor equipment. We categorized this latent factor as "*safety climate*". The cronbach's α-value for the extracted factor was 0.87.

- Latent Factor 2 (EFA_2) accounted for 11% of the total variance. It included eight safety factors, lack of work experience, lack of laborers' safety training, poor laborers' safety attitude, poor education level, poor physical health condition, poor psychological health condition, poor laborers' judgment ability, and drug abuse. We categorized this latent factor as "*personal*". The cronbach's α-value for the extracted factor was 0.83.

- Latent Factor 3 (EFA_3) accounted for 9% of the total variance. It included four safety factors, work overload, high accident history, high time pressure, and longer work duration. We categorized this latent factor as "*time constraints*". The cronbach's α-value for the extracted factor was 0.86.

- Latent Factor 4 (EFA_4) accounted for 7% of the total variance. It included four safety factors, bad weather, high noise, extreme temperature, and high humidity. We categorized this latent factor as "*environmental*". The cronbach's α-value for the extracted factor was 0.74.

- Latent Factor 5 (EFA_5) accounted for 6% of the total variance. It included two safety factors, lack of safety regulation, and unavailability of site safety personal. We categorized this latent factor as "*regulatory*". The cronbach's α-value for the extracted factor was 0.88.

- Latent Factor 6 (EFA_6) accounted for 5% of the total variance. It included two safety factors, untidy site, and poor planning and unorganized site. We categorized this latent factor as "*site condition*". The cronbach's α-value for the extracted factor was 0.76.

Table 5.7. Exploratory factory analysis loadings for 6 latent variables

Code	Factor Loadings						h^2	Common Factors	Cronbach α value
	1	**2**	**3**	**4**	**5**	**6**			
LPPE	0.40						0.54	EFA_1 : Safety Climate	0.87
USE	0.93						0.92		
PSSB	0.79						0.80		
PCSB	0.77						0.72		
PE	0.48						0.52		
LWE		0.3					0.92	EFA_2 : Personal	0.83
LWST		0.47					0.60		
PWSA		0.58					0.48		
PEL		0.28					0.38		
PPHC		0.6					0.47		
PPSC		0.83					0.72		
PWJA		0.53					0.63		
DA		0.72					0.64		
WO			0.63				0.77	EFA_3 : Time Constraints	0.86
HAH			0.65				0.67		
HTP			0.81				0.79		
LWD			0.77				0.78		
BW				0.52			0.56	EFA_4 : Environmental	0.74
HN				0.55			0.32		
HLT				0.8			0.67		
HH				0.59			0.66		
LSR					0.71		0.84	EFA_5 : Regulatory	0.88
USSP					0.64		0.68		
US						0.64	0.54	EFA_6 : Site Condition	0.76
PPUS						0.83	0.90		
AGE							0.12	Not extracted	

5.5.4 Principal Component Analysis

PCA is a statistical model that uses an orthogonal transformation to convert a set of possibly correlated variables into a set of linearly uncorrelated variables (i.e., principal components).

The respondent for the survey were from two different demographics, Nepal and USA. So it was necessary to check if there was any significant difference in the survey response between two countries. For this, we performed the PCA with the inefficiency and severity data prior to categorizing the factors into *system* and *operational inefficiencies*. The initial unforced PCA revealed the presence of two components with eigenvalues exceeding one. Figure 5.7 shows the scree plot between the PCA eigenvalues and the number of extracted features.

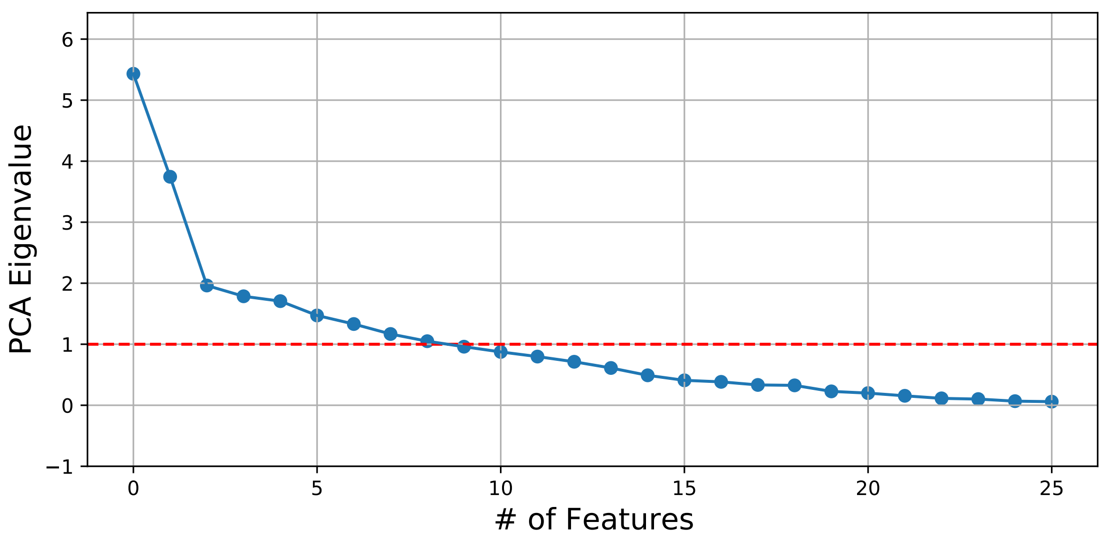

Fig. 5.7. Scree plot between PCA eigenvalues and the number of extracted features

Figure 5.8 shows the plot between principal components (PC1 and PC2) for inefficiency data. And we can observe that there is no significant statistical difference between responses from Nepal and US. We plotted the similar graph among major principal components and found no significant difference between responses from two countries. Moreover, we obtained the similar result for the severity data as well.

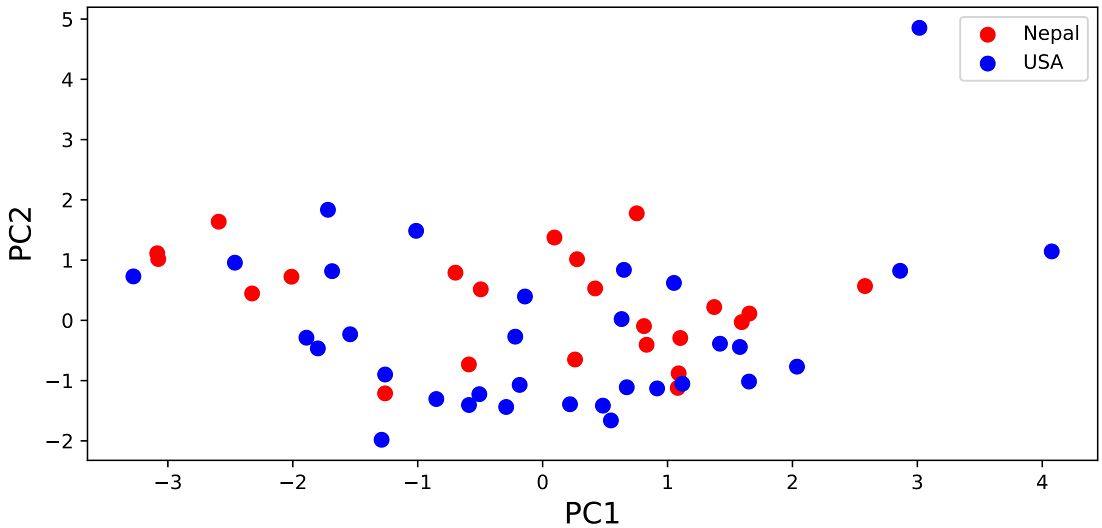

Fig. 5.8. PC1 vs PC2 plot

5.5.5 Computation of Risk Indices for System and Operational Inefficiencies

We categorized the factors into two categories using responses for questionnaire's sub-section B.1. The sub-section B.1 queried whether each safety factor was under the control of project management team or not. We categorized the safety factors under the control of project management team as *operational inefficiencies* and the safety factors not under the control as *system inefficiencies*. We quantified the "Yes, Maybe, and No" options as "1, 0, and -1" for further analysis. Then we computed the weighted mean for each safety factor based on the total year of construction experience. We categorized safety factors with positive mean as FOI and negative mean as FSI. Table 5.8 shows the safety factors, their weighted mean, and selected category.

Table 5.8. Categorization of factors into *system* (FSI) and *operational inefficiencies* (FOI)

Factors	Wt. Mean	Category	Factors	Wt. Mean	Category
AGE	0.34	FOI	HLT	-0.35	FSI
LWE	0.71	FOI	HH	-0.42	FSI
LWST	0.97	FOI	USE	0.90	FOI
PWSA	0.18	FOI	LPPE	0.96	FOI
PEL	0.08	FOI	PSSB	0.63	FOI
PPHC	0.21	FOI	PCSB	0.38	FOI
PPSC	-0.13	FSI	WO	0.75	FOI
PWJA	0.07	FOI	HAH	0.37	FOI
DA	0.05	FOI	HTP	0.67	FOI
US	0.79	FOI	LWD	0.70	FOI
PPUS	0.85	FOI	PE	0.89	FOI
BW	-0.33	FSI	LSR	0.78	FOI
HN	0.34	FOI	USSP	0.90	FOI

Based on the survey responses, we categorized four safety factors (PPSC, BW, HLT, and HH) as factors causing *system inefficiencies* (FSI). Similarly, we categorized remaining twenty-four safety factors (Age, LWE, LWST, PWSA, PEL, PPHC, PWJA, DA, US, PPUS, HN, USE, LPPE, PSSB, PCSB, WO, HAH, HTP, LWD, PE, LSR, and USSP) as factors causing *operational inefficiencies* (FOI). Then, we computed the risk indices $\boldsymbol{R_{si}}$ and $\boldsymbol{R_{oi}}$ using equations 5.5 and 5.8 respectively. For this, we used the responses for questionnaire's sub-section B.2 and B.3. The sub-section B.2 queried the severity score of each safety factor, and the sub-section B.3 queried the occurrence probability of each factor. Table 5.9 and 5.10 shows the severity score ($\boldsymbol{S_i}$), occurrence probability ($\boldsymbol{P_i}$), existence indicator ($\boldsymbol{\epsilon_i}$), and the product ($\boldsymbol{S_i P_i \epsilon_i}$) for *system* and *operational inefficiencies* respectively. The value for existence indicator ($\boldsymbol{\epsilon_i}$) was deduced based on the environmental condition during experimental data collection, subjects' information, and site condition.

Table 5.9. Severity score ($\boldsymbol{S_i}$), occurrence probability ($\boldsymbol{P_i}$), and existence indicator ($\boldsymbol{\epsilon_i}$) for system risk index computation ($\boldsymbol{R_{si}}$)

Code	$\mathbf{S_i}$	$\mathbf{P_i}$	ϵ_i	$\mathbf{S_iP_i}\epsilon_i$	Code	$\mathbf{S_i}$	$\mathbf{P_i}$	ϵ_i	$\mathbf{S_iP_i}\epsilon_i$
PPSC	3.77	0.61	0	0.00	HLT	3.13	0.51	1	1.60
BW	3.05	0.50	1	1.53	HH	2.85	0.45	1	1.28

Table 5.10. Severity score ($\boldsymbol{S_i}$), occurrence probability ($\boldsymbol{P_i}$), and existence indicator ($\boldsymbol{\epsilon_i}$) for operational risk index computation ($\boldsymbol{R_{oi}}$)

Code	$\mathbf{S_i}$	$\mathbf{P_i}$	ϵ_i	$\mathbf{S_iP_i}\epsilon_i$	Code	$\mathbf{S_i}$	$\mathbf{P_i}$	ϵ_i	$\mathbf{S_iP_i}\epsilon_i$
AGE	3.33	0.46	0	0.00	USE	4.26	0.79	1	3.37
LWE	4.04	0.64	1	2.59	LPPE	4.25	0.78	1	3.32
LWST	4.04	0.64	1	2.59	PSSB	3.91	0.73	0	0.00
PWSA	4.20	0.73	0	0.00	PCSB	3.95	0.72	0	0.00
PEL	2.92	0.42	0	0.00	WO	3.85	0.69	0	0.00
PPHC	3.74	0.62	0	0.00	HAH	3.64	0.65	0	0.00
PWJA	3.91	0.68	0	0.00	HTP	3.88	0.68	0	0.00
DA	4.32	0.80	0	0.00	LWD	3.96	0.71	0	0.00
US	3.83	0.63	0	0.00	PE	4.12	0.75	0	0.00
PPUS	4.20	0.71	0	0.00	LSR	3.91	0.67	0	0.00
HN	3.22	0.47	0	0.00	USSP	3.74	0.65	1	2.43

Using equations 5.5 and 5.8, we computed the *system risk index* ($\boldsymbol{R_{si}}$) to be 0.15 and the *operational risk index* ($\boldsymbol{R_{oi}}$) to be 0.49. For computation of *upper limit of sustainable safety* ($\mathrm{SS_{UL}}$), *upper limit of sustainable safety* ($\mathrm{SS_{LL}}$), and *sustainable safety* (SS), we used the lower back moment data for lifting and setting down tasks from Chapter 4. The methodology to compute *safety frontier* (SF) and average *observed safety* (OS) for all unique actions (stand [UA01], squat down [UA02], stay squat [UA03], squat up [UA04], and walk [UA05]) is described in Chapter 4. Using equations 5.10 and 5.11, we computed the *upper* and *lower limit of sustainable safety*. Table 5.11 and Figure 5.9 shows the lower back moment for different safety dynamics components (SF, $\mathrm{SS_{UL}}$, SS, $\mathrm{SS_{LL}}$, and OS) for the lifting and setting down tasks performed by subject_03. From Figure 5.9, we can observe that the higher the gap between the *observed safety* and *safety frontier*, higher the room for improving safety behavior and vice versa.

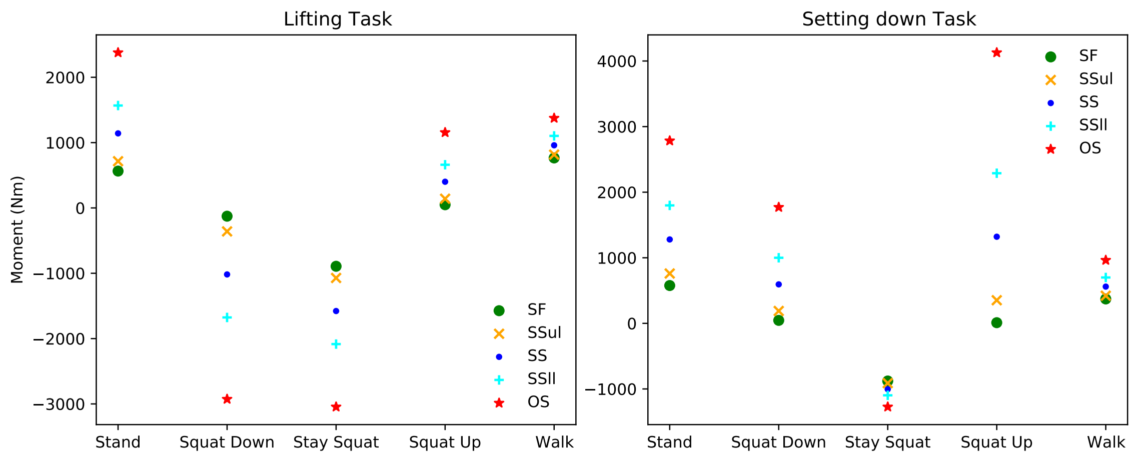

Fig. 5.9. Lower back moment for different safety dynamics components

Table 5.11. Lower back moment (Nm) for different safety dynamics components (SF, SS_{UL}, SS, SS_{LL}, and OS) for lifting and setting down tasks

Description		**Unique Actions**				
		UA01	**UA02**	**UA03**	**UA04**	**UA05**
Lifting	SF	564.24	-126.44	-892.94	48.88	765.19
	SS_{UL}	714.97	-359.23	-1071.85	140.84	815.87
	SS	1141.35	-1017.73	-1577.94	400.99	959.25
	SS_{LL}	1567.74	-1676.24	-2084.03	661.13	1102.62
	OS	2377.47	-2926.79	-3045.14	1155.17	1374.90
Setting Down	SF	576.74	45.45	-878.74	10.27	372.07
	SS_{UL}	760.23	188.83	-911.54	352.56	421.23
	SS	1279.30	594.43	-1004.34	1320.82	560.29
	SS_{LL}	1798.37	1000.03	-1097.13	2289.09	699.35
	OS	2784.12	1770.29	-1273.36	4127.89	963.44

5.6 Limitations and Discussion

5.6.1 Discussion

The chapter proposed the methodology to quantify *system* and *operational inefficiencies* to compute *upper* and *lower limit of sustainable safety* for repetitive labor-intensive construction activities. The questionnaire survey was conducted to obtain construction experts' view regarding the severity and likeliness of identified safety factor to cause safety risk. The study demonstrated the applicability of the proposed method to identify and categorize safety factors into *system* and *operational inefficiencies*. Moreover, we developed a method to quantify the safety risk associated with *system* and *operational inefficiencies* to *system* and *operational risk indices* for various repetitive labor-intensive activities such as metal plate folding, welding, reinforcement bar fabrication and installation, concreting, housekeeping, drywall installation, manual material handling, among others. The proposed method combined with *safety frontier* approach described in Chapter 4 can be used to compute the *upper* and *lower limit of sustainable safety*, that can be achieved and sustained in a construction site. We used the lower back moment data for lifting and setting down tasks from a case study in a construction lab environment to validate the proposed method [16]. Compared to the past studies related to construction laborers' safety, the following subsections describe the chapter's contributions.

Identification of Safety factors Causing System and Operational Inefficiencies

The chapter proposes and validates the method to categorize the identified safety factors into two categories, (i) factors causing *system inefficiencies* (FSI), and (ii) factors causing *operational inefficiencies* (FOI). This aids construction safety personnel a better idea regarding what factors can be controlled and provides an opportunity to improve the overall safety by minimizing the identified factors causing *operational inefficiencies*.

Identification of Key Safety factors

We used the exploratory factor analysis approach to identify the smallest number of latent constructs that can parsimoniously explain the covariation of 26 safety factors. With EFA, we grouped the 26 safety factors into six key factors, with the total variance of 84.20%. The identified six key factors are safety climate, personal, time constraints, environmental, regulatory, and workplace condition (refer section 5.5.3.

Quantification of Safety Risk Indices associated with System and Operational Inefficiencies

The chapter provides a method to compute the risk indices associated with *system* and *operational inefficiencies* using qualitative factor modeling (QFM) approach from the qualitative survey data. The *system risk index* ($\boldsymbol{R_{si}}$) was computed to be 0.07 and the *operational risk index* ($\boldsymbol{R_{si}}$) was computed to be 0.59 for the lifting and setting down tasks.

Computation of Sustainable Safety

The identification of *sustainable safety* that can be achieved and sustained in a construction site is crucial to improve the safety behavior of construction laborers. We proposed an approach to compute the *upper* and *lower level of sustainable safety* from the computed *safety frontier*, average *observed safety*, *system* and *operational* *risk indices*. The identified *sustainable safety* can be used as an achievable index for construction laborers' safety monitoring.

5.6.2 Implications and Potential Applications

The chapter provides practical approach to quantify the safety risk associated with *system* and *operational inefficiencies* responsible for construction laborers'. First, the categorization of safety factors into *system* and *operational inefficiencies* benefits construction safety personnel in identifying safety factors that are under their control. Second, the safety personnel can quantify the risk associated with each safety factor and provide special care to the ones with higher risk index. Third, the safety personnel can use the computed *sustainable safety* as a safety monitoring index. Fourth, apart from construction industry, the proposed method can be beneficial to other industries such as warehouses, supermarkets, mechanic workshops, among others. Although we computed the *sustainable safety* for lifting and seting down tasks, the similar approach can be implemented for any repetitive labor-intensive activity.

5.6.3 Limitations

Despite the contributions mentioned above, the research has some limitations which are listed below.

- Although there are numerous safety factors, we limited our scope to 26 selected safety factors based on the conducted literature review. Further literature review needs to be carried out to identify additional safety factors and incorporated in the risk index computation model.

- We used the response from the questionnaire survey to categorize safety factors into *system* (FCS) and *operational inefficiencies* (FCO), and to compute the severity score and occurrence probability for each safety factor. The number of valid response for the study was limited to 56. More responses need to be collected to further validate the obtained data.
- We used the data from a case study in a controlled lab environment for lifting and setting down tasks. More data needs to be collected in a construction site for different repetitive labor-intensive activities to validate the applicability of proposed methodology in a real construction site.

5.7 Conclusion and Future Work

Researchers have identified several factors affecting the construction laborers' safety. Not all these factors are under the control of a project management team. So it is crucial to categorize the factors depending upon whether the factor can be controlled by a safety management team or not. We categorized factors not under the control of management as *system inefficiencies* and factors under the control as *operational inefficiencies*. For this we proposed the implementation of qualitative questionnaire survey approach to capture the construction experts' responses. Then we proposed and validated a model to quantify the safety risks associated with factors causing *system* and *operational inefficiencies* by modifying QFM model developed by [18] for computing optimal productivity. The construction practitioners can implement the developed model to assess the safety risks associated with different activities and improve laborers' safety behavior by focusing on resolving factors causing *operational inefficiencies*. Moreover, the computed safety indices aid in computing the *upper* and *lower limit of sustainable safety*, that can actually be achieved in a construction site. Finally, the identified *sustainable safety* can play a pivotal role in improving construction laborers' safety by providing a feasible safety target to monitor the laborer' behavior.

Future research should incorporate ample safety factors to robustify the computed risk indices. Extensive survey needs to be carried out to capture broader demographic of construction experts to validate the survey responses. Moreover, future studies should focus on validating the overall safety dynamics components (*safety frontier*, *system* & *operational inefficiencies*, and *sustainable safety*) in a real construction site (refer section 5.2 and Figure 4.2). However, just identifying the *safety frontier* and *sustainable safety* does not serve the purpose. The laborers need to be able to visualize how they are performing versus how they should perform the task. For this, future work should explore the applicability of a need-based personalized learning environment for construction laborers performing repetitive labor-intensive construction activities in a VR environment. The authors have already started the initial work in this respect [11].

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5.9 Bibliography

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CHAPTER 6

VALIDATION OF SAFETY CONTROL SYSTEM FOR REPETITIVE LABOR INTENSIVE ACTIVITIES IN A REAL CONSTRUCTION SITE

Optimization of Safety Control System for Repetitive Labor-intensive Activities in a Real Construction Site using Machine Learning Techniques

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Abstract

Recently, "green" & "sustainable" building design and construction are gaining popularity among construction researchers and industrialists. The current sustainable design concept is focused on economic, social, ecological, and aesthetic facets. The leadership in energy and environmental design (LEED) certification program is a widely accepted green rating system to measure the sustainability of building construction. However, laborers' health and safety are getting minimal focus. Researchers have highlighted several laborers' H&S-related issues associated with the LEED concept. Moreover, the building can not be considered sustainable without incorporating laborers' H&S. So, we identified the need to develop a system incorporating laborers' H&S with building sustainability. For this, we developed a safety control system that can compute the theoretical maximum achievable level of safety, *safety frontier*, identify *system* & *operational* inefficiencies associated with laborers'

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safety, and compute the *sustainable safety* that can be achieved and sustained in a construction site. The study implements inverse kinematics and inverse dynamics approach to compute the spatiotemporal (X, Y, Z, V_x, V_y, and V_z) data and moment induced in major joints, respectively. Moreover, we explored and validated the applicability of different machine learning (ML) models to predict unique actions involved in the task and moment induced in the joints using the spatiotemporal data collected from the depth sensor camera. The study collected postural data for the metal plate bending task from a real construction site and statistically validated the applicability of the proposed safety control system to identify the sustainable "safe work procedure".

Keywords: Safety frontier, Sustainable safety, Safety Inefficiencies, Random forest, Support vector machine, One-vs-rest classifier, Deep neural network

6.1 Introduction

The construction industry has undergone a massive transformation over the past few decades, improving the quality, methodology, and safety [1, 2]. Besides technology and safety, "green" & "sustainable" building design and construction have recently gained significant attention in the US construction industry [3]. The sustainable built environment concept in developed countries focuses on economic, social, ecological, and aesthetic facets [4]. The leadership in energy and environmental design (LEED) certification program is often used to measure the sustainability in building construction [5]. The LEED certification system is the world's most widely used green rating system [6], including a set of rating systems for the design, construction, operation, and maintenance of green buildings. The major drivers for the rapid adoption of green buildings include: (i) government mandates & incentives for green construction, (ii) federal, state, or municipal government requirements for new publicly-funded buildings to be LEED-certified, (iii) increase in demand for green building in the private sector with the recognition of the long-term value of green buildings resulting from a reduction in maintenance costs, (iv) increased availability and reliability of green building supplies, and (v) decreased construction cost [7].

However, the LEED rating system puts minimal focus on laborers' health and safety (H&S). Only a few studies have investigated the impact of LEED on laborers' H&S [7]. The MGM Mirage City Center resort and casino in Las Vegas, Nevada, obtained several LEED certifications despite six work-related fatalities during the construction [5]. [6] concluded that some green elements associated with LEED generate additional safety risks to construction laborers. Dewlaney et al. [8] highlighted the negative impact of green design elements on construction safety performance as: (1) 36% increase in lacerations, strains, and sprains from recycling construction materials, (2) 24% increase in fall hazards, (3) 19% increase in eye strain symptoms, (4) 14% increase in exposure to harmful substances. [9] statistically claimed that green projects incur more OSHA recordable incidents than non-green projects. The aforestated stats further highlights the need to incorporate laborers' H&S as an integral part of sustainable building construction. Moreover, it raises an important question: *"How can building design and construction be considered sustainable if laborers' H&S is not considered?"* So, there is a need to develop a sustainable concept that incorporates the laborers' H&S and addresses all involved parties' environmental, economic, and social well-being.

To integrate laborers' H&S to sustainability, we proposed implementing a frontier approach developed in Chapter 4 (hereinafter referred as *Safety Frontier Study* [10]). The present research quantifies the theoretical maximum achievable level of safety, *safety frontier*, *observed safety*, and the highest level of safety that can be achieved and sustained in a construction site, *sustainable safety*. The *Safety Frontier Study* demonstrated the applicability of the frontier approach to compute *safety frontier* in a controlled lab environment. The chapter validates the relevance of the proposed method in a real construction site scenario. Furthermore, the current research computes the *sustainable safety* ensuring the overall building sustainability. For this, the chapter implements the methodology developedin Chapter 5 (hereinafter referred as *Inefficiency Study*).

6.2 Safety Dynamics: A Brief Overview

Based on the frontier concept, the *Safety Frontier Study* proposes four different levels of safety dynamics: (i) *Safety Standard*, (ii) *Observed Safety*, (iii) *Safety Frontier*, and (iv) *Sustainable Safety*. Safety dynamics is "the process of assessing different levels of laborers' safety existing in a changing construction environment." For brevity, please refer to *Safety Frontier Study* (Chapter 4 [10]) and *Inefficiency Study* (Chapter 5) for detailed explanation.

6.3 Objective and Scope

The objective of the research is to develop a control system that can identify the theoretical maximum achievable level of safety, *safety frontier*, incorporate existing *inefficiencies*, and compute the *sustainable safety* that can be achieved and sustained in a construction site. Figure 4.2 shows the proposed framework for computation of aforestated *safety frontier* and *sustainable safety*. The chapter demonstrates the applicability of the framework to compute safety dynamics components in a real construction environment.

6.4 Methodology

Chapter 6 implemented the methodology developed by the *Safety Frontier Study* to quantify the *safety frontier* and the *Inefficiency Study* to quantify the *sustainable safety* for a repetitive labor-intensive activity in a real construction site. We extracted the laborers' postural data using a depth-sensing camera while performing a repetitive labor-intensive activity in a construction site. Then, we manually classified a chunk of data into different unique actions involved in the activity and computed the moments induced in joints using the inverse dynamics principle. We used the manually classified actions and computed moments to train the action classification and moment prediction models, respectively. Figure 6.1 shows methodology implemented to obtain *safety frontier* and *sustainable safety*.

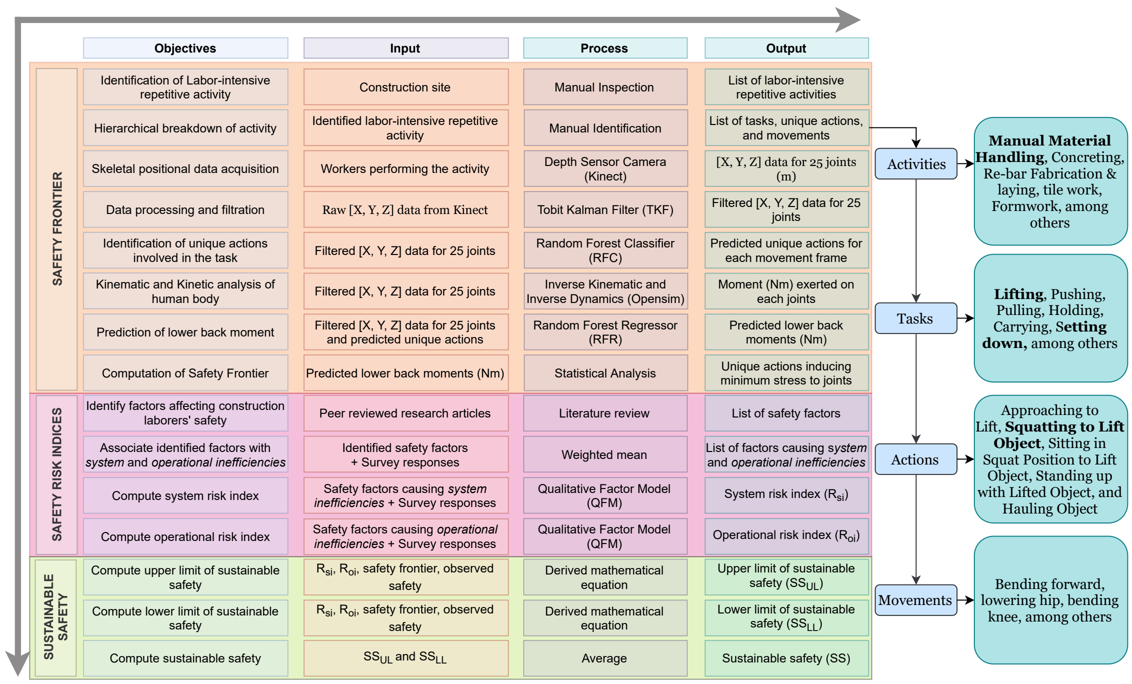

Fig. 6.1. Methodology to compute *safety frontier* and *sustainable safety*

6.4.1 Computation of Safety Frontier

The primary step to develop the safety control system involves computing *safety frontier*. The *Safety Frontier Study* provides the detailed methodology to compute the *safety frontier*. The following subsections briefly describe the key steps for computing the *safety frontier* for the metal plate bending task, as the scope of this chapter.

Identification of Labor-Intensive Repetitive Activity

Despite the recent improvement in construction methods and techniques, several activities are still repetitive labor-intensive, such as manual material handling, metal works, concrete flooring, and masonry work. We chose the metal staircase fabrication activity (metal plate folding task) for the scope of this chapter.

Hierarchical breakdown of activity

Based on the four-level hierarchical breakdown approach proposed by [11], we identified different tasks, unique actions, and movements involved in the metal staircase fabrication activity. The unique tasks include plate cutting, plate bending, welding, and painting, among others. The unique actions for the metal plate bending task include approaching the plate to lift, lifting and transferring the plate to the folding machine, bending the plate, and lifting and stacking the bent plate. For *lifting and transferring the plate to the folding machine* action, different movements include bending forward, moving hands in a forward direction, grabbing the metal plate to lift, bending the elbow to lift, walking sideways, bending forward to place the metal plate in the folding machine, and lowering hands.

Skeletal Positional Data Acquisition, Processing, and Filtration

The skeletal spatial data of laborers' posture while performing the task is essential to identify the unique actions involved and compute moments induced in joints. Recently, there are several technology that we can implement to collect the spatial data, such as motion sensors [12], accelerometers [13], depth-sensing camera [10], lumbar motion monitor [14], and computer vision [15]. For this chapter, we selected a depth-sensing camera (*Kinect*) to collect skeletal spatial data due to its features such as low cost, robustness, non-invasive, acceptable tracking range, and adaptability in the site environment. Moreover, the *Safety Frontier Study* and *Inefficiency Study* used the *Kinect* to collect the lab data to demonstrate its applicability to compute the *safety frontier* and *sustainable safety*, respectively.

The *Kinect* data generates noise due to self-occlusion, occlusion by colaborers, reduced accuracy during sudden movements, and limited tracking range [16]. First, we manually processed the *Kinect* data to separate multiple laborers' tracked, identify and remove the useless data, and identify several task instances performed by different subjects. Second, we implemented the Tobit-Kalman filter (TKF) on processed data by considering joints' speed restrictions, as proposed by [16], to filter the noise and outliers.

Unique Actions Identification using Machine Learning

The unique actions involved in the task need to be identified to determine the *safety frontier* and *sustainable safety*. Moreover, each unique action comprises of several movement frames. For instance, we can categorize the metal plate bending task into four different unique actions based on the involved movement listed in Table 6.1. Figure 6.2 shows the four unique actions involved in the metal plate bending task.

Table 6.1. List of unique actions involved in metal plate bending task (MPB)

Actions involved in MPB task	Code
Approaching the unbent metal plate to lift from a table	MPB1
Transferring the unbent metal plate to folding machine	MPB2
Bending the metal plate in folding machine	MPB3
Transferring the bent metal plate to stack in a table	MPB4

Fig. 6.2. Unique actions involved in metal plate bending task. Left to right: MPB1, MPB2, MPB3, and MPB4

We can manually identify the involved unique actions by manually observing each movement frame, which is time-consuming, error-prone, and virtually impossible to carry out in real-time. So we proposed to use a machine learning (ML) approach to classify the movement frames into unique actions. Past studies have implemented several ML models such as decision trees [17], random forest [18], deep neural networks [19], and support vector machine [20], for gait classification. We chose the support vector machine, random forest, and one-vs-rest classification model to identify unique actions for each movement frame. A random forest is widely used with extensive training data having several input features [21]. In this chapter, we had 150 total input features, including spatial data of 25 joints from the *Kinect* and their computed velocity components.

Kinematic and Kinetic Analysis of Human Motion

Computing moments induced in joints is essential to quantify *safety frontier*. For realistic motion analysis, we used an open-source software system, *OpenSim* [22], to compute the moment exerted on human body joints due to spatiotemporal movements [12]. We used the full-body lumbar spine (FBLS) musculoskeletal model developed by [23]. The model consists of 21 segments, 30 degrees of freedom, and five lumbar vertebrae, each connected by a 6 degree of freedom joint [23]. We scaled the model and performed inverse kinematics and inverse dynamics analysis to compute the force and moment exerted on human body joints for each movement frame (refer *Safety Frontier Study* for details).

[24] experimented and concluded that working mostly in a standing position is associated with low back pain among laborers. Additionally, laborers need to stand all day long while working in the plate folding machine. Moreover, one of the objectives of the current chapter was to validate the applicability of the *safety frontier* approach, developed and demonstrated in a lab setup by the *Safety Frontier Study*. So, to maintain the consistency of the analysis, we chose the same "PS_L1_VB" muscle (referred to as "lower back moment" onward) as the scope of this chapter. Furthermore, we explored the applicability of random forest regression and support vector machine algorithm to develop a lower back moment prediction model with *Kinect*'s spatial data, computed joint velocity, and predicted unique actions as the input features.

Computation of *Safety Frontier*

The *safety frontier* involves identifying unique actions exerting a minimum lower back moment. First, we separated each instance of task using action classification algorithm output. Second, we segregated groups of movements involved in each unique action. Third, we added the lower back moment induced in each movement frame for the segregated groups of movements to compute the cumulative moment for each instance of unique action. Then, from the moment data pool for several instances of unique actions, we identified the ones exerting minimum cumulative lower back moment for each unique action. Finally, we defined the *safety frontier* as the combination of segregated movements causing these unique actions with the minimum cumulative moment. We computed the individual *safety frontier* for each participating laborers and then combined them to compute the overall *safety frontier*. The following example explains the process to compute the *safety frontier*.

"Suppose, Labor_A is performing the MPB1 action safely in instance_w, MPB2 in instance_x, MPB3 in instance_y, and MPB4 in instance_z. If we combine the movement frames involved in these instances, then we get the individual *safety frontier* for Labor_A. Moreover, we can compare the individual *safety frontier* for all laborers and identify the safest instance of all four unique actions. Finally, we can compute the overall *safety frontier* by combining these identified unique actions."

6.4.2 Computation of Safety Risk Indices

The overall *safety frontier*, computed in section 6.4.1, represents a theoretical maximum level of safety and is virtually impossible to attain in a real construction site due to existing *system* and *operational inefficiencies*. So, we need to identify the *system risk index* and add it to the *safety frontier* to obtain the *upper limit of sustainable safety*. Similarly, we need to identify the *operational risk index* and remove it from the *observed safety* to obtain the *lower limit of sustainable safety*. The *Inefficiency Study* provides the detailed methodology to compute the safety risk indices using the qualitative factor modeling (QFM) approach. The following subsections briefly describe the key steps to compute the *safety risk indices* for the metal plate bending task, as the scope of this chapter.

Identification of Factors Affecting Construction Laborers' Safety

The identification of factors affecting construction laborers' safety is essential to compute *safety risk indices.* Existing research articles are an excellent source to identify these factors. [25] conducted an extensive literature review to identify several factors affecting laborers' safety. We used the factors identified by the *Inefficiency Study* from an extensive literature review.

Associating Factors with *System* and *Operational Inefficiencies*

The identified factors from subsection 6.4.2 needs to be associated with *system* and *operational inefficiencies* based on the management team's control over factors. The *Inefficiency Study* conducted a survey with construction experts to categorize factors into two categories, (i) factors causing *system inefficiencies* (FSI) and (ii) factors causing *operational inefficiencies* (FOI). For this, the survey collected responses to inefficiency type (Can management team control the factor?) on a 3 point Likert scale (-1 = No, 0 = Maybe, and 1 = Yes).

Computation of *System* and *Operational Risk Indices*

After categorizing the factors, we computed the *system risk index* ($\boldsymbol{R_{si}}$) and *operational risk index* ($\boldsymbol{R_{oi}}$) using equations 5.5 and 5.8, respectively, as proposed by the *Inefficiency Study.*

6.4.3 Computation of Sustainable Safety

After obtaining the *safety frontier* (SF), *observed safety* (OS), and *safety risk indices* ($\boldsymbol{R_{si}}$ & $\boldsymbol{R_{oi}}$), we computed the *upper* ($\mathrm{SS_{UL}}$) and *lower limit of sustainable safety* ($\mathrm{SS_{LL}}$) using equations 5.10 and 5.11, respectively (refer to the *Inefficiency Study* for detailed derivation). Finally, we computed the *sustainable safety* taking an average of ($\mathrm{SS_{UL}}$) and ($\mathrm{SS_{LL}}$).

6.5 Data Collection and Analysis

We collected data from a welding construction site located at Medley, FL. The working condition was outdoor, hot, humid, and noisy. We collected multiple days of data for the metal plate folding task of staircase fabrication activity. Although seemingly safe, the metal plate folding task requires laborers to stand and walk for the majority of work duration, increasing the risk of lower back pain. Florida International University's Institutional Review Board (IRB) evaluated and approved the study protocol. We took special precautions during the Covid-19 pandemic to collect data on the construction site. Since the optimal tracking range of *Kinect* was 1m - 3m [26], we maintained 6 feet (1.8m) distance from laborers during data collection. The average distance between the *Kinect* and the subject was 2.75m. We submitted a detailed data collection plan explaining the precautionary measures to avoid exposure to Covid-19 to the construction site manager for approval. Due to the limited access to the site during the pandemic, we collected multiple days of skeletal spatial data for only three subjects. Participation in the research was voluntary, with no provision of compensation. We obtained the signed consent from the participants before collecting the data. Irrespective of the signed consent, the participants were free to withdraw their participation at any time without providing any reason whatsoever.

For skeletal spatial data collection, we placed the *Kinect* at an approximate distance of 2.75m in front of the subject. Figure 6.3 shows the boxplot diagram for the SpineBase raw spatial data of all three subjects. In Figure 6.3, "SpineBase Z" represents the perpendicular distance from *Kinect* to the subject. We can notice that the mean distance is less than or about 3m for all three subjects, ensuring the data to be within optimal tracking range of the *Kinect* even in the Covid-19 pandemic situation. Moreover, the X and Y coordinates are within the optimal tracking range of the *Kinect* for all three subjects.

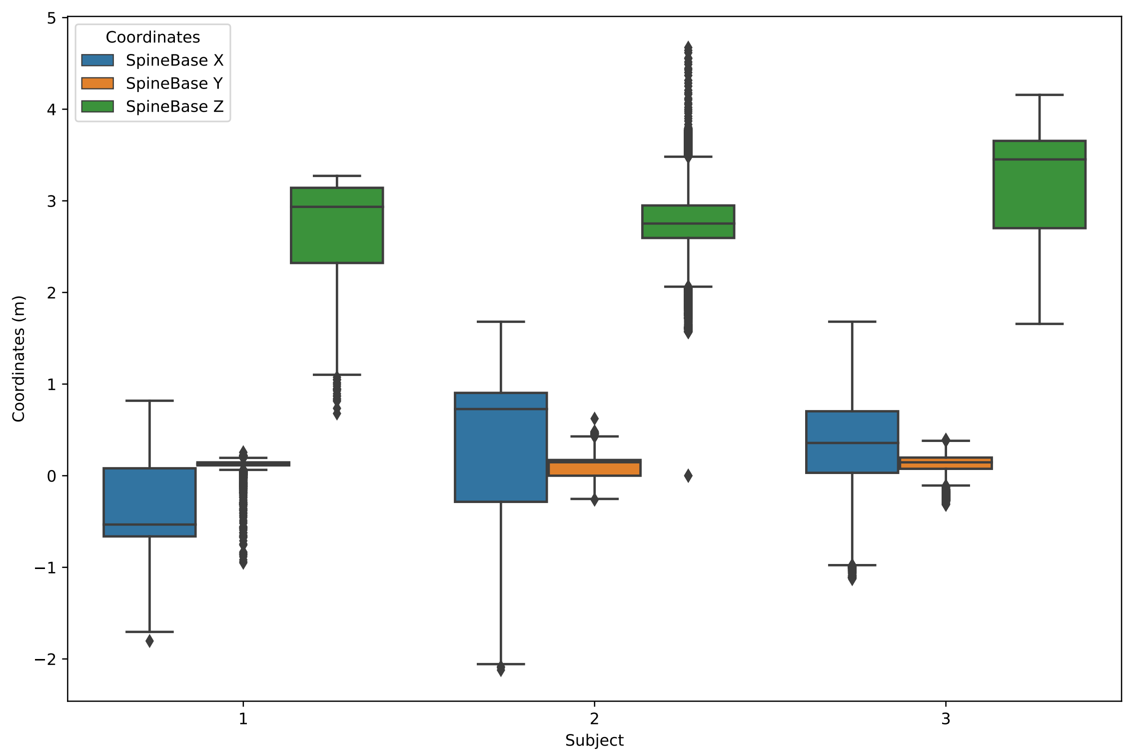

Fig. 6.3. Boxplot diagram for the SpineBase spatial data [X, Y, Z]

The data frequency was 30 Hz for the *Kinect*. Moreover, we positioned the video camera perpendicular to the *Kinect* to record the task performance at the same frequency for validating data and manually identifying unique actions of each movement frame to train the actions classification model. The following subsections describes the computation of *safety frontier*, *safety risk indices*, and *sustainable safety* analyzing the collected data.

6.5.1 Computation of Safety Frontier

Skeletal Positional Data Acquisition, Processing, and Filtration

The current study collected 94 instances of metal plate bending task for Subject_01 (46,403 movement frames), 59 instances for Subject_02 (32,082 movement frames), and 99 instances for Subject_03 (82,837 movement frames). However, Subject_02 was unavailable for the data collection from the second day, and no usable data was collected on the first day. So, we excluded Subject_02 from further analysis. Similarly, 93 task instances for Subject_01 and 84 for Subject_02 were separated after preliminary manual data processing. The staircase fabrication activity occurred around once every month. So, we collected data for four months to get the aforestated 177 valid task instances (116,194 movement frames) in total.

We implemented the TKF model to process and filter the Kinect joints' coordinates (X, Y, Z). The *Safety Frontier Study* describes the details of the TKF model implemented in the chapter. Figure 6.4 shows the raw and filtered spatial coordinates for the spine base obtained from the *Kinect* after using TKF. We can observe that the applied filter does not over-smooth the *Kinect* data and corrects the noise significantly.

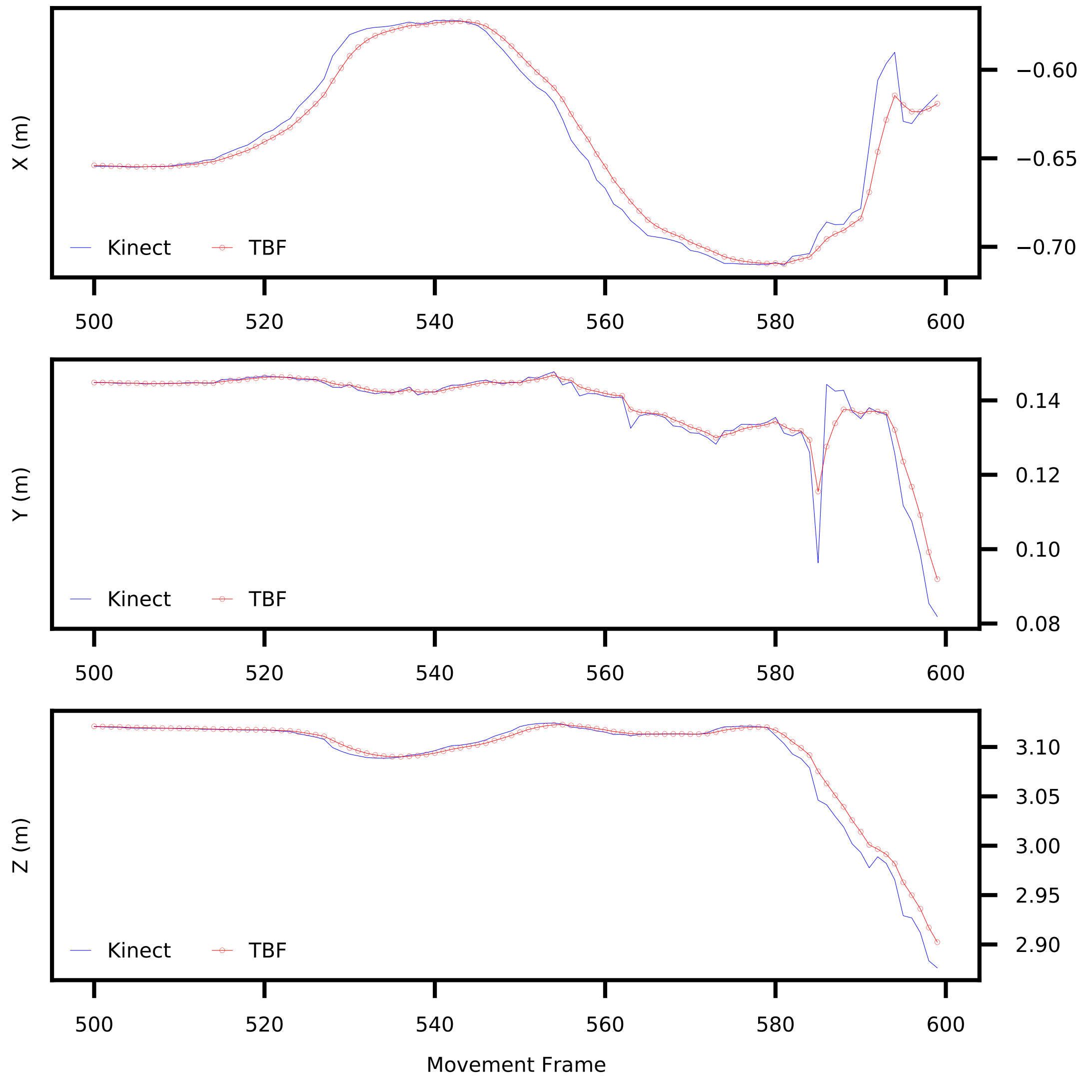

Fig. 6.4. Spatial coordinates of spine base obtained from *Kinect* before and after applying TKF

Action Identification using Machine Learning

We used the chunk of data (19,647 movement frames, 27 task instances for Subject_3) to train the unique action prediction model. We manually labeled each movement frame into different unique actions provided in Table 6.1 by running the motion in *OpenSim* and validating it with visual data. We computed the velocity components [V_x, V_y, V_z] for all 25 joints. We used the spatial coordinates (75 variables) and velocity components (75 variables) as input features to train and predict the unique action involved in each movement frame. Out of the 19,647 movement frames (27 task instances), we randomly chose 13,752 frames (70%) for model training and 5,894 frames (30%) for model testing. We further split the 30% testing data into validation data (15%) and test data (15%).

Random Forest Classifier Approach Out of the 150 input features, it is essential to identify the relevant features that can accurately classify the unique actions with the minimum computational expense. For this, we used the recursive feature elimination and cross-validation selection (RFECV) approach to eliminate irrelevant features based on the validation scores from Scikit-Learn tools in Python. We performed the 5-fold cross-validation and obtained the optimal number of features as 145. So, we decided to use all input features for the prediction model.

After determining the optimal features, we implemented random forest classifier (RFC) algorithm for model fitting. For hyperparameter tuning, we varied *n_estimators*, *max_features*, and *max_depth*. Figure 6.5 shows the out-of-bag (OOB) error for variation of RFC model with change in *n_estimators*, *max_features*, and *max_depth*. Based on the minimum OOB error, we chose the following parameters for the RFC model.

$$[n\_estimators,\ max\_features,\ max\_depth] = [500, \text{“sqrt”}, 30]$$

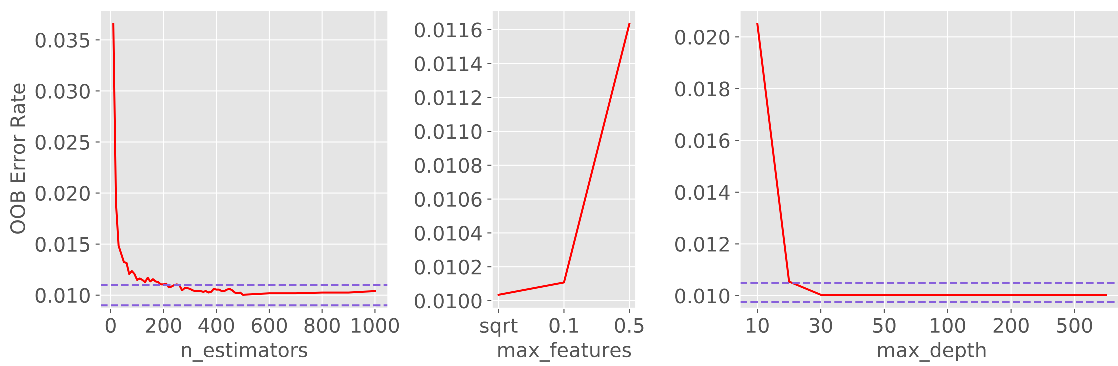

Fig. 6.5. Out-of-bag error for *n_estimators*, *max_features*, and *max_depth*

After choosing the hyperparameters, we used the Balanced Random Forest classifier (BRF) to find the proper fit for the training data set [27]. The accuracy of the BRF model was 0.978. Moreover, we performed the 5-fold cross-validation using the RFC model with the same hyperparameters and obtained an accuracy of 0.989 (+/-0.005). Figure 6.6 shows the confusion matrix for two independent test data ([Data_1: 9 task instances, 6,528 movement frames; Data_2: 15 task instances, 8,774 movement frames]) for the fitted RFC model. The error was partly due to human error during manual classification and partly due to the prediction model. However, more than 99% of the classification was accurate for all four actions.

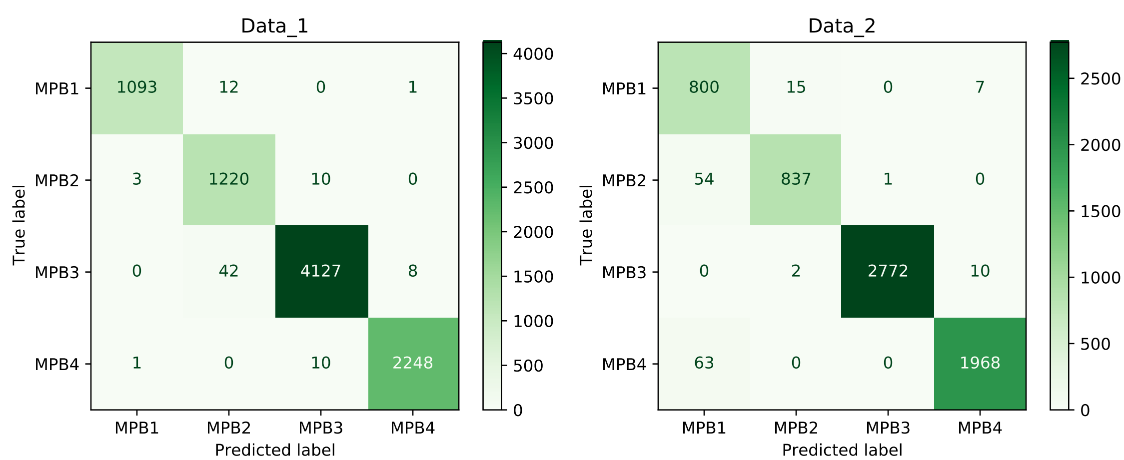

Fig. 6.6. Confusion matrix for two independent test data

Moreover, we plotted the receiver operating characteristics (ROC) (Figure 6.7) curve for independent data (Data_1) to evaluate the diagnostic ability of the selected RFC model. The ROC curve plots the true positive rate as a function of the false positive rate. The advantage of the ROC analysis is the robust description of the model's predictive ability [28]. The high value (max = 1) for the area under the curve (AUC) in Figure 6.7 represents that the selected RFC model is well-fitted for prediction. We obtained a similar result for Data_2.

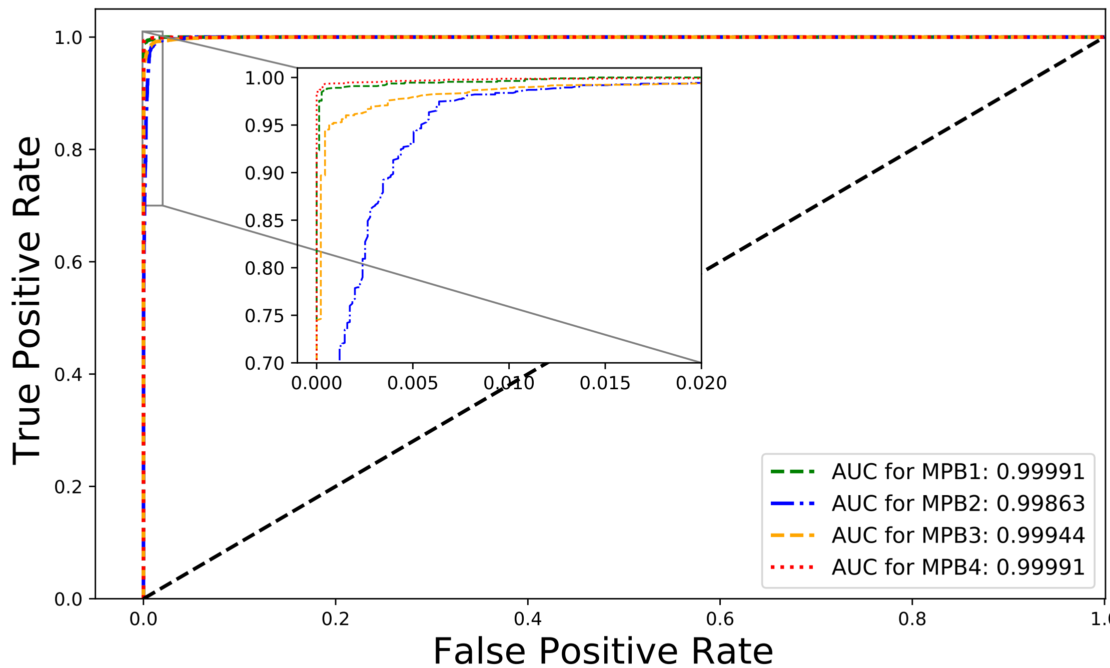

Fig. 6.7. AUC-ROC curve for the selected RFC model for independent Data_1

One-VS-Rest (OVR) Classifier Approach We explored the applicability of the OVR classification approach with the fitted RFC model as a base model. OVR is a heuristic method that leverages a binary classification algorithm for multi-class classifications. It splits a multi-class dataset into multiple binary problems and trains a binary classifier to handle each binary classification model. Final predictions are made using the most confident model. For our dataset, the binary classification can be categorized as follows:

- Problem 1: MPB1 vs. MPB2/MPB3/MPB4
- Problem 2: MPB2 vs. MPB1/MPB3/MPB4
- Problem 3: MPB3 vs. MPB1/MPB2/MPB4
- Problem 4: MPB3 vs. MPB1/MPB2/MPB3

The accuracy of the OVR model was 0.991 for the training test data. Moreover, the accuracy of the OVR model with independent data (Data_1) was 0.981, validating its applicability in unique actions classification. The AUC value for all four classifications was nearly equal to 1.0, representing the well-fitted OVR model.

Support Vector Machine (SVM) Approach We also explored the applicability of the SVM approach to our dataset. SVM is a widely used method for classification problems [29]. SVM finds the best separating (maximal margin) hyperplane between two classes of training samples in the feature space [30]. However, the SVM is extended into multi-class mode using several methods. One standard method for extending the SVM into multi-class mode is the OVR approach [29]. The accuracy of the SVM model using the OVR approach was 0.961 for the training data, suggesting a well-fitted model.

Table 6.2 shows the details of different fitted models and their performance parameters on training & independent data (Data_1). We can observe that all four models classified the unique actions with high accuracy. For further classification, we chose the RFC model based on its slightly higher performance indices.

Table 6.2. List of implemented ML models and their performance for actions classification

Mdls	[Accuracy (A), Precision (P), Recall (R), F1-score, AUC]		
	15% Validation Data	**15% Test Data**	**Independent Data_1**
RFC	[0.988, 0.989, 0.989, 0.988, 0.99]	[0.986, 0.986, 0.986, 0.986, 0.99]	[0.990, 0.990, 0.990, 0.990, 0.99]
OVR	[0.989, 0.990, 0.989, 0.989, 0.99]	[0.989, 0.990, 0.989, 0.989, 0.99]	[0.981, 0.981, 0.981, 0.981, 0.99]
BRF	[0.978, 0.978, 0.978, 0.978, 0.99]	[0.978, 0.979, 0.978, 0.978, 0.99]	[0.974, 0.975, 0.974, 0.974, 0.99]
SVM	[0.928, 0.927, 0.928, 0.927, 0.99]	[0.934, 0.933, 0.935, 0.934, 0.99]	[0.929, 0.928, 0.929, 0.927, 0.99]

Kinematic and Kinetic Analysis of Metal Plate Bending Task

We placed the 25 joint markers in the FBLS model with the spatial data from the *Kinect* representing the joints tracked. Then using the spatiotemporal data, we scaled the model and performed the kinematic and kinetic analysis. Then we computed the moment exerted in the lower back psoas major muscle (PS_L1_VB_right) (hereafter referred as "lower back moment") by performing the muscle and joint reaction analysis in *Opensim*.

With the lower back moment computed from *Opensim* as a training target, we explored multiple models (random forest regressor (RFR), lasso cross-validation regressor (LR), gradient boosting regression (GBR), and stacking regressor (SR)) to evaluate the performance accuracy and the computational load. SR model stacked the output from RFR, LR, and GBR models and used a regressor to compute the final moment prediction. Figure 6.8 shows the variance (R^2) and the computational load for different tested models. The R^2 value for the RFR, GBR, and SR were all around 0.96. However, the computational loads for SR and RFR were 100 and 10 times higher than that of GBR, respectively. So, we further explored the performance of the GBR model with independent data and computed the R^2 as 0.578 (considered low score).

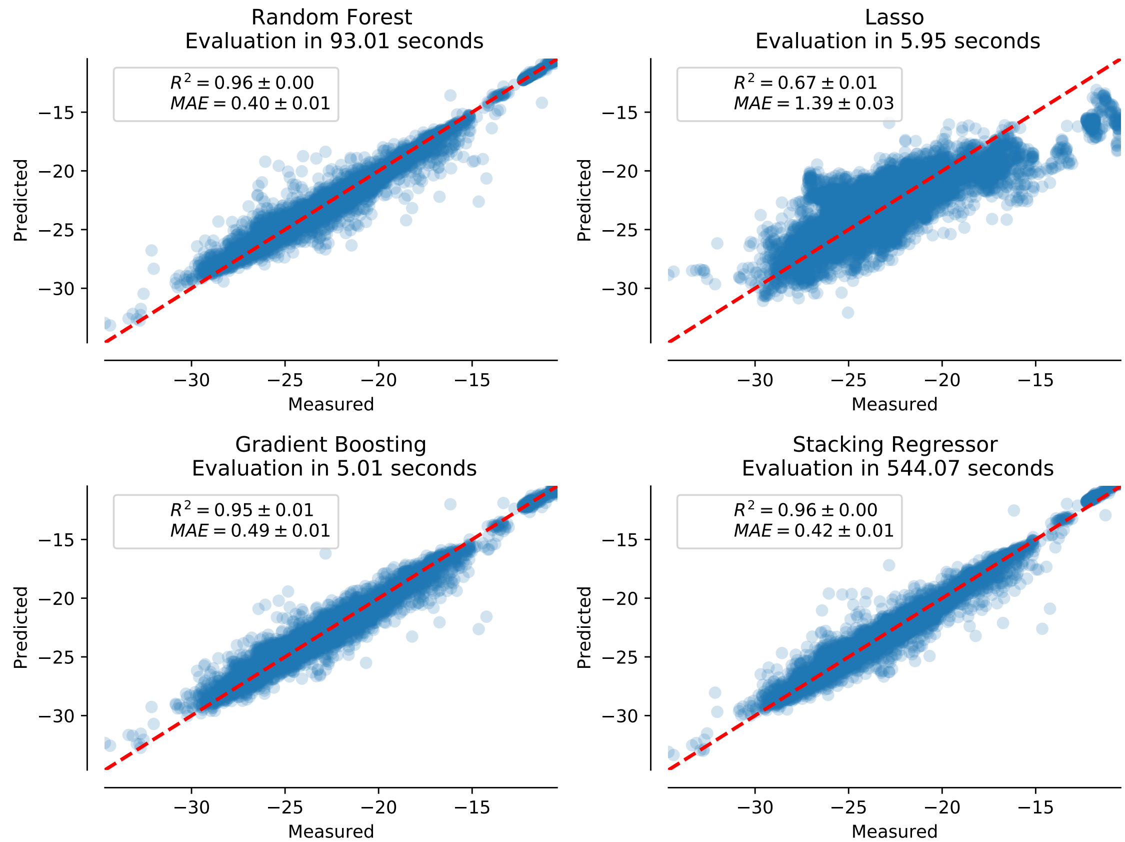

Fig. 6.8. Evaluation of different regression model to predict moment

Then, we used the random forest regression (RFR) algorithm with 5-fold cross-validation to fit the model to predict the moment with 151 input features (including the predicted action as an additional input variable) and the computed moment as a target. We split the training data as discussed earlier in Section 6.5.1. Table 6.3 shows the performance details of the implemented model for validation, test, and independent data. For assessing the predictive accuracy of a regression model, we used multiple parameters, such as mean absolute error (MAE), mean square error (MSE), mean absolute percentage error (MAPE), and coefficient of determination (R^2). The R^2 for the independent data was 0.582 meaning the model was able to explain 58.2% of the data. The lower R^2 value is due to the limitations of the *Kinect* to track the subject when facing backward. However, the MAE, MSE, and MAPE are very low suggesting the model's applicability to predict lower back moments.

Table 6.3. Performance details of implemented RFR model for moment prediction

Parameters	Validation Data	Test Data	Independent Data
MAE	0.319	0.306	0.806
MSE	0.342	0.295	1.290
RMSE	0.585	0.543	1.136
MAPE	0.014	0.013	0.034
R^2	0.901	0.909	0.582

Figure 6.9 shows the scatter plot of the observed and predicted lower back moments of the RFR model on the left, prediction error density plot on the middle, and quantile-quantile (Q-Q) plot on the right for independent test data (33 task instances and 27,914 movement frames). We can observe that most of the predicted data on the scatter plot aligns with the true data, and the errors are concentrated with a peak close to zero. Moreover, we can visually observe that the errors are normally distributed from the Q-Q plot with few outliers.

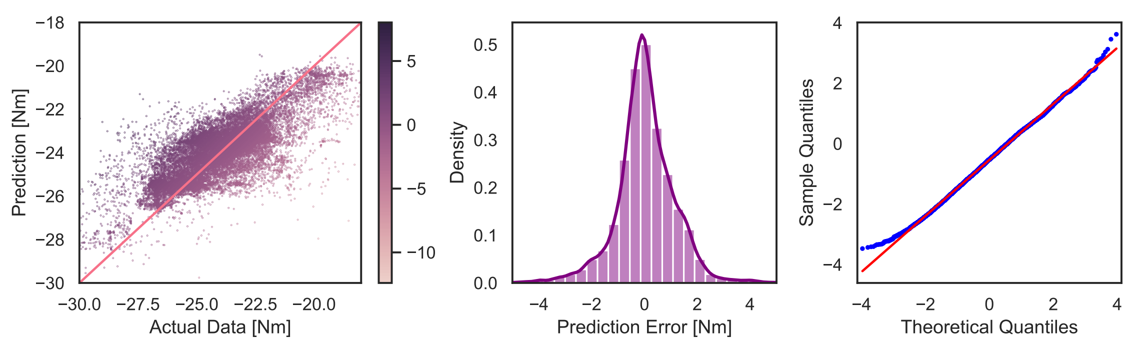

Fig. 6.9. Scatter plot (left), prediction error plot (mid), and Q-Q plot of the observed and predicted lower back moments of the RFR model)

Furthermore, we implemented a deep learning approach to increase the accuracy of prediction. We used the *Keras* library from *TensorFlow*, an open-source machine learning platform, to create a deep neural network (DNN). After multiple iterations, we chose the following parameters for the model. We used the Google Colab free GPU to train the model. We used the following parameter to define the model.

$$[optimizer, loss, epoch, batch\_size] = [\text{“Adam”}, \text{“mean\_squared\_error”}, 100, 100]$$

The DNN model performed better with 76 input features (75 spatial data from *Kinect* and the predicted unique actions). The training loss was 0.542, and the validation loss was 0.563 for the model. The DNN model increased the R^2 value from 0.582 (RFR) to 0.700 with the independent test data. Figure 6.10 shows the scatter plot of the observed and predicted lower back moments of the DNN model on the left, prediction error density plot on the middle, and Q-Q plot on the right for independent test data. From Figure 6.10, we can observe that the prediction data are more aligned in the scatter plot, and the density curve's peak (zero error) has increased from 0.50 to 0.75. The accuracy details of the DNN model with independent data set were:

$$[\text{MAE, MSE, RMSE, MAPE, R}^2] = [0.602, 0.891, 0.944, 0.026, 0.700]$$

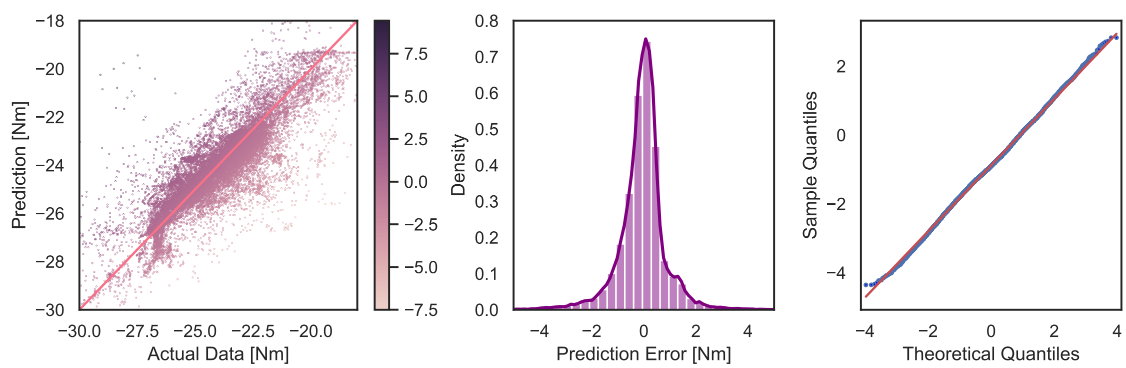

Fig. 6.10. Scatter plot (left), prediction error plot (mid), and Q-Q plot of the observed and predicted lower back moments of the DNN model)

Then, we predicted the lower back moment for both subjects using the trained DNN model. Figure 6.11 shows the predicted lower back moment for both subjects for the metal plate bending task. Each point represents the cumulative lower back moment of one instance of unique action performed by the subject. Although the task seems straightforward, we can notice the variation in the cumulative moment between subjects and within the instances performed by a subject on the same day.

For example, let us compare the MPB3 action performed by S_1 and S_3. Here we can observe a significant difference in the cumulative moment induced by the action between two subjects. For MPB3, the cumulative moment range for S_1 is [-1649.54 Nm, -6421.00 Nm] from 93 task instances, and for S_3 is [-4789.25 Nm, -33898.34 Nm] from 84 task instances. It demonstrates that there can be a considerable variation in the induced moment, even for the seemingly simple repetitive task. Moreover, the laborers should be encouraged to bring their average moment closer to the minimum moment. The significant difference between the minimum induced moment between S_1 and S_3 further highlights the necessity of peer-learning opportunities.

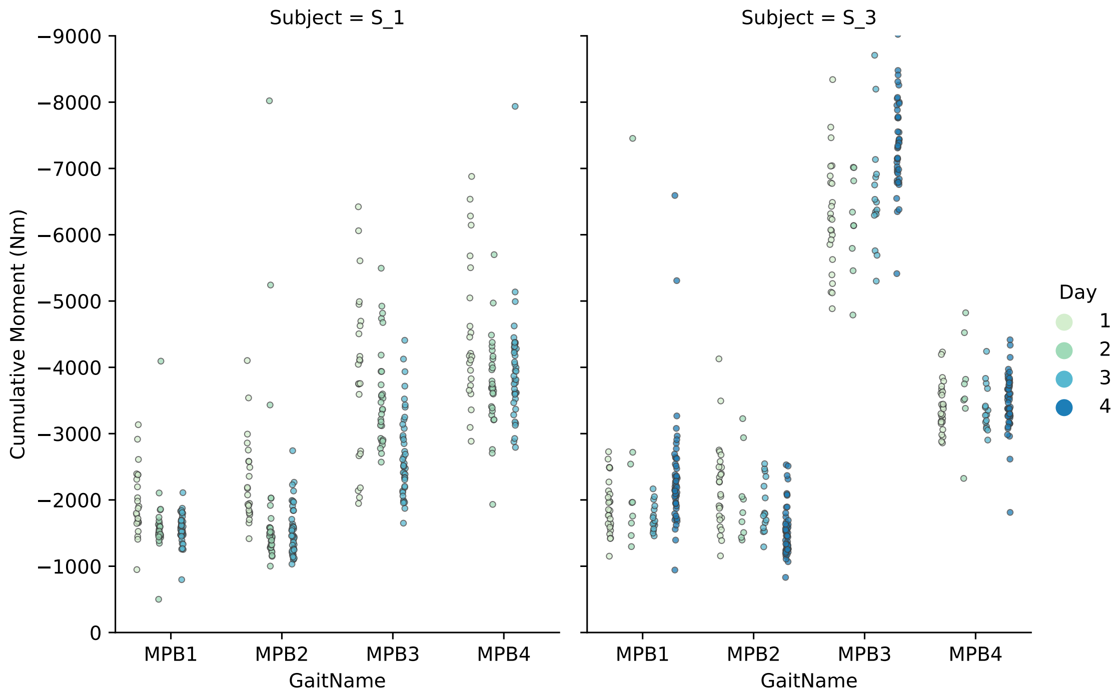

Fig. 6.11. Cumulative moment plot for each task instance for Subject_1 and Subject_3

Table 6.4 shows the mean, median, and range for each unique action for both subjects. The data in the *Min* row represents cumulative moments for the individual *safety frontier*'s unique actions. Moreover, the highlighted values in Table 6.4 represent cumulative moments for the overall *safety frontier*, and the mean values represent the average *observed safety*.

Table 6.4. Descriptive statistics of lower back moment for all task instances

Stats	**MPB1**		**MPB2**		**MPB3**		**MPB4**	
	S_1	**S_3**	**S_1**	**S_3**	**S_1**	**S_3**	**S_1**	**S_3**
n	93	84	93	84	93	84	93	84
Max	-9394.46	-12840.68	-8020.63	-17225.80	-6421.82	-33898.34	-7936.68	-15331.45
Min	**-501.05**	-942.76	-1001.59	**-831.15**	**-1649.54**	-4789.25	-1932.36	**-1811.73**
Mean	-1769.41	-2437.18	-1828.64	-1939.05	-3261.18	-9153.37	-4041.68	-3579.12
Q_1	-1476.66	-1714.03	-1324.26	-1391.28	-2505.63	-6344.89	-3597.57	-3228.12
Q_2	-1603.13	-2038.67	-1574.24	-1634.13	-3119.20	-7012.32	-3941.44	-3416.07
Q_3	-1798.58	-2382.11	-1967.30	-2082.33	-3755.98	-7953.40	-4319.89	-3731.24

6.5.2 Computation of Safety Risk Indices

The *Inefficiency Study* identified 26 different factors affecting construction laborers' safety from an extensive literature review. The identified factors are listed in Table 5.1. Moreover, the *Inefficiency Study* conducted a survey with construction experts to categorize factors into the *system* and *operational inefficiencies*; and quantify the severity & probability of occurrence of identified factors.

Based on the survey response, the *Inefficiency Study* categorized the 26 factors into factors causing *system inefficiencies* (FSI) and factors causing *operational inefficiencies* (FOI). For brevity, we omitted the categorization details here (please refer to the *Inefficiency Study*). Then, we computed the risk indices $\boldsymbol{R_{si}}$ and $\boldsymbol{R_{oi}}$ using equations 5.5 and 5.8, respectively. Tables 6.5 and 6.6 show the severity score ($\boldsymbol{S_i}$), occurrence probability ($\boldsymbol{P_i}$), existence indicator ($\boldsymbol{\epsilon_i}$), and the product ($\boldsymbol{S_i P_i \epsilon_i}$) for *system* and *operational inefficiencies*, respectively. The value for existence indicator ($\boldsymbol{\epsilon_i}$) was deduced based on the actual conditions during data collection, subjects' information, and site environment. We computed the *system risk index* ($\boldsymbol{R_{si}}$) as 0.09 and the *operational risk index* ($\boldsymbol{R_{oi}}$) as 0.54.

Table 6.5. Severity score ($\boldsymbol{S_i}$), occurrence probability ($\boldsymbol{P_i}$), and existence indicator ($\boldsymbol{\epsilon_i}$) for system risk index computation ($\boldsymbol{R_{si}}$)

Code	$\mathbf{S_i}$	$\mathbf{P_i}$	$\epsilon_\mathbf{i}$	$\mathbf{S_i P_i}\epsilon_\mathbf{i}$	**Code**	$\mathbf{S_i}$	$\mathbf{P_i}$	$\epsilon_\mathbf{i}$	$\mathbf{S_i P_i}\epsilon_\mathbf{i}$
PPSC	3.77	0.61	0	0.00	HLT	3.13	0.51	1	1.60
BW	3.05	0.50	1	1.53	HH	2.85	0.45	1	1.28

Table 6.6. Severity score ($\boldsymbol{S_i}$), occurrence probability ($\boldsymbol{P_i}$), and existence indicator ($\boldsymbol{\epsilon_i}$) for operational risk index computation ($\boldsymbol{R_{oi}}$)

Code	$\mathbf{S_i}$	$\mathbf{P_i}$	$\epsilon_\mathbf{i}$	$\mathbf{S_i P_i}\epsilon_\mathbf{i}$	**Code**	$\mathbf{S_i}$	$\mathbf{P_i}$	$\epsilon_\mathbf{i}$	$\mathbf{S_i P_i}\epsilon_\mathbf{i}$
AGE	3.33	0.46	1	1.53	USE	4.26	0.79	1	3.37
LWE	4.04	0.64	0	0.00	LPPE	4.25	0.78	1	3.32
LWST	4.04	0.64	0	0.00	PSSB	3.91	0.73	1	2.85
PWSA	4.20	0.73	1	3.07	PCSB	3.95	0.72	1	2.84
PEL	2.92	0.42	1	1.23	WO	3.85	0.69	0	0.00

Continued on Next Page…

Table 6.6. (Continued...)

Code	$\mathbf{S_i}$	$\mathbf{P_i}$	ϵ_i	$\mathbf{S_i P_i \epsilon_i}$	Code	$\mathbf{S_i}$	$\mathbf{P_i}$	ϵ_i	$\mathbf{S_i P_i \epsilon_i}$
PPHC	3.74	0.62	0	0.00	HAH	3.64	0.65	0	0.00
PWJA	3.91	0.68	0	0.00	HTP	3.88	0.68	0	0.00
DA	4.32	0.80	0	0.00	LWD	3.96	0.71	0	0.00
US	3.83	0.63	1	2.41	PE	4.12	0.75	0	0.00
PPUS	4.20	0.71	1	2.98	LSR	3.91	0.67	0	0.00
HN	3.22	0.47	1	1.51	USSP	3.74	0.65	1	2.43

6.5.3 Computation of *Sustainable Safety*

We used equations 5.10 and 5.11 to compute the upper limit, lower limit, and averaged it to get the *sustainable safety*. Table 6.7 and Figure 6.12 show the cumulative lower back moment for four unique actions of the metal plate bending task for different safety components (bottom to top points: overall SF, SS_{UL}, SS, SS_{LL}, and OS). From Figure 6.12, we can observe that the higher the gap between the *observed safety* and *sustainable safety*, the higher the room for improving the safety behavior and vice versa. Moreover, Figure 6.12 provides quick visual information regarding a task's unique actions that needs more attention. For example, it can be easily inferred that S_3 requires help with the MPB3 action. It can be a handy visual tool for safety managers to provide need-based training to laborers.

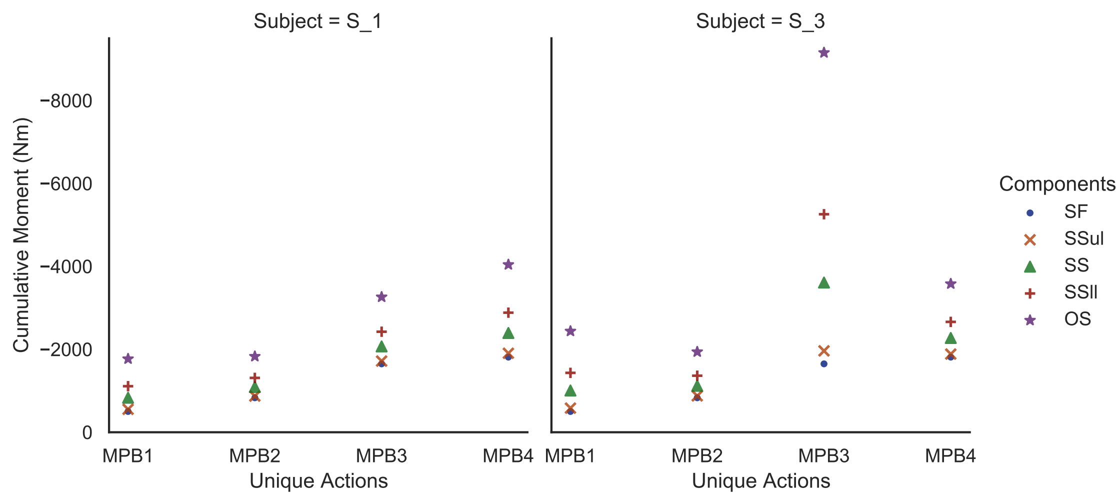

Fig. 6.12. Cumulative moment for four unique actions of the metal plate bending for different safety components

Table 6.7. Lower back moment (Nm) for different safety dynamics components (SF, SS_{UL}, SS, SS_{LL}, and OS) metal plate bending task

Cmpnts		**Unique Actions**							
		MPB1		**MPB2**		**MPB3**		**MPB4**	
		S_1	**S_3**	**S_1**	**S_3**	**S_1**	**S_3**	**S_1**	**S_3**
Indv.	SF	-501.05	-942.76	-1001.59	-831.15	-1649.54	-4789.25	-1932.36	-1811.73
	SS_{UL}	-553.96	-1005.10	-1036.09	-877.37	-1716.77	-4971.3	-2020.35	-1885.46
	SS	-832.48	-1333.26	-1217.70	-1120.65	-2070.67	-5929.62	-2483.54	-2273.56
	SS_{LL}	-1111.00	-1661.42	-1399.32	-1363.94	-2424.57	-6887.94	-2946.73	-2661.66
	OS	-1769.41	-2437.18	-1828.64	-1939.05	-3261.18	-9153.37	-4041.68	-3579.12
Overall	SF	-501.05		-831.15		-1649.54		-1811.73	
	SS_{UL}	-553.96	-581.81	-872.76	-877.37	-1716.77	1962.56	1904.75	-1885.46
	SS	-832.48	-1006.97	-1091.80	-1120.65	-2070.67	-3610.33	-2394.43	-2273.56
	SS_{LL}	-1111.00	-1432.13	-1310.84	-1363.94	-2424.57	-5258.11	-2884.11	-2661.66
	OS	-1769.41	-2437.18	-1828.64	-1939.05	-3261.18	-9153.37	-4041.68	-3579.12

For brevity, let us focus on the "MPB3" action performed by S_3 in Figure 6.12 and Table 6.7. The gap between the *safety frontier* and *observed safety* of S_3 for the "MPB3" action is more, indicating significant room for improvement. Since the *system risk index* value is low, there is not much difference between the *safety frontier* and *upper limit of sustainable safety.* However, the *operational risk index* value was more, indicating considerable room for reducing the *observed safety* moment [-9153.37 Nm] to an average *sustainable safety* moment [-3610.33 Nm] for each task instance. And if we compare individual *safety frontiers* and select the minimum value for four unique actions, we get the overall *safety frontier* for the metal plate bending task. Moreover, we can observe that the individual and overall *safety frontier* moment differ by -3139.71 Nm for the "MPB3" action. Furthermore, the resulting individual and overall *sustainable safety* moment differ by -2319.29 Nm. It indicates that S_3 can additionally improve performance by using the overall *sustainable safety* as a monitoring index.

6.6 Discussion and Limitations

6.6.1 Discussion

The current study proposed and validated the applicability of a *safety control system* to optimize laborers' safety while performing repetitive labor-intensive activities in a real construction site. We computed the *safety frontier* proposed by the *Safety Frontier Study* and identified existing *inefficiencies*, computed *safety risk indices*, and computed *sustainable safety* proposed by the *Inefficiency Study* in a real-world scenario. The chapter demonstrated and validated the proposed method for the metal plate bending task. However, the study demonstrated the applicability of the proposed safety control system to identify the theoretical and sustainable safety limits for various repetitive labor-intensive activities such as manual material handling, concreting, and masonry work. The following subsections describe the research's novel contribution compared to the existing MSDs studies.

Computation of ***Safety Frontier***

The chapter validated the applicability of the method proposed by the *Safety Frontier Study* in a real construction environment. Although we implemented the *Kinect* for postural data extraction, any other posture tracking technology such as motion sensors, accelerometers, and inertial measurement units can be used. The current research also explored and demonstrated the applicability of different ML models to precisely identify the unique actions involved in any repetitive labor-intensive activity. The chapter's scope included the prediction of four unique actions for the metal plate bending task, and we obtained an accuracy of 99% with RFC, 98.1% with OVR, 97.4% with BRF, and 92.9% with SVM. The higher accuracy validates the applicability of any ML model to predict tunique actions involved in a task in a real construction environment.

Furthermore, we explored the applicability of ML models to predict the biomechanical workload for repetitive labor-intensive activities. The chapter's scope included predicting the lower back moment for every movement frame of the metal plate bending task. We explored different ML models and obtained the R_2 of 58.8% with RFR and 70.0% with DNN. The lower R_2 was due to the limitations of *Kinect* in accurately tracking the posture and minimum variation in the moment data among four unique actions. However, the prediction models' MAPE, MAE, and RMSE values were very low; 0.034, 0.806, and 1.136 for RFR and 0.026, 0.602, and 0.944 for DNN, respectively. Moreover, we plan to explore the applicability of more robust postural data extracting technology in the future to validate the robustness of the model.

Computation of Safety Risk Indices

We validated the applicability of the method proposed by the *Inefficiency Study* to compute the risk indices associated with *system* and *operational inefficiencies* using the qualitative factor modeling (QFM) approach from the qualitative survey data. The *system risk index* ($\boldsymbol{R_{si}}$) was computed as 0.09, and the *operational risk index* ($\boldsymbol{R_{si}}$) was computed as 0.54 for the metal plate bending task based on the site information.

Computation of Sustainable Safety

We validated the applicability of the method proposed by the *Inefficiency Study* to compute the *upper* and *lower level of sustainable safety* from the computed *safety frontier*, average *observed safety*, and *system* & *operational risk indices* (refer to Table 6.7). The identified *sustainable safety* can be used as an achievable index for construction laborers' safety monitoring.

Self-learning Opportunity for Construction Laborers

The computed individual *safety frontier* provides a self-learning opportunity to construction laborers from multiple task instances that they perform (Refer Table 6.7 and Figure 6.12). Researchers have identified self-learning as an essential learning tool for construction laborers [31]. We demonstrated that the task for an individual performance varies with repetitions (refer to Figure 6.11). The individual *safety frontier* can serve as a personalized safety monitoring index.

Peer Learning Opportunity among Construction Laborers

The overall *safety frontier* can be used for peer learning among construction laborers. The overall *safety frontier* is derived based on the performance of different laborers and can provide additional room for improvement (refer to Figure 6.12). From the overall *safety frontier*, laborers get a platform to learn from each other, visualizing the safe work procedure using a VR environment, which researchers validate as an effective way to train laborers [32]. Moreover, the laborers can be trained in a virtual reality (VR) environment using the extracted skeletal data and *safety frontier*.

6.6.2 Implications and Potential Applications

Chapter 6 provided a complete validation of the proposed safety control system in a real construction environment. The study demonstrated the applicability of the *Safety Frontier Study* approach to compute the *safety frontier* and the *Inefficiency Study* method to compute safety *inefficiencies* and *sustainable safety*. The developed safety control system is equally essential to both construction researchers and industrialists. To industrialists, the computed *sustainable safety* provides an achievable higher index for safety monitoring. In addition, it provides a collaborative learning opportunity for construction laborers. Moreover, the proposed method is equally applicable to other industries such as supermarkets, grocery stores, and movers, among others. Third, the researchers can implement the proposed system to compute the *safety frontier* and *sustainable safety* for any repetitive labor-intensive activity

The chapter's scope was limited to the computation of lower back *safety dynamics components* for the metal plate bending task. However, the same method can be applied to compute *safety dynamics components* for any body part while performing any repetitive labor-intensive activity. Moreover, the presented framework is independent of the technology implemented for postural data extraction. So, the *Kinect* can be replaced by more robust technologies in the future with minimal change in the methodology.

Similarly, the study provides a practical approach to quantify the *system* and *operational inefficiencies* responsible for creating the safety risk. The separation of safety factors into the *system* and *operational inefficiencies* eliminate the confusion regarding what factors are under the control of safety personnel to focus on controllable factors. Moreover, the computed quantitative risk factors help safety personnel identify the safety factors with higher probability of causing injury to monitor. Furthermore, the computed *sustainable safety* provides an achievable safety monitoring index.

6.6.3 Limitations

Despite the contributions mentioned above, the study still has several limitations.

- We used *Kinect* to extract the postural data due to its features such as low cost, acceptable accuracy & reliability, and robustness to varying site conditions. However, it has limitations such as limited tracking range, self-occlusion, occlusion by colaborers, and inability to track properly while back facing. Due to these limitations, the extracted postural data had some errors. Although we used the robust Tobit Kalman Filter (TKF) to reduce the noise, the data inherited some errors, mainly affecting the prediction of lower back moments. The future work should explore the applicability of robust technologies, such as computer vision, motion sensor system, and IMU, to improve the accuracy and increase the reliability and accuracy of the prediction model.
- We limited the chapter's scope to computing *safety dynamics components* for the lower back while performing the metal plate bending task. Multiple major

joints (knee, shoulder, hip, among others) should be considered to robustify the proposed framework. Similarly, we need to vary the construction activities to validate the adaptability and robustness of the proposed framework.

- We inherited the *Inefficiency Study*'s survey result to compute the *system* and *operational risk indices*, thus inheriting the study's limitations. Additional safety factors need to be identified by extensive literature review and interviews with construction experts and incorporated in computed risk indices. Similarly, more survey responses need to be collected to robustify the computed *safety risk indices*.

6.7 Conclusion and Future Work

Sustainable building design and construction have gained popularity in the US construction industry. However, the current sustainable construction puts minimal focus on laborers' H&S. This raises an important question: "*How can a building be considered sustainable without incorporating laborers' H&S in the process?*" We proposed a novel safety control system to integrate laborers' H&S with sustainability and identify the *sustainable safety* for laborers performing repetitive labor-intensive activities.

For this, we collectively implemented the methods proposed by the *Safety Frontier Study* and *Inefficiency Study* for computing the *safety frontier* and *sustainable safety*, respectively. The computed *safety frontier* provides a theoretical maximum attainable level of safety and identifies any room for performance improvement. Moreover, the computed *sustainable safety* provides an achievable safety benchmark. Without this benchmark, it might not be feasible to judge if what is happening on a construction site is: (i) acceptable, (ii) a small amount of planning, investment, or time can boost the safety level significantly, or (iii) it requires a tremendous change to bring about a slight improvement. This knowledge can assist the project management team in developing their safety plans accordingly.

Similarly, the computation of *safety risk indices* is another vital component of safety dynamics. There are several factors affecting laborers' safety. However, the project management team does not have control over all factors, so it is crucial to identify controllable factors for optimal safety monitoring. The research demonstrated the applicability of the proposed method to quantify the safety risks associated with each factor causing *system* and *operational inefficiencies* using the QFM model developed by [33] for computing the productivity frontier. The construction practitioners can implement the proposed method to assess safety risks for different construction activities and improve laborers' safety performance by focusing on factors causing *operational inefficiencies*. Moreover, the computed *sustainable safety* provides a feasible safety index for laborers' safety performance monitoring.

Furthermore, the proposed method is applicable in a real construction site to monitor and improve safety performance. As mentioned before, the computed safety dynamics components (refer to Figure 6.12) provide instant visualization of what actions within a activity need to be improved for a specific laborer. Moreover, the presented framework can significantly improve traditional safety training. Traditional safety training provides the same training to entire laborers without considering their personal needs and shortcomings. However, the study can develop a need-based personalized training environment for construction laborers performing repetitive labor-intensive activities in a VR environment. The laborers can visualize how they performed versus how they should perform the task using individual and overall *safety frontier* and *sustainable safety* as a reference.

The *safety frontier* and *sustainable safety* are safety optimization approaches that depend upon other construction dimensions such as cost, productivity, and time. Future research should consider all interrelated construction dimensions and find an optimum solution to ensure sustainable cost, time, quality, and safety. Moreover, future research should incorporate a broader demographic of construction laborers of different ages, physiques, experiences, and expertise. However, just identifying the *safety frontier* and *sustainable safety* does not serve the purpose. The laborers need to be educated about how they are performing versus how they should perform the task. For this, future work should explore the applicability of a need-based personalized learning environment for construction laborers performing repetitive labor-intensive construction activities in a VR environment. The authors have already started the initial work in this respect [34].

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6.9 Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this chapter.

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CHAPTER 7

CONCLUSIONS, RECOMMENDATIONS, AND LIMITATIONS

7.1 Research Summary

Repetitive labor-intensive activities are regular in construction. Construction workers have a higher risk of developing musculoskeletal disorder (MSD) related injuries while performing such activities. Moreover, it is virtually impossible to manually monitor the workers' safety behavior in a dispersed environment. Furthermore, the workers are suffering from MSDs related injuries in the construction sector. This problem necessitates the development of a system to identify and monitor the postural behavior of construction workers to ensure minimum stress was exerted to essential joints.

For this, the study proposed applying available technology, a depth-sensing camera, to track the postural behavior of construction workers. The kinematic and kinetic analysis was performed to compute the stress exerted in essential joints. The research implemented the machine learning approach to identify the unique actions and moments exerted to essential joints for each movement frame. The safe work procedure, *safety frontier*, was computed by combining the unique actions exerting minimum cumulative moment to the essential joint (lower back). The identified *safety frontier* provides the highest benchmark to monitor real construction site safety behavior. Furthermore, the *sustainable safety* was computed by adding *sytstem inefficiencies* to the *safety frontier* and removing *operational inefficiencies* to the *observed safety.* The *sustainable safety* provides the work procedure that can be achieved and sustained in a construction site.

Specifically, we tested three hypotheses in this research work: (i)There exists a theoretical maximum level of safety, *safety frontier* for a given construction task.

(ii)The theoretical maximum level of safety, *safety frontier* can be determined using the proposed methodology. (iii) A safety control system can be developed by identifying and removing *system inefficiencies* and *operational inefficiencies* to obtain *sustainable safety*.

The research methodology was tested in two case studies, (i) lifting and setting-down tasks in a lab setup and (ii) metal plate folding tasks in a real construction site. The result indicated:

1. The *safety frontier* exists for any repetitive labor-intensive task.
2. The *safety frontier* can be computed by implementing the previously mentioned methodology in Chapters 4 and 6.
3. The *system* and *operational inefficiencies* can be computed by conducting a questionnaire survey with construction experts, as explained in Chapter 5.
4. The *sustainable safety* can be achieved by adding *system inefficiencies* to the *safety frontier* and removing *operational inefficiencies* to the *observed safety*, which was demonstrated and statistically validated in Chapters 5 and 6.

7.2 Contributions

The past studies focus on assessing the workers' MSD exposure and implementing different observational and instrumental techniques to reduce the risk of MSDs. At present, the construction industry relies upon the safety guidelines provided by safety regulating agencies such as OSHA to monitor the laborers' safety. However, the safety guidelines only provide the minimum safety requirement. Moreover, little or no research is targeted towards identifying "how safely can a worker perform an activity?" The research provides the method to identify the worker's maximum achievable level of safety individually, *safety frontier*, using recent posture tracking technology. The study implemented depth-sensing technology (Kinect) for postural data extraction, but any other posture tracking technology such as motion sensors, inertial measurement units, accelerometers, among others, can be used.

The kinematic and kinetic analysis of human body ergonomic was the key to the computation of the *safety frontier*. The study explored and validated the applicability of several ML models (RFR, BRF, OVR, and SVM) to identify the unique actions involved in repetitive labor-intensive activities. The implemented algorithms predicted the unique actions accurately in a controlled-lab environment and a real construction site. The computation of stress, induced in critical joints, with real-time data is computationally demanding. The dissertation demonstrated the applicability of the RFR and DNN models to predict the stress developed in the lower back while performing such activities. The implemented algorithm predicted the lower back moment with acceptable accuracy.

The presented research framework provides practical applications to both researchers and industrialists in the construction domain. First, the computed *safety frontier* provides a higher index to industrialists for monitoring the safety performance of construction workers. It also provides a platform for training the workers in a virtual environment. Second, apart from the construction industry, the proposed method can benefit other industries such as warehouses, supermarkets, mechanic workshops, movers, and housecleaning, where repetitive labor-intensive activities are regular. Third, the researchers can implement the presented method to explore the safety of other major joints such as knees and shoulders.

The study demonstrated the applicability of the proposed safety control system in a controlled-lab environment for lifting and setting-down tasks and a construction site for a metal plate bending task. Moreover, with the availability of more robust technologies to track postural data in the future, the *Kinect* implemented in the research can be easily replaced with minimal change in methodology. Thus, there is an excellent potential for the implementation of the *safety frontier* approach to identify the maximum achievable level of safety for any repetitive labor-intensive activity.

The research provides a method to compute the risk indices associated with *system* and *operational inefficiencies* using the qualitative factor modeling (QFM) approach from the qualitative survey data. The identified risk indices for each safety factor help construction industrialists identify controllable factors with a higher chance of causing injuries.

The identification of *sustainable safety* that can be achieved and sustained in a construction site is crucial to improve the safety behavior of construction laborers. The dissertation proposed an approach to compute the *upper* and *lower level of sustainable safety* from the computed *safety frontier*, average *observed safety*, and *system* and *operational risk indices.* The identified *sustainable safety* can be used as an achievable index for construction laborers' safety monitoring.

Overall, the research proposed and validated the applicability of the safety control system to optimize laborers' safety while performing repetitive labor-intensive activities in a real construction site. The computed *safety frontier* and *sustainable safety* provide self-learning and peer learning opportunities to construction laborers. Moreover, the workers can be trained in VR environments using the extracted skeletal data and safety dynamics components.

7.3 Limitations

Despite the contributions mentioned above, the study still has several limitations.

- We used *Kinect* to extract the postural data due to its features such as low cost, acceptable accuracy and reliability, and robustness to varying site conditions. However, it has limitations such as limited tracking range, self-occlusion, occlusion by colaborers, and inability to track properly while back facing. Due to these limitations, the extracted postural data had some errors. Although we used the robust Tobit Kalman Filter (TKF) to reduce the noise, the data inherited some errors, mainly affecting the prediction of lower back moments. The future work should explore the applicability of robust technologies, such as computer vision, motion sensor sytem, and IMU, to improve the data accuracy and increase the reliability and accuracy of the prediction model.

- We limited the dissertation's scope to the computation of *safety dynamics components* for lower back while performing repetitive labor-intensive activities. Multiple crucial joints (knee, shoulder, hip, among others) should be considered to robustify the proposed framework. Similarly, we need to vary the construction activities to validate their adaptability and robustness.

- Although there are numerous safety factors, we limited our scope to 26 selected safety factors based on the literature review. Additional safety factors need to be identified by extensive literature reviews and interviews with construction experts and incorporated in computed risk indices. Similarly, more survey responses need to be collected to robustify the computed *safety risk indices.*

- The postural behavior is affected by the weight involved in the activity, duration of the activity, and working capacity of the human body. The research only focused on identifying the safest posture while performing activity with nominal load. Future research should consider load variation and its' effect on postural behavior to define the safe working capacity. Furthermore, longitudional research needs to be carried out to study the long-term effect of repetitive activities on workers' health.

7.4 Future Works

The proposed method demonstrated its applicability in a real construction site to monitor and improve safety performance. As mentioned before, the computed safety dynamics components (refer to Figure 6.12) provide instant visualization of what actions within an activity need to be improved for a specific laborer. Moreover, the presented framework can significantly improve traditional safety training. Traditional safety training provides the same training to entire laborers without considering their personal needs and shortcomings. However, the study can develop a need-based personalized training environment for construction laborers performing repetitive labor-intensive activities in a VR environment. The workers can visualize how they performed versus how they should perform the task using individual and overall *safety frontier* and *sustainable safety* as a reference. Furthermore, the developed framework has potential application in automated construction industry. The *safety control system* approach can be implemented to compute the optimum work procedure exerting minimum stress to automated system (robot, robotic arm, among others).

The computation of the *safety frontier* and *sustainable safety* is a safety optimization problem with inter-dependency upon other construction dimensions (cost, productivity, and time). The cost of monitoring and training workers increases with the uptick in the safety level. However, the expenses related to workers' compensation claims, decreased productivity, and the cost of training new workers decreases with increased safety level. Future research should consider other construction dimensions and find an optimum solution to ensure sustainable cost, time, quality, and safety. Moreover, future research should incorporate a broader demographic of construction laborers of different ages, physiques, experiences, and expertise. However, simply identifying the *safety frontier* and *sustainable safety* does not serve the purpose. The workers need to be educated about how they are performing versus how they should perform the task. For this, future work should explore the applicability of need-based personalized training for construction laborers.

Appendix A: Upper and Lower Limits of Sustainable Safety

When we add estimated *system inefficiencies* to the *safety frontier*, we get the *upper limit of sustainable safety.* Similarly, when we remove estimated *operational inefficiencies* from the *observed safety*, we get the *lower limit of sustainable safety.*

$$SS_{UL} = SF + \delta_{si} \tag{1}$$

$$SS_{LL} = OS - \delta_{oi} \tag{2}$$

Using the QFM method, the estimated *system* and *operational inefficiencies* can be computed using Equation 3 and 4.

$$\delta_{si} = R_{si} * (SS_{LL} - SF) \tag{3}$$

$$\delta_{oi} = R_{oi} * (OS - SS_{UL}) \tag{4}$$

where, $\boldsymbol{R_{si}}$ and $\boldsymbol{R_{oi}}$ are the risk indices of factors causing *system* and *operational inefficiencies* respectively, given by Equation 5.

$$R_{si} = \frac{\sum_{i=1}^{m} S_i P_i \epsilon_i}{\sum_{j=1}^{m+n} S_j \epsilon_j} \qquad and \qquad R_{oi} = \frac{\sum_{i=1}^{n} S_i P_i \epsilon_i}{\sum_{j=1}^{m+n} S_j \epsilon_j} \tag{5}$$

where, $\boldsymbol{S_i}$ & $\boldsymbol{S_j}$ are severity scores of safety attributes $\boldsymbol{i}$ & $\boldsymbol{j}$ respectively, $\boldsymbol{P_i}$ is the probability of occurrence of a factor $\boldsymbol{i}$, $\boldsymbol{\epsilon_i}$ & $\boldsymbol{\epsilon_j}$ are existence indicators of safety attributes $\boldsymbol{i}$ & $\boldsymbol{j}$ (0 = not present, 1 = present), and $\boldsymbol{m}$ & $\boldsymbol{n}$ are the number of factors causing *system* & *operational inefficiencies* respectively.

The summation of the risk due to *system inefficiencies* ($\boldsymbol{R_{si}}$) and *operational inefficiencies* ($\boldsymbol{R_{oi}}$) represents the total risk ($\boldsymbol{R_i}$) involved in the activity and is given by Equation 6.

$$R_i = R_{oi} + R_{si} = \frac{\sum_{i=1}^{m+n} S_i P_i \epsilon_i}{\sum_{i=1}^{m+n} S_i \epsilon_i} \leq 1 \tag{6}$$

Comparing Equation 1 and 3, we get:

$$\delta_{si} = SS_{UL} - SF = R_{si} * (SS_{UL} - SF) \tag{7}$$

$$SS_{UL} = R_{si} * SS_{LL} + (1 - R_{si}) * SF \tag{8}$$

Similarly, comparing Equation 2 and 4, we get:

$$\delta_{oi} = OS - SS_{LL} = (OS - SS_{UL}) * R_{oi} \tag{9}$$

Replacing the value of SS_{UL} from Equation 8, we get:

$$OS - SS_{LL} = (OS - [R_{si} SS_{LL} + (1 - R_{si}) * SF]) * R_{oi} \tag{10}$$

$$\mathbf{S}_{\mathrm{LL}} = \frac{\mathbf{(1 - R_{oi})}}{\mathbf{(1 - R_{si} R_{oi})}} \mathbf{OS} + \frac{\mathbf{R_{oi}(1 - R_{si})}}{\mathbf{(1 - R_{si} R_{oi})}} \mathbf{SF} \tag{11}$$

Replacing the value of SS_{LL} (Equation 11) in Equation 8, we get:

$$SS_{UL} = \left[\frac{(1 - R_{oi})}{(1 - R_{si} R_{oi})} OS + \frac{R_{oi}(1 - R_{si})}{(1 - R_{si} R_{oi})} SF \right] R_{si} + (1 - R_{si}) SF \tag{12}$$

$$SS_{UL} = \frac{R_{si}(1 - R_{oi})}{(1 - R_{si} R_{oi})} OS + \frac{R_{oi} R_{si}(1 - R_{si}) + (1 - R_{si})(1 - R_{si} R_{oi})}{(1 - R_{si} R_{oi})} SF \tag{13}$$

$$\mathbf{SS_{UL}} = \frac{\mathbf{R_{si}(1 - R_{oi})}}{\mathbf{(1 - R_{si} R_{oi})}} \mathbf{OS} + \frac{\mathbf{(1 - R_{si}}}{\mathbf{(1 - R_{si} R_{oi})}} \mathbf{SF} \tag{14}$$

Special Conditions:

Condition 1: $R_{si} = 0.0$ & $R_{oi} = 1.0$

$$SS_{UL} = SS_{LL} = SF$$

Condition 2: $R_{si} = 0.25$ & $R_{oi} = 0.75$

$$SS_{UL} = \tfrac{4}{13}\ \text{OS} + \tfrac{9}{13}\ \text{SF} \qquad \| \qquad SS_{LL} = \tfrac{1}{13}\ \text{OS} + \tfrac{12}{13}\ \text{SF}$$

Condition 3: $R_{si} = 0.5$ & $R_{oi} = 0.5$

$$SS_{UL} = \tfrac{1}{3}\ \text{OS} + \tfrac{2}{3} \qquad \| \qquad SS_{LL} = \tfrac{2}{3}\ \text{OS} + \tfrac{1}{3}\ \text{SF}$$

Condition 4: $R_{si} = 0.75$ & $R_{oi} = 0.25$

$$SS_{UL} = \tfrac{12}{13}\ \text{OS} + \tfrac{1}{13} \qquad \| \qquad SS_{LL} = \tfrac{9}{13}\ \text{OS} + \tfrac{4}{13}\ \text{SF}$$

Condition 5: $R_{si} = 1.0$ & $R_{oi} = 0.0$

$$SS_{UL} = SS_{LL} = OS$$

Finally, the optimal *sustainable safety* can be computed as an average of *upper* and *lower limit of sustainable safety*.

$$\mathbf{SS} = \mathbf{\frac{1}{2}}[\mathbf{SS_{UL}} + \mathbf{SS_{LL}}] \tag{15}$$

Appendix B: Questionnaire Survey Form

Participant's Information

Job Location	
Job Designation	
Overall Experience (Years)	
Construction Site Experience (Years)	

SN	Factors Affecting Workers' Safety while performing labor-intensive repetitive tasks (masonry work, tile work, manual material handling, among others)	Can this safety factor be controlled by management team? (Y/N)	Severity of factor						Probability of Factor Causing Injury (%)										
			No Effect	Very Low	Low	Moderate	High	Very High	0	10	20	30	40	50	60	70	80	90	100
1	**Personal Factors**																		
	Age (Low or High)																		
	Lack of Work Experience																		
	Lack of Workers' Safety Training																		
	Poor Workers' Safety Attitude																		
	Poor Education Level																		
	Poor Physical Health Condition																		
	Emotion (Psychological Health Condition)																		
	poor Workers' Judgement Ability																		
	Drug Abuse																		
2	**Environmental Factors**																		
	Untidy Site																		
	Poorly Planned and Unorganized Site																		
	Bad Weather																		
	High Noise																		
	High/Low Temperature																		
	High Humidity																		
3	**Organizational Factors**																		
	Unavailability of Safety Equipment																		
	Poor Supervisors' Safety Behavior																		
	Poor Coworkers' Safety Behavior																		
	Work Overload																		
	High Accident History																		
	High Time Pressure																		
	Longer Working Duration																		
	Lack of Personal Protective Equipment (PPE)																		
	Poor Equipment																		
4	**Regulatory Factors**																		
	Lack of Safety Regulation																		
	Unavailability of Site Safety Personnel																		

VITA

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