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Evaluating the Impact of Employee Engagement on Occupational Health and Safety: A Data-Driven Methodology (SEED-DM)

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Abstract

Occupational health and safety (OHS) are essential for both the well-being of employees and organizational performance. While the existing literature suggests that employee engagement can have a positive effect on occupational health and safety outcomes, empirical evidence remains limited. This study addresses this gap by introducing SEED-DM, a data-driven methodology designed to evaluate the impact of employee engagement on OHS using operational data from manufacturing organizations. SEED-DM tests four hypotheses using a variety of statistical methods such as time-series causality analysis, correlation, and linear regression to assess the relationship between employee engagement and the frequency and severity of safety incidents. Additionally, the methodology incorporates expert validation and literature comparisons to confirm the reliability of the findings. We evaluated SEED-DM by applying it to the real-world data of a manufacturing organization through a case study. The results indicated a positive impact of employee engagement on occupational safety outcomes, demonstrating both correlation and causality. Furthermore, we found that employee engagement reduced the occurrence of severe injuries, with the most pronounced effect observed 15 weeks after implementing safety interventions. The case study identified several opportunities to enhance SEED-DM, such as incorporating external factors into the analysis and expanding employee engagement implementation strategies within organizational settings. Through our work, we contributed to the OHS literature by proposing a data-driven methodology for evaluating the impact of employee engagement on occupational safety, along with providing empirical evidence supporting this relationship through a case study.

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List of Acronyms

EE Employee Engagement

OHS Occupational Health and Safety

OSHA Occupational Health and Safety Administration

ASTM American Society for Testing and Materials

SEED-DM Safety Employee Engagement Data-Driven Methodology

CRISP-DM Cross Industry Standard Process for Data Mining

ADF Augmented Dickey-Fuller

EDA Exploratory Data Analysis

SOM Self-Organizing Map

DTW Dynamic Time Warping

OLS Ordinary Least Squares

PCA Principal Component Analysis

MSE Mean Squared Error

Chapter 1

Introduction

Occupational Health and Safety (OHS) is a critical field concerned with the well-being of workers in various occupations and industries. Originally defined in 1950 by the World Health Organization and the International Labour Organization, OHS focuses on promoting and maintaining the highest degree of physical, mental, and social well-being among employees [1]. The scope of occupational safety primarily involves safeguarding workers from accidents, injuries, and exposure to hazardous substances during their employment. On the other hand, occupational health is concerned with the mental and emotional well-being of workers. Employers have the legal responsibility to ensure a safe working environment and implementing measures to prevent and mitigate the risk of accidents and minimize their severity.

Data from the government labor departments underscore the critical role of occupational health and safety practices, with the United States alone recording 5,190 fatal injuries in 2021, an increase of 8.9% from previous years (Department of Labor). Globally, approximately 340 million occupational accidents are recorded each year, and around 160 million develop chronic illnesses [2]. The implications of occupational health and safety extend beyond individual health to organizational performance. Inadequate OHS practices directly contribute to decreased worker productivity, absenteeism, and reduced product quality, all of which negatively impact organizational outputs and competitiveness [3]. In addition to the costs of lost productivity and low product quality, employers bear substantial financial burdens due to occupational injuries and illnesses. These expenses include compensation claims, insurances, and legal liabilities that are estimated to be about 1 billion dollars per week for US employers [4].

Unsafe workplaces have clear consequences for both employees and organizations. The importance of occupational health and safety has also gained increasing recognition in the research community. Although numerous studies have investigated the causes of workplace accidents, safety behaviours and their relationship with organizational practices, the interdependence between underlying factors remains uncertain. The academic literature identifies several organizational practices that influence occupational health and safety, with employee engagement in safety practices being particularly prominent. Employee Engagement (EE) encompasses the involvement of employees in raising safety concerns, facilitating safety communication, and sharing safety information. Feedback and hands-on experience from front-line workers is believed to reveal safety issues that would not stand out at a higher hierarchical level [5]. In addition, the active participation of workers in safety decision making is expected to enhance their understanding and compliance with safety regulations. Although existing research suggests that employee engagement positively influences workplace safety, a significant gap in the literature persists since no study used empirical data from both employee engagement and occupational safety to conclusively prove this relationship and its impact. This gap highlights the need for further research to validate the assumed benefits of employee engagement on workplace safety outcomes using concrete data.

1.1 Research Objective

The goal of this study is to validate and quantify the effect of employee engagement on occupational health and safety, addressing the current gap in the literature. Specifically, we investigate the relationship between these two by using empirical data from a manufacturing organization. To achieve this objective, a *Safety Employee Engagement Data-Driven Methodology (SEED-DM)* is designed to analyze the existence and strength of this relationship. The methodology involves conducting a series of experiments to measure the impact of various levels of employee engagement on OHS indicators. In addition, we employ a linear regression model in combination with feature engineering to identify key drivers and evaluate the intensity of these influencing factors. This methodology allows us to gain a deeper understanding of how specific aspects of employee engagement contribute to OHS outcomes. The results of our analysis are thoroughly examined and validated in collaboration with stakeholders to ensure the accuracy and applicability of our findings.

Ultimately, we aim to achieve two main objectives: 1) to contribute to the academic literature by introducing a data-driven methodology to evaluate the impact of employee engagement on occupational safety and providing empirical evidence through a real-world case study, and 2) to provide organizations with data-driven insights into how employee engagement can be leveraged to improve occupational health and safety. By bridging the gap between theory and practice, we intend to facilitate the development of effective strategies that promote a safer and more engaging work environment.

1.2 Research Questions

Following from our research objective, the main question that will be addressed in this study is the following:

MRQ: *To what extent does employee engagement impact occupational health and safety?*

The primary research question is answered through four hypotheses which are designed to be empirically tested. The first two hypotheses focus on examining the existence of a significant relationship between employee engagement and occupational health and safety:

H1: *There exists a relationship between employee engagement and occupational health and safety events.*

H2: *There exists a relationship between employee engagement and severity of occupational health and safety events.*

The last two hypotheses aim to provide a more nuanced understanding of the relationship between employee engagement and its impact on occupational health and safety.

Specifically, these hypotheses investigate the extent to which varying levels of employee engagement influence the overall health and safety outcomes within the workplace.

H3: *Enhanced employee engagement contributes to a reduction in occupational health and safety events.*

H4: *Enhanced employee engagement contributes to a reduction in the severity of occupational health and safety events.*

To establish a data-driven methodology for investigating the proposed hypotheses and to effectively employ occupational health and safety indicators prevalent in academic research, a thorough literature review will be conducted. This review aims to address the following research sub-questions:

SRQ1: *How is occupational health and safety defined in the literature?*

SRQ2: *What methods have been researched for measuring the impact of organizational practices on occupational health and safety?*

SRQ3: *How does employee engagement influence occupational health and safety across industries and countries?*

1.3 Paper Outline

The remainder of this paper is structured as follows. Chapter 2 offers an in-depth review of the academic literature, addressing the proposed research sub-questions. Building on these insights, Chapter 3 outlines and justifies the design of our data-driven methodology used to test the proposed hypotheses. Chapter 4 presents the results obtained through applying the methodology in a case study in a manufacturing organization. Chapter 5 provides insights obtained from the validation of the methodology and findings with the stakeholders. Chapter 6 offers a discussion of the findings and the feedback received from the stakeholders. Finally, Chapter 7 addresses the implications of our findings and presents the conclusions drawn from the study.

Chapter 2

Literature Review

This chapter offers a comprehensive overview of the existing literature on the indicators and techniques used to evaluate the impact on occupational health and safety, aiming to address the proposed sub-research questions. Furthermore, it examines previous studies investigating the relationship between employee engagement and occupational safety across different industries and countries. A detailed analysis of the relevant indicators, techniques, and key findings is essential for building a well-informed methodology. This approach ensures that the results of this study are both comparable with existing research and applicable to organizations in practice. To meet these goals, a systematic literature review has been conducted, which is detailed in the following sections. This review helps identify gaps in the current literature, highlight best practices and foster the development of the data-driven methodology.

2.1 Systematic Literature Review

The guidelines introduced by Kitchnham et al. [6] and the systematic literature review presented by Buksh et al. [7] have been used as the direction for this review. This section provides a complete overview of the steps undertaken in the review process, including the search strategy, and the formulation and application of inclusion, exclusion, and appraisal criteria. The study selection process is summarized in Figure 1.

2.1.1 Search Strategy

The literature review process was structured around the sub-research questions and guided by the methodologies outlined in the guidelines of Kitchenham et al. [6]. Scopus was selected as the digital library for this exploration due to its extensive collection of studies and publications from major journals, as well as its recognition as the most comprehensive and user-friendly research database [8]. The search in Scopus has been carried out on 19th of July 2024 using the following string search in the publication title, abstract and keywords:

organizational practices AND impact AND (occupational safety OR workplace safety OR occupational accidents)

The strategic combination of keywords was essential for gathering relevant publications that address our research questions, particularly since the terminology for occupational health and safety varies across the literature. The use of the AND operator ensures the correct relational context between the keywords, while the OR operator allows for the in-

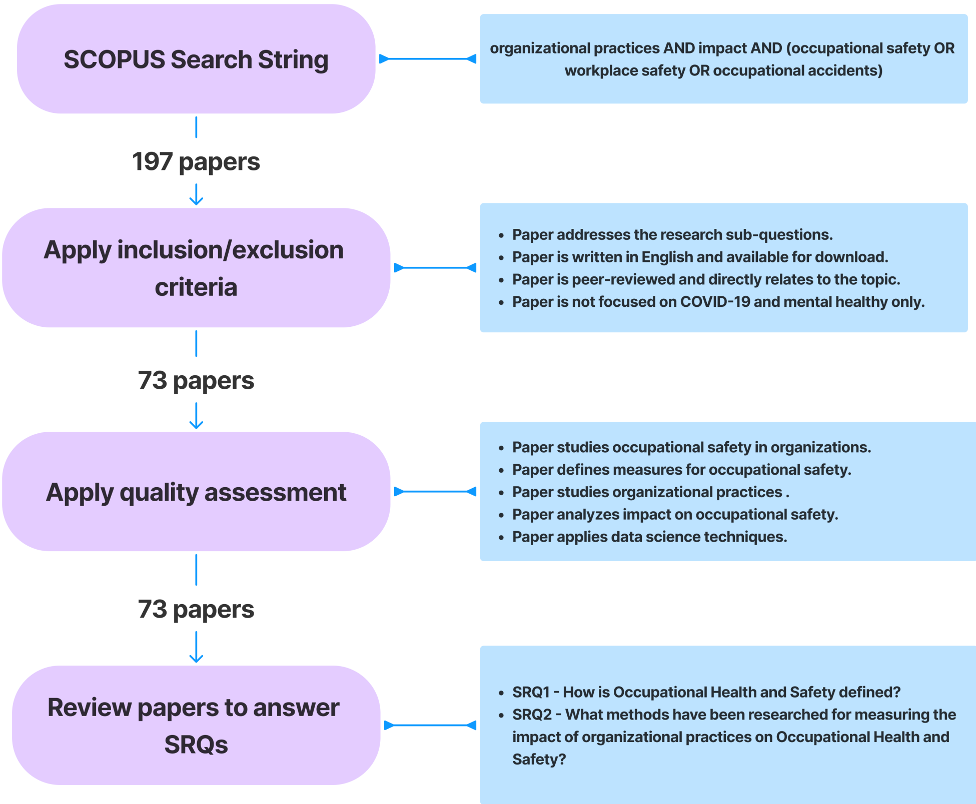


Figure 1: Systematic literature review outline

clusion of a range of relevant terms, thereby ensuring no pertinent material is overlooked. This search strategy yielded a total of 197 papers.

2.1.2 Inclusion and Exclusion Criteria

During the preliminary phase, the studies have been evaluated based on their title, abstract and publication space. For this initial review, the following inclusion criteria (IC) and exclusion criteria (EC) have been considered. The inclusion criteria have been defined as follows:

- **IC1** The paper directly relates to the topic of review. The paper looks at organizational practices and explores the impact on occupational safety.
- **IC2** The paper addresses the sub-research questions.
- **IC3** The paper is published in a peer-reviewed journal or conference.
- **IC4** The paper is written in English.
- **IC5** The paper is available for download.

Subsequently, the exclusion criteria have been formulated as follows:

- **EC1** The paper talks about workplace safety as a side topic.
- **EC2** The paper talks about organizational practices as a side topic.
- **EC3** The paper is not peer-reviewed.
- **EC4** The paper only considers the impact of COVID-19.
- **EC5** The paper is exclusively focused on mental health.

2.1.3 Critical Appraisal Criteria

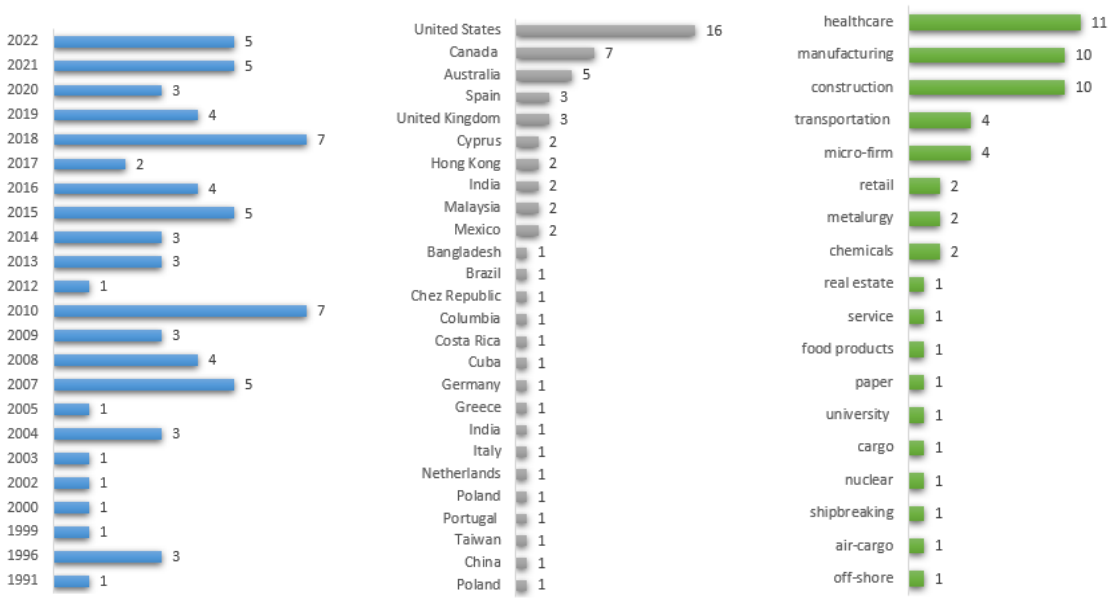
The inclusion and exclusion criteria were applied during the initial selection phase based on the abstract of the collected studies. In the next step, the critical appraisal criteria were applied with regard to the method, results, and discussion of each paper. The goal of using the critical appraisal criteria was to determine the quality of the studies in articulating the answers to the sub-research questions. Hence, these criteria were defined in relation to each research sub-question and applied to all studies passing the inclusion criteria.

- Does the paper look at occupational safety of employees in an organization?
- Does the paper clearly define measures for occupational safety?
- Does the paper look at organizational practices enforced by employers for safety performance?
- Does the paper analyze the impact of these organizational practices on workplace safety?
- Does the paper use data science techniques to derive answers and conclusions?

The quality assessment questions were formulated through an analysis of the collected literature sources, critically assessing the information needed to answer the proposed sub-research questions. Each study was evaluated based on these five questions, awarding 1 point for each criterion. The papers with a score higher than or equal to 1 have been further selected for in-depth analysis. Appendix A elaborates on the collected studies and their assigned scores for each quality assessment criterion.

2.2 Literature Findings

Figure 2 provides a demographic analysis of the studies selected through the literature review. Figure 2a shows the distribution of the selected studies by year, revealing that the research base spans from 1996 to 2022. This temporal range offers a comprehensive understanding of the evolution of the research direction over time. Similarly, Figure 2b and 2c illustrate the distribution of the selected studies across different countries and industries, respectively. The diversity in geographical and industrial representation underscores the global scope and applicability of the research findings.



(A) Year (B) Country (C) Industry

FIGURE 2: Demographics of papers gathered through literature review

2.2.1 SRQ1 - Occupational Health and Safety Indicators

Historically, companies have predominantly measured their safety performance through frequency injury rates. These rates are typically calculated based on reported injuries, lost workdays, and recordability, commonly referred to as lagging indicators. These indicators have been widely adopted to compare safety performance across different companies and to observe trends over time. However, research has identified several limitations inherent in these lagging indicators that suggest that they provide limited information for effective safety risk management [9]. Dekker and Pitzer further noted that sole reliance on lagging indicators can lead to undesirable behaviors such as under-reporting incidents to show good performance metrics [10]. To address these shortcomings, leading indicators have been introduced as a more proactive approach, aiming to provide a comprehensive overview of safety performance and procedures.

Although all of the selected studies addressed occupational health and safety, only 17 explicitly defined the indicators used to measure safety, thus satisfying the second quality criterion - *Does the paper clearly define measures for occupational safety?*. Among these 17 papers, we identified 19 leading indicators and 21 lagging indicators. The indicator most frequently cited was the safety climate, found in 10 articles. However, each paper defined a different approach for assessing safety climate. In particular, the research by Casey et al. [11] made a significant contribution by proposing six distinct scales to measure the safety climate in order to bridge the gap between the research on leading indicators and practice. The most common lagging indicators identified were the number of injuries, injury rates and absenteeism due to injuries. Figure 3 provides a summary of the various types of leading indicators and lag indicators used to measure safety output results, which are elaborated in more detail in the following subsections.

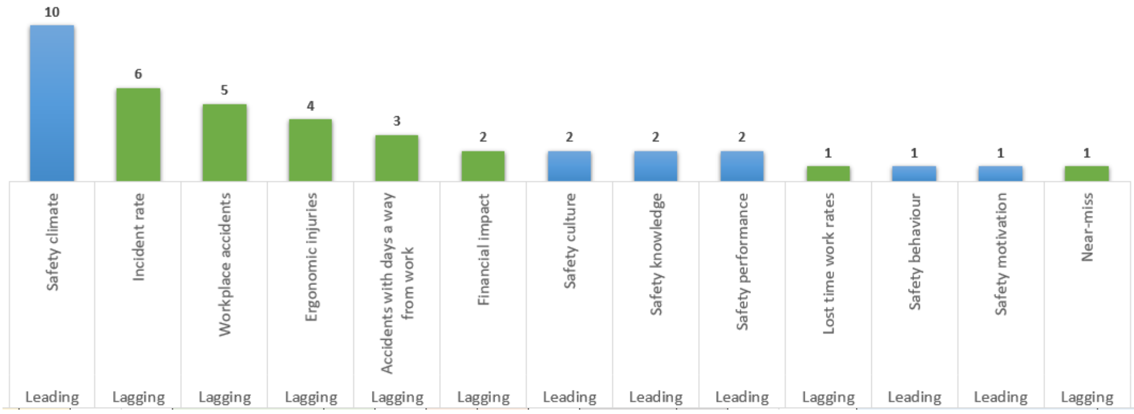


FIGURE 3: Occupational safety indicators identified through literature review

Lagging Indicators

An analysis of the lagging indicators revealed a predominant focus on quantifying workplace safety through measurement of the frequency, severity, and associated costs of the injury. Research efforts often build on these indicators as a basis and consequently explore various types of injuries and their corresponding severities. Financial impacts are commonly evaluated using indicators such as absenteeism rates and claims costs. For example, Cook et al. [12] utilized the standard injury recordable rates defined by Occupational Health and Safety Regulations in the United States. Similarly, Hinze et al. [13] employed the total recordable injury rate to assess the effectiveness of safety practices. In Cuba, safety statistics are measured using an incident rate metric, which represents the total number of incidents per 100 employees [14].

In terms of financial indicators, Huang et al. [15] adopted the injury frequency rate, defined as the number of workers' compensation claims per $1 million in payroll. In another study, Milczarek and Najmiec [16] evaluated occupational accidents by examining the severity based on the number of days employees were absent from work. Arocena et al. [17] used a similar metric to analyze the effectiveness of preventive measures, focusing on accidents that resulted in more than one day of absence from work. A study conducted in Costa Rica similarly analyzed work-related injuries that led to at least one day of absence [18]. Another approach, proposed by Birgit et al. [19], involved a balanced scorecard to measure the financial impact of occupational safety issues, considering productivity, absenteeism, and quality. In Denver, Glazner et al. investigated the bivariate relationship between safety interventions and injury occurrence by calculating both lost work time rates and non-lost work-time rates [20].

Several studies measured safety performance by counting all types of occupational injuries and accidents, regardless of severity [21, 22, 23, 24]. In addition, d'Ettorre et al. [25] examined ergonomic risks, such as acute low-back pain resulting from extended work hours and physical activity. In the ship breaking industry, Tanha et al. assessed safety performance simply by counting the total number of injuries and fatalities [26]. In the healthcare sector, Gershon et al. [27] evaluated organizational practices by measuring blood exposures and musculoskeletal disorders to determine their impact on nurses' well-being. Zacharatos et al. [28] analyzed safety incidents by looking at injuries that required first-aid help, as well as near misses that had the potential to cause human injury, environmental or equipment damage, or an interruption in normal operations.

Leading Indicators

The objective of leading indicators in occupational health and safety is to facilitate proactive measurement, contrasting with lagging indicators, which assess safety in a reactive manner. Leading indicators emphasize the anticipation and prevention of safety incidents by focusing on aspects such as employee safety behavior, perceptions, compliance, and the effectiveness of safety initiatives. These indicators offer a forward-looking perspective, providing more immediate insights into potential safety gaps and opportunities for improvement. Among the various leading indicators identified in the literature, safety climate has emerged as one of the most frequently adopted measures by researchers. However, the lack of a standardized or universally accepted method for assessing safety climate and other leading indicators forces researchers to introduce their own approaches, making it difficult to compare results across different studies.

Subsequently, Rosa and Martinez [29] developed a survey designed to measure the safety attitudes of both employees and higher management, highlighting the importance of safety perceptions at different organizational levels. Similarly, Milczarek and Najmiec [16] aimed to define workers' inclinations toward safety-related beliefs, values, and behaviors, both in professional and personal contexts, emphasizing the holistic nature of a safety culture. Tsung-Chiu et al. [30] study adopted the 'safety scale' developed by Wu and Lee [31], measuring employees' perceptions of safety climate and commitment to safety, thereby providing a benchmark for organizational safety culture.

In a study in Cuba, Caristina et al. [14] introduced a safety knowledge scale that assesses workers' understanding of injury prevention, safety responsibilities, the use of protective equipment, and the impact of alcohol intake on safety. This tool was developed to advocate for the importance of knowledge in shaping safety behavior. In another study, Mullen [32] found that employees with a high risk perception are more likely to adopt safe work practices, suggesting that risk awareness is a crucial factor in promoting a safety-conscious work environment. Meanwhile, Hadjimanolis et al. [33] created a comprehensive safety performance measure by developing a summative index that includes seven key aspects of safety performance, such as legal compliance, safety systems, and the use of protective equipment.

In the commercial construction sector, Marie et al. [34] developed a sub-contractor safety scale focusing on the perception of safety and behavior from the contractor to co-worker and personal levels, reflecting the multi-tiered nature of safety culture in complex work environments. Within Chinese workplaces, Jiuhua et al. established a safety performance score using a six-point Likert scale aimed at measuring safety performance from the employees' viewpoint, highlighting the cultural nuances in safety perceptions [35].

Vinodkumar and Bhasi contributed to this body of research by measuring employees' perceptions of six safety management practices, along with their safety knowledge and motivation [36]. Anderson et al. [37] further validated the reliability of a safety climate measure initially defined by Gershon [38], which emphasized compliance with safety protocols. In the nuclear sector, García-Herrero et al. [39] defined safety culture by adhering to the nine characteristics established by the International Atomic Energy Agency (IAEA) [40]. These include recognizing safety as a core value, ensuring clear accountability for safety, integrating safety into all organizational activities, promoting strong leadership for safety, and adopting a learning-driven approach to safety management.

Lastly, Tucker at al. [41] examined safety through the lens of perceived organizational and coworker support for safety, identifying these factors as predictors of employee safety voice, or the willingness to raise concerns about safety issues. Casey et al. [11] aimed to bridge the gap between research on leading indicators and their practical application by proposing six different scales for measuring safety climate, thereby offering a more nuanced approach to understanding and improving safety outcomes. In a related effort, Beus et al. [42] defined safety climate as the propensity of employees to adhere to safety policies, procedures, and workplace safety standards, underscoring the behavioral aspect of a safety culture.

Summary SRQ1

The first research sub-question *How is Occupational Health and Safety defined in the literature?* was formulated to establish a solid foundation for the indicators used to evaluate occupational health and safety. The primary objective of addressing this question is to integrate these insights into the design of measures suitable for the application in this study. The literature review revealed a diverse array of safety indicators, highlighting the complexity and multidimensional nature of occupational health and safety assessment. These indicators are generally categorized into two main types: leading and lagging indicators.

Lagging indicators are widely adopted across industries to facilitate the comparison of safety performance and to monitor trends over time. However, a significant limitation of relying solely on lagging indicators is that they provide a reactive approach to safety management, focusing on incidents after they have occurred rather than preventing them. This reactive nature makes it challenging to implement proactive safety measures, but they are useful in assessing the effectiveness of these measures. To address the limitations of lagging indicators, leading indicators have been introduced as a complementary approach. Leading indicators emphasize proactive aspects of safety management, such as safety behavior, knowledge, compliance, and effectiveness of safety initiatives. By focusing on these forward-looking indicators, organizations aim to enhance their ability to predict and prevent potential safety issues. However, the lack of universal standardization of the leading indicators remains a challenge due to their subjective nature and the varying contexts in which they are applied.

In summary, the literature review that was conducted identified 17 studies that clearly defined their measures of safety. These studies collectively contributed to the identification of 19 leading indicators and 21 lagging indicators, as presented in Figure 3. The comprehensive compilation of these indicators not only highlights the complexity of OHS measurement, but also provides a valuable resource for designing safety indicators for empirical testing in this study. This dual approach, which incorporates both leading and lagging indicators, ensures a more holistic assessment of occupational health and safety performance.

2.2.2 SRQ2 - Methods for Measuring the Impact of Organizational Practices on Occupational Health and Safety

The second research sub-question aimed to identify methods to measure the impact and relationship between organizational practices and occupational safety. Out of the selected studies, 18 articles met the final quality assessment criteria by exploring and quantifying this relationship. Several key approaches were identified including regression models, statistical testing, qualitative, probabilistic and forecasting models. Among these, the variations of the regression models were the most commonly used by researchers, followed by statistical testing and qualitative research, as shown in Figure 4. The following subsections provide a detailed discussion of how these methods were applied across different studies.

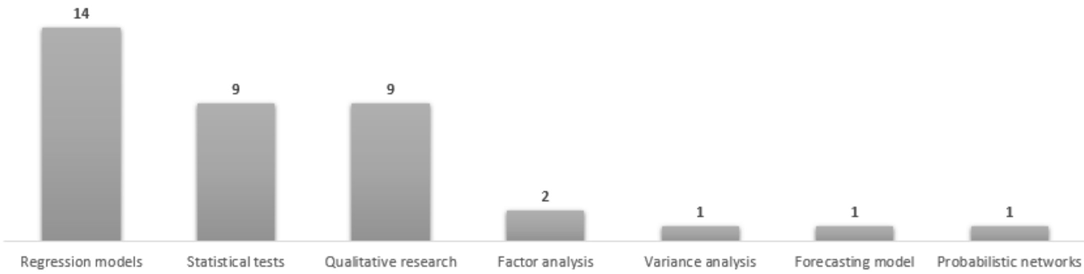


FIGURE 4: Methods for measuring relationship between organizational practices and occupational safety identified through literature review

Regression Models

A regression model is a statistical technique used to describe the relationship between one or more independent variables and a target (dependent) variable. In the context of occupational safety research, the target variable typically represents safety outcomes, while the independent variables include organizational practices or demographic factors. The linear regression model is the most widely employed in the literature, as it seeks to estimate the correlation between two variables. However, various studies have applied different types of regression models to better capture the complexity of the relationships between organizational factors and safety outcomes.

In the study of McCaughey et al. [21], a series of four regression models were developed to examine the proposed relationships between supervisor and senior management safety leadership (independent variables) and the safety perceptions and unit safety grades of support service employees (dependent variables). This approach provided a nuanced understanding of how leadership at different organizational levels influences safety perceptions among employees. Similarly, Cook et al. [12] created a simple linear regression model to describe the relationship between employee injury and illness rate and the results of the safety climate survey. This model provided a straightforward method to assess the impact of perceived safety climate on actual injury and illness outcomes.

Recognizing the limitations of traditional linear regression models, Arocena et al. [17] adopted a Generalized Linear Model (GLM) to account for the non-continuous nature of occupational accident data. The authors argued that the application of classic linear regression models to such this type of data could lead to inconsistent estimates, given that the number of occupational accidents is a discrete variable. The GLM allows for dependent variables to follow distributions other than the normal distribution, thus offering a more flexible and accurate representation of the data.

In another study, Sorensen et al. [43] developed multiple logistic regression models to investigate the likelihood of safety participation based on employee characteristics such as job role, gender, worksite, and exposure levels. This approach allowed for the identification of specific demographic and occupational factors that may influence an employee's likelihood of engaging in safety-related behaviors. Furthermore, Gimeno et al. [18] employed a dichotomous variable to determine the likelihood of work-injury-related absence, using an unconditional logistic regression model. This model was particularly effective in predicting the probability of injury-related absenteeism based on the presence or absence of certain conditions.

Furthermore, Arboleda et al. [44] analyzed perceptions of safety within the transportation industry using linear regression, distinguishing between three hierarchical levels: drivers, dispatchers, and directors. This hierarchical approach provided insights into how safety perceptions differ across various levels of the organizational structure. Similarly, Gershon et al. [27] applied multiple regression analysis to explore the relationship between four organizational dimensions and safety behavior, finding that three of the four dimensions had a significant predictive value. This study highlighted the importance of considering multiple organizational factors when assessing safety behavior outcomes.

In the context of safety practices in China, Jiuhua et al [35] employed a multiple regression correlation analysis to examine the relationship between four safety practices and their impact on safety involvement and behavior. This analysis provided evidence of the significant influence of specific safety practices on employee engagement in safety-related activities. Finally, Tucker et al. [41] conducted a hierarchical regression analysis on data collected from 213 bus drivers, revealing a positive relationship between organizational support and employee safety voice. This study underscored the role of organizational support in encouraging employees to speak up about safety concerns.

In all of these studies, regression models played a key role in understanding the complex relationships between various organizational practices and safety outcomes. By treating organizational practices as independent variables and safety outputs as dependent variables, these models have facilitated a deeper understanding of how different factors contribute to workplace safety.

Statistical Testing

Statistical testing includes a variety of methodologies designed to evaluate quantitative data with the aim of identifying patterns and trends. In the area of worker safety research, numerous statistical techniques have been employed to gain insights into different facets of workplace safety. In a study by Milczarek and Najmiec, the authors used factor analysis of a worker questionnaire to develop empirical measure of worker safety [16]. This analysis revealed three principal factors, which were subsequently employed in hypothesis testing using variance analysis. In a similar manner, d'Ettorre et al. [25] conducted both a chi-square test and a t-test to investigate the relationships between categorical and continuous variables.

In a study performed by Tsung-Chiu et al. [30], one-way MANOVA was used as the primary analytical method. In this case, organizational and individual factors served as the independent variables, while safety climate was treated as the dependent variable. This approach allowed the researchers to test their hypotheses with a 95% confidence level. A comparable methodology was adopted by Dale et al. [34] to assess safety performance differences between contractor and subcontractor companies. In a study in the Denver airport, Glazner et al. applied Poisson regression to explore the relationship between lost time work rates and safety practices [20]. Additionally, Spearman rank correlations were computed to evaluate the strength of association between these variables.

In a different approach, Sorensen et al. [43] employed the Breslow-Day test to evaluate the homogeneity of the worker population in the study, and subsequently used the chi-square test to validate the hypothesis that white-collar workers engage more actively in safety practices compared to their blue-collar colleagues. In the context of micro firms, Hadjimanolis et al. [33] utilized correlation analysis to investigate the relationships between demographic characteristics, organizational variables, and their effects on safety performance. In another study, Beus et al. [42] conducted a statistical analysis revealing a curvilinear relationship between worksite tenure and safety climate strength.

Lastly, Han et al. [23] explored the correlation between shift patterns and accident occurrences using a System Dynamics model. Schwatka et al. [45] employed a range of statistical techniques including the chi-square test, standardized root mean square residual, and root mean square error of approximation to assess the reliability of their measures and the validity of their study hypotheses. Each of these methods contributed uniquely to the understanding of safety dynamics in various organizational contexts.

Qualitative Analysis

Studies conducting qualitative analyses offer refined insights into how safety performance is perceived and managed at both individual and managerial levels. Through in-depth interviews and observations, these research efforts captured the complexities of safety attitudes, behavioral motivations, and organizational dynamics that quantitative methods might overlook. Whereas statistical testing helps validate the proposition that organizational practices influence safety performance, the qualitative analyses enrich the understanding of these relationships by highlighting specific contextual factors and personal experiences. Moreover, the diverse qualitative approaches facilitate a more comprehensive exploration of safety performance, complementing the quantitative analysis and contributing to a more holistic view of the subject.

Using qualitative methods, Mullen [32] conducted semi-structured interviews with employees across diverse professions to explore the underlying reasons for unsafe practices at work. Alternatively, Ahmad [46] provides a thorough review of paradigms concerning work quality and organizational conditions that contribute to employees' perceptions of safety and professional satisfaction. Similarly, Homann et al. [47] conducted open-ended conversations with both workers and leadership on the production line to gain insights into safety attitudes. In the ship-breaking industry, Tanha et al. [26] gathered data through interviews, site observations, and industry reports to investigate safety practices. Silva and Prata [48] examined shift duration and rotation by conducting phone interviews with 88 organizations across Canada. Lastly, a number of studies [49, 50, 51] held interviews with employees and management to gather insights relevant to their research questions.

Probabilistic Networks and Forecasting Models

In the investigation of safety culture and accident causation, sophisticated analytical methods have proven effective in consolidating the underlying insights. One such method is the Bayesian Network, as demonstrated by García-Herrero et al. [39]. This approach was employed to unravel the intricate dependencies between organizational culture and safety culture. The Bayesian Network was calibrated using survey data, which contained twelve distinct variables related to safety culture. A high confidence threshold was used to ensure the reliability of the significant relationships identified within the network, thereby enhancing the precision of the results and providing a robust framework for understanding safety dynamics.

In a study by Mohandes et al. [52], the authors adopted forecasting methods to analyze the causation of accidents within the construction sector. The process began with an exhaustive inventory of potential causes of accidents, drawing from a broad spectrum of the literature. Safety experts then ranked these causes based on their criticality, creating a prioritized list for further analysis. The Fuzzy DEMATEL technique was subsequently applied to map out the interrelationships among these critical issues. This technique not only facilitated a clearer visualization of how various factors interact, but also provided a structured approach to understanding their impact on accident causation. Validation of the findings through expert interviews ensured the credibility and applicability of the results. By integrating a comprehensive array of causes and employing advanced forecasting methods, this approach yielded insightful information crucial for accident prevention and safety management.

Altogether, these probabilistic and forecasting methods achieve a multi-faceted approach to analyzing and improving safety culture and accident prevention strategies. Collectively, these methods contribute to a sophisticated understanding of safety culture dependencies and a more comprehensive safety management framework.

Summary SRQ2

The second research sub-question *What methods have been researched for measuring the impact of organizational practices on Occupational Health and Safety?* aimed to gain a comprehensive understanding of the methodologies utilized in the literature to study occupational health and safety. Specifically, the goal was to identify promising approaches and techniques that can serve as guidelines for the methodology design of the proposed study. From the literature review we identified four principal approaches: regression models, statistical testing, qualitative research, and forecasting models.

The literature review found statistical testing to be particularly effective in validating the relationship between organizational practices and occupational health and safety. By applying various statistical techniques, researchers can confirm the existence and strength of these relationships, providing empirical evidence of the impact. Regression models further enhance this understanding by examining how specific organizational practices influence occupational health and safety, allowing for a detailed analysis of the interactions between independent variables (organizational practices) and dependent variables (safety outcomes). These models can identify not only the direction but also the magnitude of these effects. Additionally, qualitative research methods, including interviews and case studies, offer critical insights into the subjective experiences and perceptions of both employees and managers. This approach adds depth to the quantitative findings by capturing the context of how organizational practices are experienced and interpreted at different levels within the organization. An integration of these different methodologies ensures a comprehensive view of the impact of organizational practices on occupational health and safety, thereby enabling a more holistic and refined analysis.

2.2.3 SRQ3 - Employee Engagement Impact on Occupational Safety across Industries and Countries

Extensive research has established the significant role of employee participation in organizational decision-making, particularly with regard to enhancing workplace safety. Several studies have consistently found that active involvement among employees not only contributes to a safer working environment, but also yields broader organizational benefits such as improved job performance, higher job satisfaction, enhanced organizational commitment, and reduced absenteeism and turnover. Moreover, worker participation in safety decision-making processes has been found to deepen employees' understanding and adherence to safety regulations, thereby fostering a stronger safety culture within organizations. From the systematic literature review, we identified 15 key studies across various industries and countries that explored the impact of employee participation on organizational safety outcomes, thereby addressing SRQ3. These studies collectively outline the positive effects of worker involvement in safety matters, regardless of the industrial and cultural context.

Construction Industry. In the construction industry, Hallowell et al. [13] conducted a comprehensive study aimed at identifying the most effective safety programs. The study developed a detailed list of 104 construction safety strategies based on existing literature and assessed their effectiveness by analyzing the recordable injury rate across multiple projects. The findings indicated that worker involvement in hazard assessment was consistently effective, demonstrating its critical role in enhancing safety outcomes across construction projects.

Manufacturing Industry. Homann et al. [47] conducted an in-depth investigation into the factors driving worker engagement with health and safety practices in a production-line process. The study involved 38 semi-structured interviews, which were analyzed using template analysis to identify themes that promote or hinder engagement. The findings highlighted the crucial role of supervisors in fostering workers' engagement with health and safety, underscoring the need for supervisors to possess specific skills to enhance engagement. Furthermore, the study emphasized that workers' feelings of being heard, involved, and valued by the company were essential in fostering a sense of psychological safety and meaningfulness, which in turn positively influenced their engagement with health and safety behaviors. Figure 5 illustrates the engagement framework resulted from the study and provides an understanding of the factors that drive worker engagement in health and safety.

Nuclear Industry. In the nuclear industry, García-Herrero et al. [39] investigated the interplay between organizational and safety cultures. Utilizing Probabilistic Bayesian Networks, the study analyzed data from a survey conducted among employees at a Spanish nuclear power plant. The research demonstrated that constructive and collaborative norms, particularly involving employees in decisions that affect them, significantly enhanced the safety culture. The study also provided a ranking of organizational cultures that could be used to improve safety outcomes, further reinforcing the link between employee participation and safety performance.

Healthcare Industry. Within the context of cancer prevention initiatives, Sorensen et al. [53] analyzed workers' perceptions of management actions aimed at reducing occupational exposures. The study surveyed 6,450 workers to assess their participation in health promotion programs. Results indicated that both employee and management involvement were

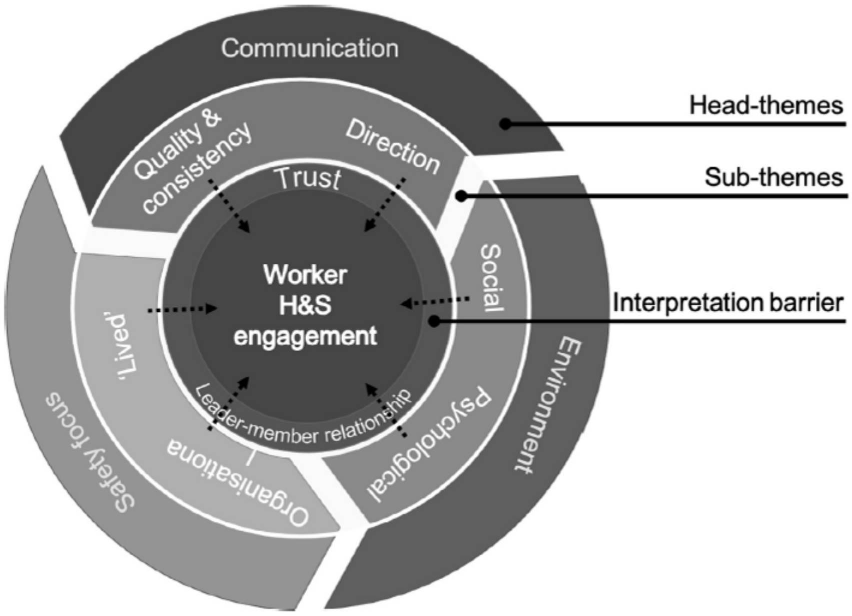


FIGURE 5: Derived health and safety engagement factor framework by F. Homann et al. [47]

crucial in effectively conducting health promotion initiatives, highlighting the importance of collaborative efforts in these programs.

Spain. Arocena et al. [17] explored the relationship between risk mitigation practices and occupational injuries in 213 Spanish industrial establishments. Through linear regression analysis of data collected via questionnaires, the study examined the influence of worker participation on the occurrence of workplace accidents. Respondents rated worker participation on a scale from 1 to 10, and workplace accidents was defined as incidents resulting in at least one day off work which served as the dependent variable. The study found that proactive prevention activities, the intensive use of quality management tools, and the empowerment of workers were significant factors in reducing workplace accidents.

India. The study by Vinodkumar and Bhasi [36] measured employees' perceptions on six safety management practices and self-reported safety knowledge, safety motivation, safety compliance and safety participation by means of survey. A questionnaire was sent to 1566 employees representing eight major accident hazard process industrial units in Kerala, a state in southern part of India. Through use of descriptive statistics and structural equation modelling, direct and indirect relations with safety compliance and safety participation were found.

Poland. Widerszal-Bazyl et al. [54] found that a low level of employee participation had a negative effect on performance and organizational resilience during times of crisis. Managers from 192 companies filled out the Employee Direct Participation in Organisational Change questionnaire measuring employees' direct participation in organisational decisions. Workplace safety was measured by the number of accidents, the number of employees working in hazardous conditions, accident absenteeism and sickness absence. It was found that employee direct participation had a positive influence on workplace safety, even if involvement was not directly related to safety.

Job Satisfaction. Ahmad [46] explored the broader implications of employee participation, arguing that it not only improves safety outcomes but also enhances job satisfaction and employment security. This aligns with the findings from Clark et al. [55], who conducted a qualitative review of interventions aimed at creating sustainable jobs and improving worker health in the healthcare sector. The review found that employee participation schemes positively impacted job satisfaction and as well as overall employee well-being.

Employee Voice. The role of employee voice in safety-related matters has also been a focal point in the literature. Tucker et al. [41] contributed to this body of work by evaluating the critical role of employee voice in safety engagement. The study highlighted the importance of employees speaking out about safety issues, a behavior that is significantly influenced by perceived organizational and coworker support. Mullen [32] further supported these findings, demonstrating that employees are more likely to report safety concerns when they believe that management will take their input seriously and that they will not be blamed for it.

Literature Gap and Contribution

While the existing literature provides substantial evidence of the beneficial effects of employee engagement on occupational health and safety, a significant gap was identified in the existing methodologies. The majority of studies to date have relied heavily on qualitative and subjective data obtained through interviews and surveys. Although these methods yield valuable insights, they are also prone to limitations such as the potential biases in respondents' answers, the influence of current experiences and emotions, and variability in the interpretation of questions. Respondents may feel pressured to provide socially desirable answers or may lack the reflective awareness needed to accurately report on the evolution of their experiences over time. Additionally, survey-based studies often face challenges with regard to the representatives of their sample populations, as the perspectives of respondents may differ substantially from those of non-respondents [56]. Consequently, the voluntary nature of survey participation can lead to concerns about the generalization of the findings.

The methodological limitations discussed are also documented and recognized in the literature. A number of studies (e.g. [36]) have acknowledged the inherent biases and errors associated with subjective survey data. The lack of objective data management systems to validate self-reported safety practices further complicates the ability to accurately assess the efficacy of these practices in reducing injury numbers. In light of these challenges, there is a pressing need to address this gap by integrating objective data sources into a data-driven analysis of employee engagement and its impact on occupational safety.

The aim of this study is to fill the literature gap by leveraging data from management systems that monitor safety issues and the implementation of safety practices. This approach will enable a more fact-based measurement of employee engagement both on a daily basis and over an extended period of time. By correlating these objective engagement indicators with occupational safety outcomes, this research aims to empirically validate the relationship between employee engagement and safety performance.

The contributions of this study are twofold. Firstly, it addresses the literature gap by studying the relationship between employee engagement and occupational health and safety using objective data, rather than relying on self-reported measures. Secondly, this study provides data-driven recommendations for organizations aiming to enhance workplace safety through more effective employee engagement strategies. Consequently, the study's contributions not only enrich current academic knowledge but also provide valuable and actionable insights for practical implementation.

Chapter 3

SEED-DM Design

3.1 Methodology Introduction

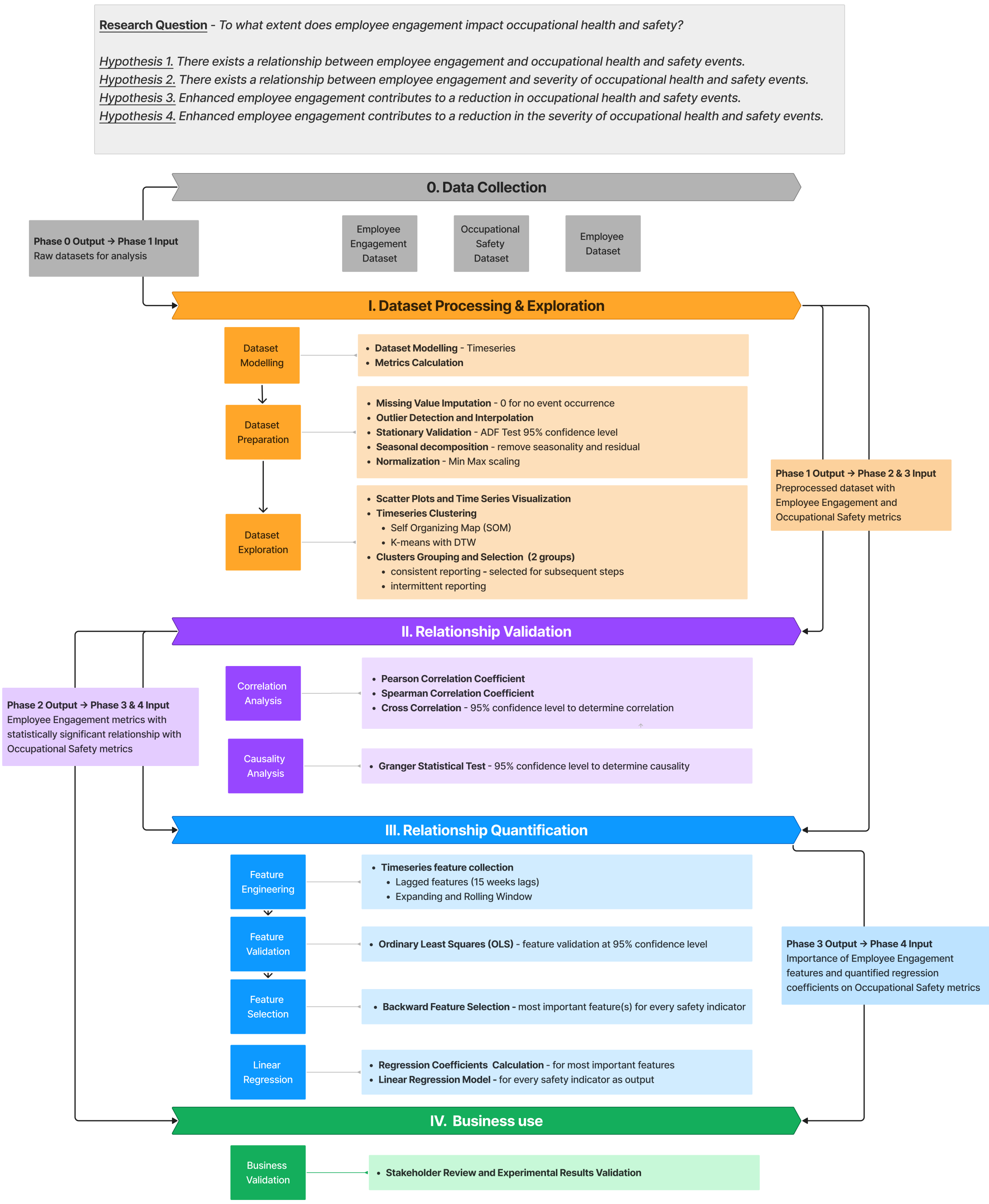
In this chapter we present SEED-DM, a data-driven methodology designed to evaluate the impact of employee engagement on occupational health and safety. The methodology is based on the Cross Industry Standard Process for Data Mining (CRISP-DM), which is widely recognized as one of the most effective frameworks for data science projects [57]. CRISP-DM provides a structured approach for transforming raw data into valuable insights through six iterative phases: business understanding, data understanding, data preparation, modeling, evaluation, and deployment. This framework is particularly valuable for designing research methodologies, as it emphasizes a systematic approach to data handling, ensuring alignment between research objectives and data analysis processes. By following the CRISP-DM framework, we maintain a clear focus on the research problem, apply appropriate modeling techniques, and critically evaluate outcomes prior to implementation. This ensures that findings are not only scientifically valid but also applicable to practice, effectively bridging the gap between theoretical research and real-world application. Furthermore, the iterative nature of CRISP-DM allows for continuous refinement of the research process, accommodating new insights or data, thereby enhancing the overall rigor and relevance of the research.

SEED-DM was developed by incorporating insights from the research sub-questions answered in Chapter 2, with the aim of generating data-driven results to evaluate the impact of employee engagement on occupational health and safety. A schematic overview of SEED-DM is given in Figure 6, with the design being applicable to any organization with operational data on employee engagement and occupational safety. SEED-DM aims to provide data-driven conclusions by testing four hypotheses, as formulated in Section 1.2:

- **H1:** *There exists a relationship between employee engagement and occupational health and safety events.*
- **H2:** *There exists a relationship between employee engagement and severity of occupational health and safety events.*
- **H3:** *Enhanced employee engagement contributes to a reduction in occupational health and safety events.*
- **H4:** *Enhanced employee engagement contributes to a reduction in the severity of occupational health and safety events.*

SEED-DM is structured into five phases, each designed to ensure a thorough examination and analysis of the data. As a preliminary step, in Phase 0, the data necessary for this study is collected. In Phase 1, we begin with a thorough data preparation and cleaning process, crucial for eliminating inconsistencies and ensuring the reliability of subsequent steps. Moreover, an exploratory data analysis is conducted to uncover key trends and characteristics within the data. These steps are essential for developing a foundational understanding of the dataset, thereby guiding the design activities in the following phases.

FIGURE 6: Schematic overview of SEED-DM methodology



Phase 2 of the methodology is dedicated to testing Hypotheses 1 and 2, which investigate the potential relationship between employee engagement and occupational health and safety. Statistical tests are employed to examine the possible correlation and causality between the variables. This phase aims to establish whether there exists a significant relationship between the two variables, providing the foundation for further analysis. Building upon these findings, Phase 3 aims to quantify the relationship by testing Hypotheses 3 and 4. This involves the application of advanced statistical modeling techniques and linear regression to measure the strength and nature of the relationship between the variables. Hence, our goal is to understand not only the existence but also the magnitude and implications of this relationship.

Finally, in Phase 4 the results are consolidated and translated into actionable business recommendations. These data-driven recommendations are intended to guide organizations in leveraging employee engagement as a strategic tool to enhance occupational health and safety outcomes. By offering evidence-based insights, we aim to empower organizations to make informed decisions that drive both employee well-being and organizational success. These results are further validated with occupational health and safety leadership and experts.

3.2 Phase 0 - Data Collection

To empirically test the proposed hypotheses, the SEED-DM aims to make use of a real-world dataset to generate data-driven conclusions and recommendations. The dataset includes two critical variables central to the analysis: employee engagement and occupational health and safety. In addition, the employee dataset was introduced as a control variable to account for possible variations due to changes in employee and operational conditions within the organization. The following subsections provide an in-depth overview of the data points required for the analysis.

Employee Engagement Dataset

As discussed in the literature review, employee engagement is a multifaceted concept that involves the active participation of employees at all organizational levels, particularly front-line workers, in identifying safety hazards and contributing to safety-related decision-making processes. Previous studies often relied on subjective measures, such as interviews and opinion surveys, to assess the degree of employee engagement in organizational safety matters. However, these methods can introduce biases and may not accurately and objectively capture the extent of employee engagement. To address these limitations, our methodology utilizes a factual dataset derived from a system specifically designed to foster and track employee engagement, hereafter referred to as the EE system.

Occupational Health and Safety

The literature review conducted for the first sub-research question (SRQ1), *How is Occupational Health and Safety defined in the literature?*, highlights the variety of perspectives and methods used to measure occupational health and safety. This diversity in definitions underscores the complexity of accurately assessing OHS data. For the hypotheses testing in this methodology, a dataset is chosen that supports the calculation of lagging indicators. Compared to leading indicators, lagging indicators offer several advantages in the context of this analysis. First, lagging indicators, such as injury rates, enable precise quantitative calculations, making them ideal for statistical testing. They also help to track trends over time, allowing the identification of significant changes. Furthermore, because lagging indicators assess safety retrospectively, they provide insight into the impact of organizational factors such as employee engagement. Lastly, lagging indicators benefit from standardization, facilitating comparison with other studies in the field.

Employee Dataset

Finally, to ensure that the analysis of occupational safety and employee engagement is not influenced by fluctuations in employee growth or operational changes within the organization over time, the employee dataset is utilized as a key control variable. This dataset provides a comprehensive record of the number of active employees and worked hours, allowing for precise tracking of workforce dynamics. By integrating these variables, this dataset helps isolate the effects of organizational changes on employee-related outcomes, thereby enhancing the reliability of the hypothesis testing.

3.3 Phase 1 - Dataset Processing and Exploration

3.3.1 Dataset Modeling

In the dataset modeling phase, the objective is to merge the three individual datasets into a unified dataset to enable further analysis. Since these datasets may originate from different sources or systems, the goal is to join them based on common attributes. The unified data set will include information such as the number of submitted employee suggestions, injuries, active employees, and total hours worked per day throughout the organization. The goal of this unified dataset is to support the subsequent steps in testing the proposed hypotheses.

Within this step, an in-depth analysis of the three data sources is necessary. During this analysis, the relevant attributes needed for hypothesis testing are identified and selected from each dataset. Additionally, the common attributes between the datasets are identified and used to merge the datasets into one. The unified data set is then treated as a time series, with the date serving as the key attribute to track changes over time. Modeling the data as time series allows for a more detailed analysis of the proposed hypotheses. Time series analysis helps identify underlying trends, leading to a better understanding of long-term patterns. It also enables the detection of seasonal effects and periodic fluctuations, supporting more accurate and informed conclusions.

Once the dataset is consolidated, a list of employee engagement and safety indicators is calculated to facilitate further analysis of the relationship between these variables. The employee engagement indicators track overall engagement levels, with factors included to identify specific drivers of engagement. Occupational health and safety include a set of lagging indicators consistent with those in the literature, allowing for cross-study comparisons and monitoring changes over time. To ensure the analysis remains valid despite organizational shifts, the total number of work hours is factored into rate calculations. All metrics used are quantitative, as this allows for statistical analysis, providing measurable data that can be easily compared, analyzed, and used to identify trends.

3.3.2 Dataset Preparation

When preparing time series data for analysis and statistical testing, it is essential to implement a rigorous data cleansing process to ensure the accuracy and reliability of the results. The first step of this process is focused on addressing missing values, where it is key to select an appropriate data imputation method tailored to the specific characteristics of the data. For the datasets scoped in this methodology, instances of missing employee engagement data or unrecorded injuries should be addressed by imputing the missing values with a constant value of zero, reflecting the absence of such submissions.

Removing outliers from the dataset is essential, as they can distort statistical analysis and lead to misleading conclusions by skewing the mean and standard deviation. Boxplot is a particularly effective method for identifying outliers as it summarizes the data distribution while clearly highlighting outliers as points that fall outside the "whiskers" of the plot. Subsequently, the interquartile range (IQR) test can be applied to determine potential outliers by calculating the difference between the first quartile (Q1) and the third quartile (Q3), which encompasses the middle 50% of the data. The IQR is then multiplied by a constant factor, typically 1.5, to determine the lower and upper bounds of the expected data range. Data points falling outside these bounds are considered potential outliers. The identified outliers can be further addressed using interpolation, a method that estimates values within the data range. Interpolation is particularly appropriate for handling outliers because it allows for the replacement of extreme values with estimates that are consistent with the overall trend of the data. By using nearby data points to inform the estimation, interpolation preserves the underlying structure of the dataset, minimizing the risk of introducing bias. Additionally, this technique maintains the continuity of the data, which is essential for our statistical tests.

A fundamental concept in time series analysis is stationarity, which is essential for ensuring reliable modeling and accurate prediction [58]. A stationary time series is characterized by the series having a constant mean, variance, and covariance over time. Since the majority of statistical models assume stationarity, non-stationary data can result in unreliable model outputs and flawed forecasts. Consequently, ensuring these statistical properties is critical as it helps to better capture the underlying dynamics of the data, thereby improving the model accuracy. The Augmented Dickey-Fuller (ADF) test is a commonly used statistical procedure to assess stationarity. This hypothesis test evaluates whether a time series is non-stationary (the null hypothesis) by examining the presence of a unit root. The ADF test produces a p-value, which is obtained through regression surface approximation (as per MacKinnon, 1994 [59], and updated with the 2010 tables [60]). A p-value below the significance level of 0.05 supports the rejection of the null hypothesis, thus confirming the stationarity of the time series.

In order to achieve stationarity, the removal of trend and seasonality is required. Time series decomposition is a prevalent and straightforward method for this purpose. This technique involves breaking down the time series into three components: trend, seasonality, and residual, which have been illustrated in Figure 7. From these components, the trend component represents the long-term progression of the data, the seasonality captures recurring patterns within specific intervals (e.g., daily, monthly, or annually), and the residual accounts for random fluctuations that do not follow the trend or seasonality [61]. For further analysis, the seasonality and trend are removed from non-stationarity series, keeping only on the residual component to maintain stationarity. Eliminating seasonality from

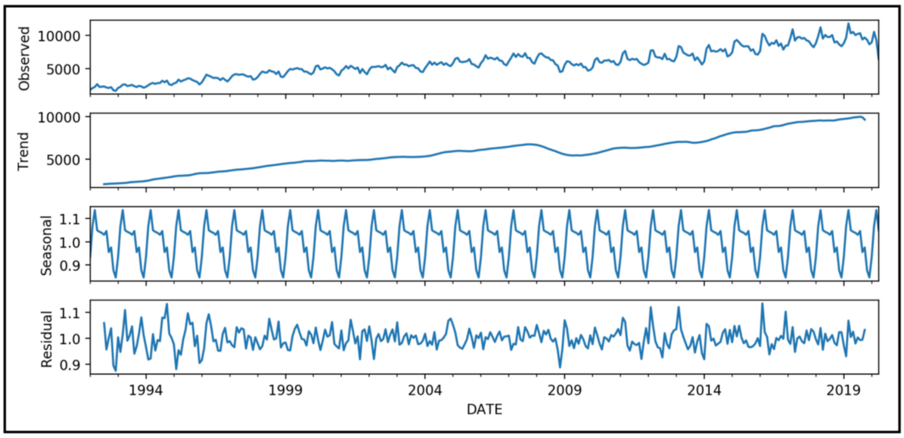


FIGURE 7: Time series seasonal decomposition. The trend and seasonality are removed to achieve stationarity

time series data is essential for focusing on the core behavior, improving results accuracy, preventing misleading conclusions, and enabling more meaningful comparisons over time.

The final step is to normalize the data. Without normalization, features with larger ranges could dominate the learning process or affect distance calculations, leading to biased or suboptimal results. By following all these steps in the data preparation process, we ensure that the dataset is accurate and reliable for our analysis, free from distortions caused be outliers or seasonality and suitable for statistical modelling.

3.3.3 Exploratory Data Analysis

Before proceeding to statistical testing, an Exploratory Data Analysis (EDA) is conducted to establish a solid foundational understanding of the data and guide the subsequent phases of the study. EDA serves as a critical preliminary step in data analysis, where the dataset is thoroughly examined and visually represented to uncover valuable insights, identify recurring patterns, and detect any anomalies. Within the context of this methodology, the primary objective of EDA was to gain an initial understanding of the trends in employee engagement and occupational health and safety. During this phase, two primary methods can be used: time series analysis with visualization techniques and time series clustering.

Time Series Analysis and Scatter Plots

The goal of the time series analysis is to understand how trends in employee engagement and occupational health and safety evolve over time. Visualizing these trends is particularly valuable as it helps communicate findings effectively to stakeholders, especially to those without a strong statistical background. In addition, scatter plots are used to explore potential relationships between the two variables irrespective of the time at which they were observed. These plots provide a visual way to assess the strength of the relationship between the variables. Within SEED-DM, scatter plots are useful in visually exploring the proposed hypotheses and illustrating the strength of the relationship between employee engagement and occupational health and safety.

Time Series Clustering

For the last part of the exploratory analysis of the dataset, time series clustering is used to identify patterns within the data. Clustering serves as a powerful technique during the exploratory phase by enabling the grouping of similar reporting trends based on their characteristics [62]. The resulting groups not only simplify the analysis but also enable conclusions to be drawn at higher organizational levels, rather than focusing on granular insights. As a data mining technique, clustering is particularly effective for classifying large datasets for which there is no prior knowledge about the class labels. This process involves placing similar data points into related or homogeneous groups without predefined definitions about the groups [63]. Specifically, clusters are formed by grouping data points that exhibit a high level similarity, while minimizing the similarity with the data points from other groups. In the context of time series data, where multiple data points evolve over time, clustering is especially advantageous as it facilitates the discovery of significant patterns within complex datasets [64]. In general, there are three different ways for clustering time series data: shape-based, feature-based, and model-based [62]. The feature and model-based approaches both require the time series to first be converted into other data structures before they can be used as input to the clustering algorithms. Instead, in this methodology we opted for shape-based clustering, which directly utilizes the raw time series to avoid any preprocessing steps that might bias the results.

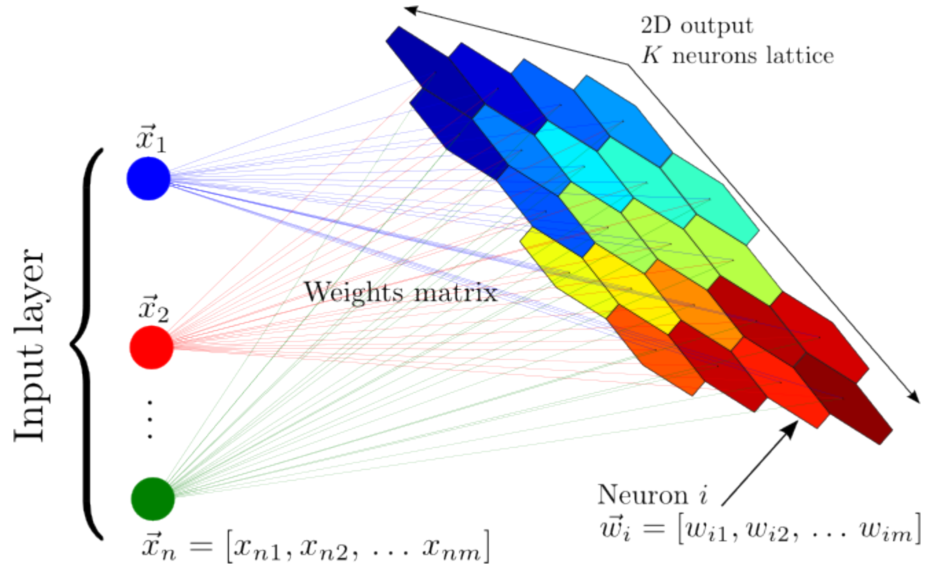


FIGURE 8: Self-Organizing Map architecture [65]

SEED-DM proposes two clustering techniques: Self-Organizing Map (SOM) and K-means with Dynamic Time Warping (DTW). Both methods are effective for visualizing and processing high-dimensional data, such as time series, and operate unsupervised in the process [63]. Incorporating both SOM and K-means into a study allows for a thorough exploration and understanding of time series data. This combined approach leverages the strengths of each method and facilitates cross-cluster validation, leading to better informed results. Analyzing the same dataset with different algorithms enhances understanding, as each method may reveal unique insights into the data.

Self-Organizing Map (SOM) clustering is an unsupervised machine learning technique that uses neural networks to map high-dimensional data into a lower-dimensional grid, typically with two dimensions. The SOM algorithm initializes a grid of neurons, each representing a potential cluster. During training, each data point is compared to the neurons, and the neuron that most closely resembles the data point—known as the Best Matching Unit (BMU) is identified [66]. The BMU and its neighboring neurons are then adjusted to become more similar to the data point. Over time, this iterative process leads to the clustering of similar data points on the map, revealing the underlying structure of the data and facilitating easier visualization. Figure 8 provides a visual representation of the organizing process behind SOM. SOMs are particularly effective for time series clustering due to their ability to reduce high-dimensional data into a more manageable, lower-dimensional map while preserving the inherent temporal relationships. By maintaining the topological structure, SOMs ensure that similar time series are mapped close to each other on the grid, facilitating the identification of clusters and patterns within complex datasets.

The second clustering algorithm, K-means, is a widely used method for partitioning data series into a predetermined number of clusters based on similarity. This algorithm iteratively assigns data points to the nearest cluster centroid and then recalculates the centroids as the mean of the points in each cluster. This process continues until the centroids stabilize, resulting in clusters of time series that exhibit similar patterns [67]. K-means is valued for its simplicity and efficiency, making it an ideal choice for datasets where the number of clusters is predetermined. Before clustering time series, Principal Component Analysis (PCA) is applied to reduce the dimensionality of the data. By transforming the original features into a new set of orthogonal components (principal components), PCA captures the most significant patterns in the data with fewer dimensions [68]. Reducing the dimensionality with PCA leads to more meaningful clusters that focus on the most significant features, while at the same time reducing the computational complexity.

The K-means algorithm makes use of a distance measure to calculate the similarity between the different data points. In SEED-DM methodology, we utilize *Dynamic Time Warping*, a technique which assesses the similarity between two time series that may vary in speed or temporal alignment [69]. Unlike conventional distance measures such as the Euclidean distance, DTW computes the optimal alignment between the sequences by considering shifts and distortions over time. It does this through a dynamic programming approach, which involves constructing a matrix in which each cell represents the cumulative cost of aligning subsequences up to that point. By iteratively calculating the minimum distance required to align each point in one sequence with points in the other sequence, DTW identifies the path with the lowest cumulative cost [69]. DTW optimizes K-means clustering by providing a more flexible and accurate measure of similarity for time series data, leading to more meaningful and accurate clusters.

The clustering algorithms are used to classify the time series into three main categories: (1) consistent engagement, (2) intermittent engagement, and (3) no engagement. In the case of consistent engagement, the time series displays a steady and sustained level of engagement across the observed time frame, indicating that employees remain consistently involved in their tasks or roles. Intermittent engagement refers to fluctuating levels of engagement, where employees may exhibit varying degrees of involvement, alternating between high and low engagement phases. Finally, no engagement reflects time series data where there is little to no observable engagement throughout the period. These classifications are not only useful for organizing the data but are also essential for hypothesis testing. By distin-

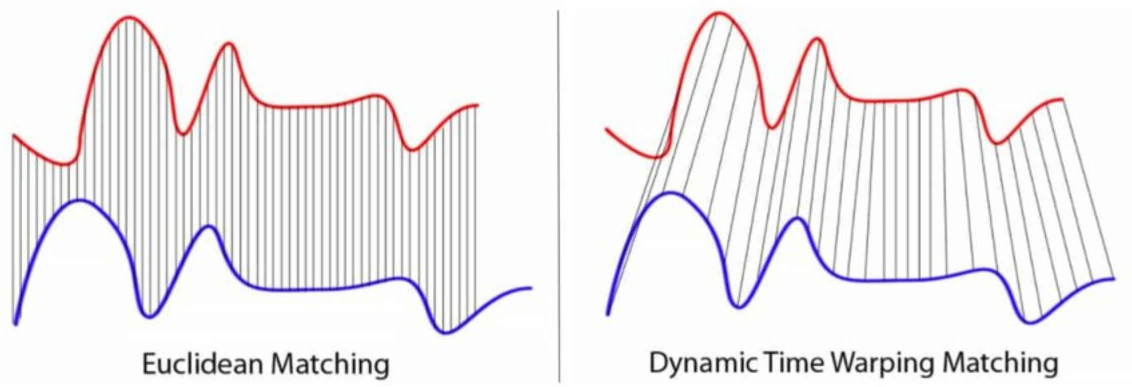


FIGURE 9: DTW vs Eucledian Distance for measuring similarity in time series data

guishing these different engagement levels, we can analyze how varying degrees of employee engagement affect occupational health and safety more precisely.

3.4 Phase 2 - Relationship Validation

Phase 1 serves as a critical foundation for preparing the dataset and ensuring its readiness for subsequent statistical analysis. The preprocessed dataset and clusters generated are carried forward into Phase 2, where the primary objective is to empirically validate the existence of a relationship between employee engagement and occupational health and safety by testing the first two hypotheses.

- *Hypothesis 1 - There exists a relationship between employee engagement and occupational health and safety events*
- *Hypothesis 2 - There exists a relationship between employee engagement and severity of occupational health and safety events*

Testing these hypotheses using real-world time series data offers a significant contribution to the existing body of research and provides practical insights for organizations, especially since no empirical validations have yet been recognized, as indentified in SRQ3 in Section 2.2.3. To validate these hypotheses, SEED-DM uses statistical tests conducted to examine the existence of two types of relationships: correlation and causality. The selection of these methods is guided by the findings of SRQ2 in Section 2.2.2, which identified them as prevalent and effective techniques for assessing the impact of organizational practices on occupational health and safety. The following subsections will provide a detailed explanation of the statistical approaches used in this methodology.

3.4.1 Correlation Testing

Correlation testing is a statistical method used to evaluate the strength and direction of a linear relationship between two or more quantitative variables. This technique is essential in hypothesis testing, as it helps reveal how closely related the variables are. The relationship is measured using a correlation coefficient that ranges from -1 to +1. A coefficient close to +1 indicates a strong positive relationship, indicating that as one variable increases, the other tends to increase proportionally. Conversely, a coefficient near -1 suggests a strong negative correlation, where an increase in one variable corresponds with a decrease in the other variable. When the coefficient is around 0, it indicates that there is no linear relationship between the variables.

In the context of proposed hypotheses, correlation testing is utilized to explore the relationship between employee engagement indicators and occupational safety indicators. It is important to note that although correlation analysis helps to identify associations between variables, it does not establish causation. In other words, while the analysis can detect if two variables are related, it cannot determine if one variable influences or causes changes in the other. Hence, variables that demonstrate correlations require further investigation to uncover the underlying mechanisms driving these relationships. There are several methods for determining statistical correlations, each suitable for different types of data and relationships. The most commonly used methods include Pearson's correlation coefficient and Spearman's rank correlation coefficient. Additionally, cross-correlation analysis is particularly useful for understanding the correlation between time series data with temporal shifts.

Pearson Correlation Coefficient

The Pearson correlation coefficient is one of the most widely used statistical tools for measuring the strength of a linear relationship between two continuous variables. It is a dimensionless coefficient, meaning it does not depend on the units of measurement of the variables, thereby allowing for a straightforward interpretation of the results. The Pearson coefficient is highly effective when the relationship between the variables is linear. However, its applicability is limited when the relationship is non-linear, in which case the coefficient may fail to accurately represent the true association between the variables. The Pearson correlation coefficient (r) is calculated using the following formula:

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}}$$

Where:

- r = Pearson correlation coefficient between variables x and y
- n = number of observations
- xi = value of x (for the ith observation)
- yi = value of y (for the ith observation)

Spearman Correlation Coefficient

Spearman rank correlation is a non-parametric test that is used to measure the degree of association between two variables. Unlike Pearson's correlation, Spearman's rank correlation does not assume that the data is normally distributed and is suitable for variables measured on an ordinal scale. Spearman's correlation assesses the strength and direction of a monotonic relationship between two variables, meaning it can capture relationships where one variable consistently increases (or decreases) as the other variable increases, without necessarily being linear. Spearman's rank correlation is particularly useful when dealing with ranked data or when the assumptions of Pearson's correlation (such as linearity and homoscedasticity) are violated. Spearman correlation (p) is calculated using the following formula:

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)}$$

Where:

- p = Spearman correlation coefficient
- n = number of observations
- di = difference between the ranks of each corresponding pair of values

Cross Correlation

Cross-correlation analysis is a more advanced technique used to measure the correlation between two time series variables at different points in time. Unlike the previous two methods in which a correlation coefficient is calculated at a specific point in time, cross-correlation assesses the correlation between two time series under various temporal shifts. This method is particularly valuable in time series analysis, where one variable may have a delayed effect on another, uncovering complex temporal dynamics that simple correlation measures may overlook.

In the context of SEED-DM, cross-correlation analysis is particularly useful as it enables the examination of the temporal relationship between employee engagement and occupational safety indicators. For instance, changes in employee engagement may not immediately reflect in occupational safety indicators as it takes time to influence safety behaviors, practices and outcomes. By applying cross-correlation analysis, we can uncover these time-lagged relationships, offering deeper insights into how fluctuations in employee engagement may affect future outcomes of occupational safety.

The computation of cross-correlation between two time series involves systematically shifting one time series in relation to the other and calculating the correlation coefficient (Pearson or Spearman) for each shift. In this methodology, employee engagement serves as the independent time series, which is shifted either forward or backward by a fixed interval, known as the lag. A positive lag indicates that the independent variable (employee engagement) precedes the dependent variable (occupational safety outcomes), whereas a negative lag indicates that it follows the dependent variable.

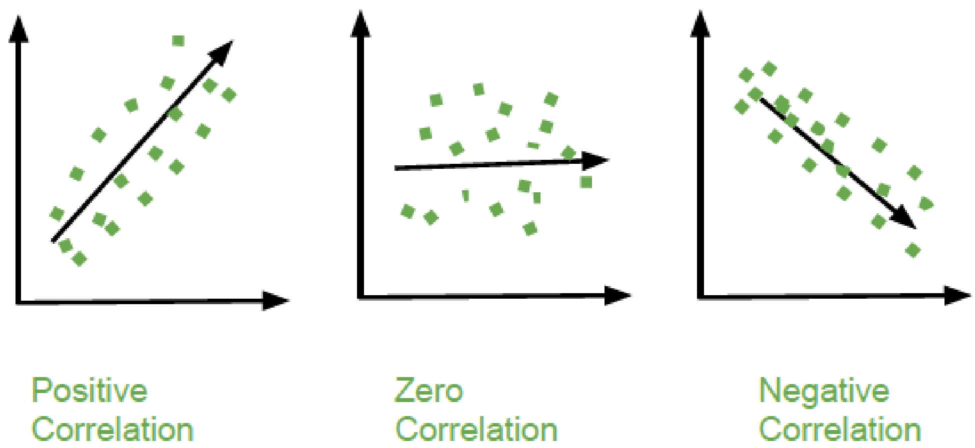


FIGURE 10: Correlation testing results

Interpreting Results

When interpreting the results of correlation testing, it is essential to consider both the magnitude and direction of the correlation coefficient. As recognized by Akoglu [70], a coefficient ranging from +0.7 to +1 indicates a strong positive correlation, where the two variables increase together. In contrast, a coefficient between -0.7 and -1 reflects a strong negative correlation, meaning that as one variable increases, the other decreases proportionally. Coefficients between (+/-) 0.3 and (+/-) 0.7 suggest a moderate relationship, while those between 0 and (+/-) 0.3 indicate a weak relationship. A coefficient equal to 0 denotes no meaningful linear relationship between the variables. Figure 10 illustrates the different outcomes out of correlation testing. The accuracy of correlation analysis is influenced by the sample size, where larger samples generally lead to more reliable estimates of the correlation coefficient. Regardless of the method used, the size and quality of the data play a critical role in ensuring the validity of the statistical tests.

3.4.2 Causality Testing

Causality testing, also referred to as causal inference, comprises a set of statistical methods aimed at determining whether one variable (the cause) influences another (the effect). SEED-DM uses causality testing to assess whether employee engagement has a measurable impact on occupational health and safety. Unlike correlation, which merely identifies a relationship between variables, causality testing seeks to establish a cause-and-effect connection. To investigate this relationship, we use Granger causality testing, a popular test developed by Clive Granger [71]. The Granger causality test assesses whether the observations from one time series can be used to predict the observations from another. It is important to note that this test does not measure true causality in a strict scientific sense. Rather than testing whether variable X causes variable Y, Granger causality examines whether past values of X improve the predictive accuracy for future values of Y. Specifically, X is said to Granger-cause Y if incorporating past values of X enhances the forecast of Y compared to predictions based solely on past values of Y.

The null hypothesis in Granger causality tests states that observations for the independent variable X do not Granger-cause observations for the dependent variable Y. In our analysis, X represents a measure of employee engagement, while Y corresponds to an indicator of occupational safety. In essence, the primary objective is to determine whether employee engagement Granger-causes occupational safety outcomes. To establish this relationship, we conduct a series of statistical tests on lagged values of X and Y. Specifically, we utilized t-tests (such as the chi-square test and likelihood ratio test) and F-tests (including the F-test and SSR F-test). These tests evaluate whether lagged values of X provide statistically significant information for predicting future values of Y. The null hypothesis, X does not Granger-cause Y, is rejected if the p-values are below a predefined significance threshold. A p-value threshold of 0.05 is generally used, allowing to assess Granger causality between employee engagement and occupational safety with 95% confidence.

3.5 Phase 3 - Relationship Quantification

The goal of Phase 3 is to build on the findings from Phase 2 and gain a more detailed understanding of the relationship between employee engagement and occupational safety. Specifically, this phase aims to quantify the strength of this relationship and identify possible key factors that have a significant impact on occupational health and safety. This deeper analysis is essential for validating the last two hypotheses proposed in this study:

- *Hypothesis 3 - Enhanced employee engagement contributes to a reduction in occupational health and safety events.*
- *Hypothesis 4 - Enhanced employee engagement contributes to a reduction in the severity of occupational health and safety events.*

To achieve these objectives, SEED-DM uses various techniques. Detailed features are engineered and tested for statistical significance on occupational safety indicators. Using advanced statistical techniques, this phase examines the relative importance of different dimensions of employee engagement and their specific effects on both the frequency and severity of safety incidents. Finally, a linear regression model is developed to quantify the relationship between employee engagement and various occupational health and safety indicators. As highlighted in the literature review in Section 2.2.2, linear regression showed as the most popular technique for evaluating the impact of organizational practices on occupational health and safety indicators.

3.5.1 Feature Engineering

Feature engineering is the process of leveraging domain-specific knowledge to extract meaningful attributes (features) from raw data. In the case of time series, the data often contains complex structures which may not be immediately visible in the raw data. Feature engineering can be used to capture these complex temporal factors, thereby enhancing the prediction performance of a statistical model. For this purpose, the raw data is transformed into meaningful features such as lagged observations, rolling statistics, and time-based variables. Without effective feature engineering, models are likely to struggle with identifying subtle temporal patterns resulting in suboptimal performance. Additionally, well-crafted features can improve the model's interpretability and robustness against noise, making them indispensable for effective time series analysis. In context of this methodology, several techniques are used: lagged time series, rolling window calculations and expanding window calculations.

Lagged Features

Lagged features are a fundamental aspect of feature engineering in time series analysis, critical for capturing temporal dependencies and autoregressive patterns within sequential data. A lagged feature is generated by taking the value of a variable from a previous point in time and incorporating it as a predictor of the model at the current point in time. This process involves shifting the time series data by a specified number of time steps, known as time lag. By including these lagged values as features, models can effectively learn from historical data to forecast future outcomes, thereby capturing the relationship between past observations and subsequent values. In our hypotheses testing, lagged features allow to examine how employee engagement in the preceding days or weeks influences occupational injuries over time. A careful selection and tuning of lagged features is crucial, using too few lags may overlook important dependencies, while too many lags can introduce noise and complexity, potentially leading to overfitting.

Rolling and Expanding Window Features

In time series analysis, the creation of window features is another critical technique that can improve a model's capacity to capture and leverage temporal dependencies within the data. A window is computed by applying a statistical function such as the mean, standard deviation, or sum over a fixed-size window that sequentially moves across the time series data. For example, when calculating the mean over a rolling window with the size of N, the first value corresponds to the mean of the initial N observations; the next value represents the mean of the second observation until $N+1$, and so forth. In contrast, an expanding window starts with a small subset of initial observations and progressively increases the window size as it advances through the series. For instance, the expanding mean begins with the mean of the first observation, then the mean of the first two observations, and continues in this manner, accumulating more data with each step. Unlike the rolling window, which maintains a constant window size, the expanding window continuously incorporates additional historical data, enabling the model to account for an ever-expanding context in its calculations.

The key difference between the two methods lies in their treatment of temporal information. Rolling windows focus on a fixed-size subset of recent observations, thereby emphasizing short-term trends and local variability. On the other hand, expanding windows integrate all past data up to the current point, offering a broader, cumulative perspective on the time series. These characteristics make rolling windows particularly effective for capturing localized, transient behaviors, whereas expanding windows are more suitable for identifying long-term trends and ensuring the utilization of the full historical context in the analysis. Employing both techniques can considerably improve a model's ability to generate informed, contextually nuanced predictions. The size of the window is a crucial parameter, as it determines the balance between smoothing the series and capturing relevant short-term dynamics. The developed window features will enable models to dynamically assess the evolution of variables over time, offering insights into trends, volatility, and other temporal dynamics that might be overlooked when examining raw data alone.

3.5.2 Feature Validation

The objective of feature validation in this study is to determine which of the developed features have a statistically significant impact on occupational safety indicators. We assess the importance of these features from two perspectives, consistent with our hypotheses: (1) their effect on all occupational injuries and (2) their effect on severe occupational injuries. To achieve this, we employ the Ordinary Least Squares (OLS) method on each feature developed during feature engineering.

Ordinary Least Squares (OLS) is a widely-used technique for estimating the coefficients of linear regression equations that describe the relationship between one or more independent quantitative variables (the engineered features) and a dependent variable (safety indicators) [72]. The primary objective of OLS is to minimize the sum of the squared residuals - the differences between the observed data points and the values predicted by the linear model. This minimization results in a line that best fits the data according to the least squares criterion. OLS is an effective method for feature validation, providing a mechanism to evaluate the importance of each independent variable in explaining the variance of the dependent variables. Figure 11 illustrates an example of the results obtained from OLS. The coefficients derived from OLS estimation reflect both the strength and direction of the relationship between each feature and the outcome variable. Features with larger absolute coefficients indicate stronger associations, while those with smaller or near-zero coefficients may be considered less influential or redundant. The interval for each coefficient provides insight into its variability. Additionally, OLS assesses the statistical significance of each feature's impact, as indicated by the p-value. By applying OLS to every engineered feature, the objective is to select only the features which show a statistically significant impact on occupational safety indicators. This process not only facilitates the identification of the most relevant features but also aids in dimensionality reduction, thereby improving model interpretability and enhancing predictive performance by focusing on variables that contribute most significantly to the model.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:             astm_hours   R-squared:                       0.298
Model:                            OLS   Adj. R-squared:                  0.292
Method:                 Least Squares   F-statistic:                     47.95
Date:                Mon, 16 Sep 2024   Prob (F-statistic):           2.81e-10
Time:                        09:22:29   Log-Likelihood:                -149.84
No. Observations:                 115   AIC:                             303.7
Df Residuals:                     113   BIC:                             309.2
Df Model:                           1
Covariance Type:            nonrobust
=========================================================================================
                            coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------------
const                     0.0365      0.084      0.435      0.664      -0.130       0.203
tch_submitted_safety7    -0.6578      0.095     -6.925      0.000      -0.846      -0.470
==============================================================================
Omnibus:                       32.812   Durbin-Watson:                   0.012
Prob(Omnibus):                  0.000   Jarque-Bera (JB):                7.830
Skew:                           0.290   Prob(JB):                       0.0199
Kurtosis:                       1.861   Cond. No.                         1.15
==============================================================================
```

FIGURE 11: Ordinary Least Squares (OLS) result sample

3.5.3 Feature Selection

Feature selection is a critical process in the development of robust and efficient machine learning models, significantly enhancing model performance, interpretability, and computational efficiency. The primary objective of feature selection is to identify the most important features for predicting the output, thereby reducing the dimensionality of the dataset. By isolating the most relevant and significant variables from a potentially large set of features, feature selection mitigates the risk of overfitting and improves the model's generalization capability on unseen data. Furthermore, excluding irrelevant or redundant features reduces the computational burden associated with training and deploying models, which is particularly advantageous when handling large datasets or operating within resource-constrained environments. In the context of SEED-DM, feature selection serves a dual purpose: it improves model performance and helps identify which aspects of employee engagement are most influential in impacting occupational safety.

To select the most important features, we use backward elimination, a widely used technique for model optimization in regression and classification tasks [73]. We apply this method to features identified in the previous step as having a statistically significant impact on the output. Backward feature elimination begins by including all candidate features in the model and iteratively removes the least significant ones based on predefined criteria, such as R-squared. In each iteration, the feature contributing the least to the model's performance is excluded, and the model is re-evaluated without it. This process continues until a stopping criterion is met, such as when further removal of features no longer improves the model's performance. Backward elimination is particularly advantageous because it considers the interactions between features throughout the elimination process, enabling the identification and retention of the most relevant subset of variables that collectively contribute to the model's predictive power. During the backward elimination process, the model's performance is evaluated at each step. The combination of features that provided the best model performance while maintaining a limited list of features is selected.

3.5.4 Linear Regression

Linear regression is a commonly used statistical method in academic research for modeling the relationship between a dependent variable and one or more independent variables [74]. By assuming a linear relationship, this technique estimates the coefficients of the linear equation that predicts the dependent variable based on the values of the independent variables. Its simplicity and interpretability make linear regression particularly valuable in understanding both the strength and direction of relationships within data, enabling informed conclusions about the factors that influence the outcome. In SEED-DM, the primary goal of applying this linear regression model is to evaluate how well the relationship between selected features and safety indicators could be generalized to estimate employee engagement in safety initiatives.

The accuracy of the model was evaluated using two key metrics: R-squared (R^2) and Mean Squared Error (MSE). R-squared is a statistical measure that indicates how well the independent variables explain the variability of the dependent variable [75]. It is calculated by dividing the sum of squared prediction errors by the total sum of squares, where the total sum of squares is computed by replacing the predicted values with the mean of the observed values. R-squared value ranges from 0 to 1, with higher values indicating a better fit between the predicted and actual values. A higher R-squared value suggests that the model explains a larger portion of the variance in the dependent variable, making it a useful measure of the model's overall performance. While R-squared provides a relative measure of how well the model fits the dependent variables, Mean Squared Error (MSE) offers an absolute measure of the model's accuracy. MSE is calculated by summing the squares of the prediction errors, which are the differences between the true values and the predicted values. Squaring these errors ensures that both positive and negative errors contribute equally to the overall error metric, avoiding the issue of canceling out [76]. The result of the MSE calculation gives us a clear indication of how much the predictions deviate, on average, from the actual values. In this case, a lower MSE indicates a model with better predictive accuracy, as it suggests that the predictions are closer to the true values.

By using both R-squared and MSE, we obtain a comprehensive understanding of the model's performance. R-squared helps us gauge the proportion of variability captured by the model, while MSE provides insight into the precision of the model's predictions. Together, these metrics allow us to evaluate the effectiveness of the linear regression model in estimating employee engagement based on the selected safety indicators, ultimately contributing to a deeper understanding of the factors that drive safety performance in the workplace.

3.6 Phase 4 - Business Use

The ultimate objective of Phase 4 is to summarize and validate the findings of the central research question: *"To what extent does employee engagement impact occupational health and safety?"*. Building on the insights gained from Phases 1, 2 and 3, this phase aims to synthesize and integrate those findings in order to fulfill the two main goals of this research: (1) make a meaningful contribution to the academic literature by providing empirical evidence that clarifies the impact of employee engagement on occupational health and safety; (2) translate these data-driven findings into practical insights that can be implemented within organizations to improve health and safety outcomes.

The empirical findings obtained through Phases 1, 2, and 3 will form the basis for a comprehensive evaluation of how employee engagement influences health and safety performance. The data will then undergo a interpretation process to generate actionable recommendations that businesses can implement to improve their health and safety practices. Ultimately, these findings and recommendations will be presented to health and safety practitioners and organizational leaders for validation. Their expert feedback is crucial in refining the methodology and recommendations, ensuring that they are both feasible and aligned with the realities of workplace dynamics. This collaborative approach not only enhances the relevance of the methodology results but also ensures their effective integration into existing occupational health and safety strategies.

3.7 Methodology Summary

In conclusion, this chapter has introduced SEED-DM, a data-driven methodology that evaluates the relationship between employee engagement and occupational health and safety outcomes. By adhering to the CRISP-DM framework, SEED-DM ensures a systematic and iterative approach to data analysis, promoting alignment between research objectives and practical applications. The structured phases of SEED-DM not only facilitate thorough data preparation and analysis but also allow for the testing and quantification of hypotheses concerning the impact of employee engagement on occupational health and safety events. Importantly, SEED-DM is designed to be generalized and applied across various organizations that own factual data on safety and employee engagement, making it a versatile tool for diverse contexts. Ultimately, this methodology aims to produce data-driven actionable insights that empower organizations to harness the benefits of enhanced employee engagement, thereby fostering a safer and more productive work environment. As we transition into the next chapter, we will explore the application of the SEED-DM methodology through a real-world case study, demonstrating its effectiveness and practicality in generating valuable insights for organizations aiming to improve their occupational health and safety outcomes.

Chapter 4

Case Study: Applying SEED-DM in a Manufacturing Organization

This chapter presents the results of applying the SEED-DM methodology, as defined in Chapter 3, in a manufacturing organization. Testing the methodology through a case study is essential for validation, as it demonstrates its effectiveness in real-world scenarios, ensuring the findings are not only accurate but also relevant to practical challenges. By applying SEED-DM to this case study, we aim to highlight both the strengths of the methodology and areas for future work. Additionally, this case study serves as a concrete example of how SEED-DM can be implemented in an organization that has empirical data on employee engagement and occupational safety. Finally, the findings from the case study will ultimately help address the central research question.

The structure of this section follows the methodological steps outlined in Figure 6. First, the dataset undergoes the preparation process required for the analysis. The employee engagement trends are then analyzed using time series clustering, which informs the selection of relevant departments for further study. Next, the results of causality and correlation testing are presented, exploring the potential relationships between employee engagement and key safety indicators. Lastly, we analyze fine-grained features within employee engagement by validating and quantifying their impact on occupational safety.

4.1 Phase 0 - Datasets

Phase 0 provides a detailed exploration of the dataset, highlighting its structure, sources, and rationale underpinning its selection. To empirically test the hypotheses proposed by SEED-DM, we made use of a real-world dataset. This dataset originates from a manufacturing company in the United States and includes two critical variables central to the investigation: employee engagement and occupational health and safety data. In addition, the employee dataset was introduced as a control variable. The following subsections provide an in-depth overview of these datasets.

4.1.1 Employee Engagement Dataset

The Employee Engagement dataset is extracted from the organization's system used to track employee engagement. This EE system was implemented throughout the entire company to facilitate the submission of ideas and reports related to safety improvements and occupational hazards. The system encourages employees to proactively share suggestions for enhancing workplace safety and to report any potential hazards encountered during their daily tasks. Supervisors are then responsible for reviewing and addressing these submissions, with all actions and communications being transparently documented within the system. This transparency fosters a culture of involvement and collaboration, ensuring that employee contributions are recognized and acted upon.

The EE dataset spans a period from January 2021 to June 2024 and includes a substantial volume of data. Specifically, it comprises 676,582 submissions from 23,207 employees, distributed across 302 different departments within the company. This extensive dataset provides a rich source of information for analyzing the relationship between employee engagement and occupational safety outcomes. Table 1 offers a detailed breakdown of the attributes of the dataset, highlighting key variables and their relevance to the research objectives.

TABLE 1: Overview Employee Engagement dataset

Field	**Data Type**	**Description**
Date	Date	Date when the suggestion was submitted in the system
Department	Categorical	Department for which the employee suggestion was submitted
Has action	Boolean	Indicator if the suggestion is submitted with a follow-up action
Action	Text	Action derived from the provided suggestion
Closed	Boolean	Indicator if submitted suggestion is successfully implemented and closed in the system
Closed date	Date	Date when the suggestion is marked as successfully implemented in the system
Category	Categorical	Topic of the submitted suggestion: Safety, People, Accuracy, Rate, Compliance
Life	Boolean	Indicator if the suggestion is related to one of the high severity life occupational hazards
Description	Text	Description of the submitted suggestion

4.1.2 Occupational Health and Safety Dataset

The Occupational Health and Safety dataset originates from a workplace safety reporting system designed to document incidents of workplace injuries and accidents. This system allows recording of detailed information about each injury, including the circumstances, severity, and outcomes. Once an incident is reported, the workplace health team manages the case, determining the severity of the injury, arranging for worker replacements if needed, and handling workers' compensation claims. Table 2 provides a detailed inventory of the variables included in the safety dataset.

Table 2: Overview Safety dataset

Field	Data Type	Description
Date	Date	Date when workplace injury occurred
Department	Categorical	Department in which the workplace injury occurred
ASTM	Boolean	Indicator if the injury is classified as ASTM severity [77]
OSHA	Boolean	Indicator if the injury is classified as OSHA recordable [78]
OSHA Type	Categorical	Type of OSHA injury: Restricted, Lost Days, Other [78]
Ergo	Boolean	Indicator if the injury is classified as ergonomic case
Life	Boolean	Indicator if the injury is classified as high potential severity for life occupational hazards
Lost Days	Int	Number of lost work days resulted from the injury
Severity	Categorical	Category for the actual severity of the injury: Low, Medium, High

4.1.3 Employee Dataset

The employee dataset provides a comprehensive record of the number of active employees on a daily basis, allowing for precise tracking of workforce dynamics. Additionally, the dataset includes detailed records of hours worked, as captured by the organization's tracking system.

4.2 Phase 1 - Dataset Modelling

The goal of the dataset modeling is to merge the three datasets into one to facilitate further analysis. The common attributes among these datasets are the date and department, which were used to join these sets. The unified dataset includes information on the number of employee suggestions submitted, injury occurrences, active employees, and total hours worked for each day across all departments within the organization. Figure 12 illustrates the relationship diagram resulting from the dataset modeling process.

With the dataset consolidated, a list of employee engagement and safety indicators was calculated to facilitate further analysis of the relationship between these variables. The employee engagement indicators take into account various aspects, allowing to assess significant factors driving the engagement and its impact. For example, for the total number of submissions a distinction is made between those with and without actions taken, as well as between different categories such as safety and life. Occupational health and safety indicators include a set of lagging indicators consistent with those in the literature, allowing for comparison between studies and monitoring changes over time. To ensure the analysis

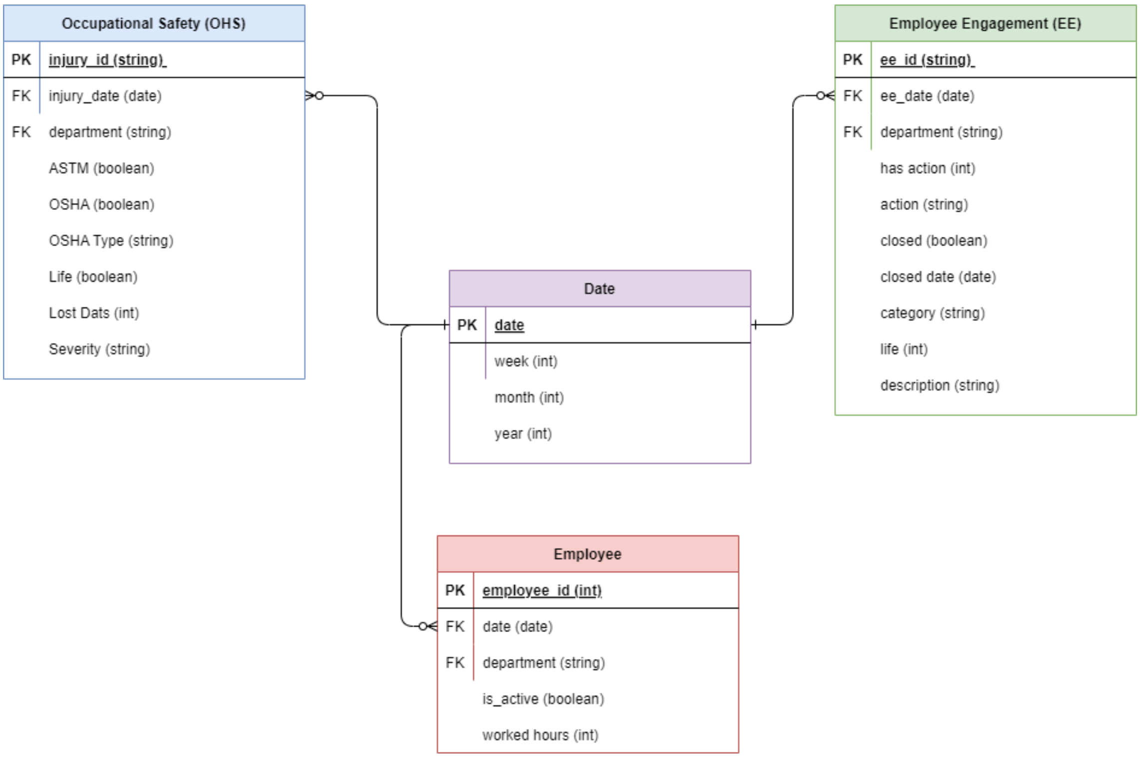


FIGURE 12: Dataset entity relationship diagram

remains robust despite organizational shifts, the total number of work hours was factored into rate calculations. The complete inventory of metrics used in this study is provided in Table 3. As expected by the design of SEED-DM, all indicators used are quantitative, providing measurable, numerical data that can be easily compared, analyzed, and used to identify trends.

4.3 Phase 1 - Dataset Preparation

The goal of dataset preparation is to ensure that the data is in optimal condition for subsequent analysis, free from outliers and seasonal distortions that can skew the final results. The first step in this process is data imputation. Out of the 302 departments, only 94 had at least one employee engagement submitted. In particular, about 73% of the weeks for these 94 departments did not receive any submissions. Data imputation to address these missing values resulted in a significant proportion of data being recorded as zero.

To address outliers, we applied Interquartile Range (IQR) as explained in Section 3.3.2. From the total dataset, 4.1% of the data points were identified as outliers and were subsequently interpolated. A stationarity test was conducted on the 94 departments with at least one submission. Aggregating the time series for these departments across the 16 indicators defined in Table 3 resulted in 1504 distinct time series. Of these, 85% passed the Augmented Dickey-Fuller (ADF) stationarity test. For the time series that did not pass the ADF test, we used seasonal decomposition to remove trends and seasonality. After taking only the residuals from the non-stationary series, only 3% remained non-stationary. Finally, we performed data normalization using a Min-Max scaler, which rescales the data to a range between 0 and 1 while preserving the original shape of the distribution.

TABLE 3: Employee Engagement and Occupational Safety Indicators. EE and OHS fields are extracted from Tables 1 and 2.

Employee Engagement (EE) Metrics	
EE submitted	Count(EE submitted) * 2000 / sum(hours)[1]
EE closed	Count(EE closed) * 2000 / sum(hours)[1]
EE closed with action	Count(EE closed, has action = 1) * 2000 / sum(hours)[1]
EE submitted LIFE	Count(EE submitted, Life = 1) * 2000 / sum(hours) [1]
EE closed LIFE	Count(EE closed, Life = 1) * 2000 / sum(hours) [1]
EE submitted safety	Count(EE submitted, category = safety) * 2000 / sum(hours) [1]
EE closed safety	Count(EE closed, category = safety) * 2000 / sum(hours) [1]
EE participation	Count(EE submitters) / Count(employees)
Occupational Safety Indicators	
All injuries	Count(injuries) * 2000 / sum(hours)[1]
Low injuries	Count(injuries, severity = low) * 2000 / sum(hours) [1]
ASTM injuries	Count(injuries, ASTM = 1) * 1000000 / sum(hours) [2]
LIFE injuries	Count(injuries, Life = 1) * 1000000 / sum(hours) [2]
OSHA injuries	Count(injuries, OSHA = 1) * 200000 / sum(hours) [3]
Days Away from Work injuries	Count(injuries, OSHA = 1, OSHA Type = 'Days Away') * 200000 / sum(hours) [3]
Restricted injuries	Count(injuries, OSHA = 1, OSHA Type = 'Restricted') * 200000 / sum(hours) [3]
Ergo injuries	Count(injuries, ergo = 1) * 200000 / sum(hours) [3]

[1] 2000 is a common assumption of total hours worked per employee per year
[2] 1000000 is a standard multiplicator for calculating American Society for Testing and Materials (ASTM) Rates [77]
[3] 200000 is a standard multiplicator for calculating Occupational Health and Safety Administration (OSHA) Rates [78]

Figure 13: Clusters derived from SOM and K-means. The color boxes indicate the type of cluster with regard to employee engagement trend: (1) green = consistent reporting, (2) purple = intermittent reporting, (3) blue = no reporting

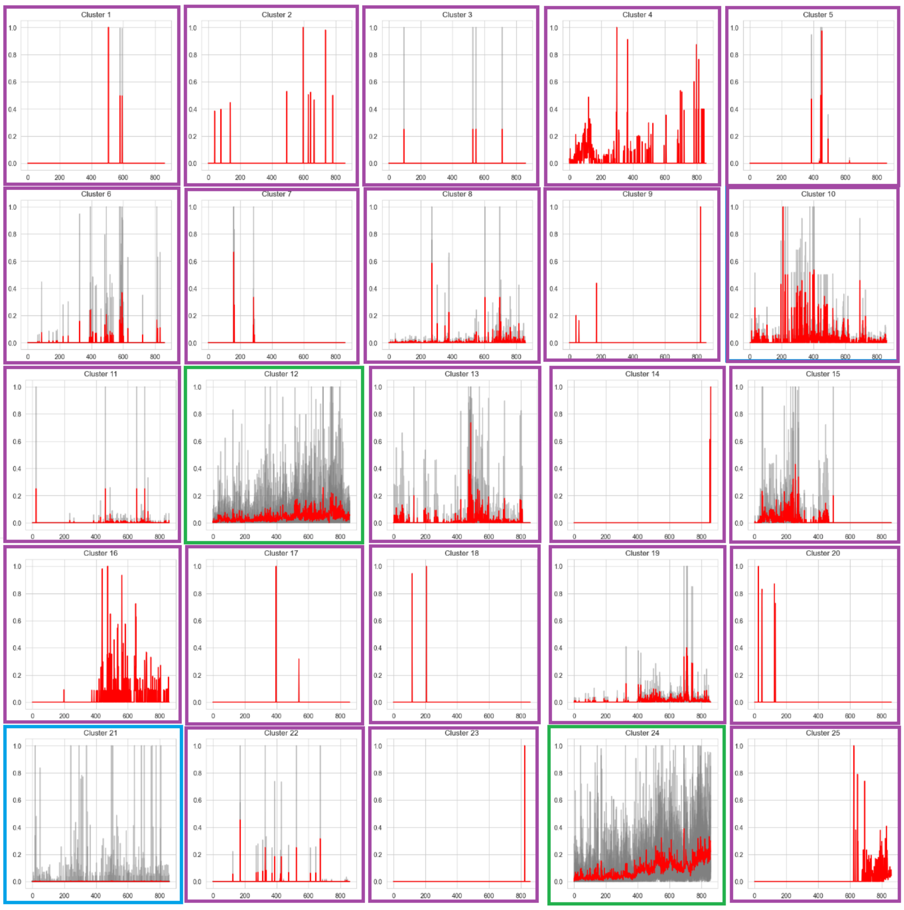


Figure 14: Clusters derived from SOM clustering

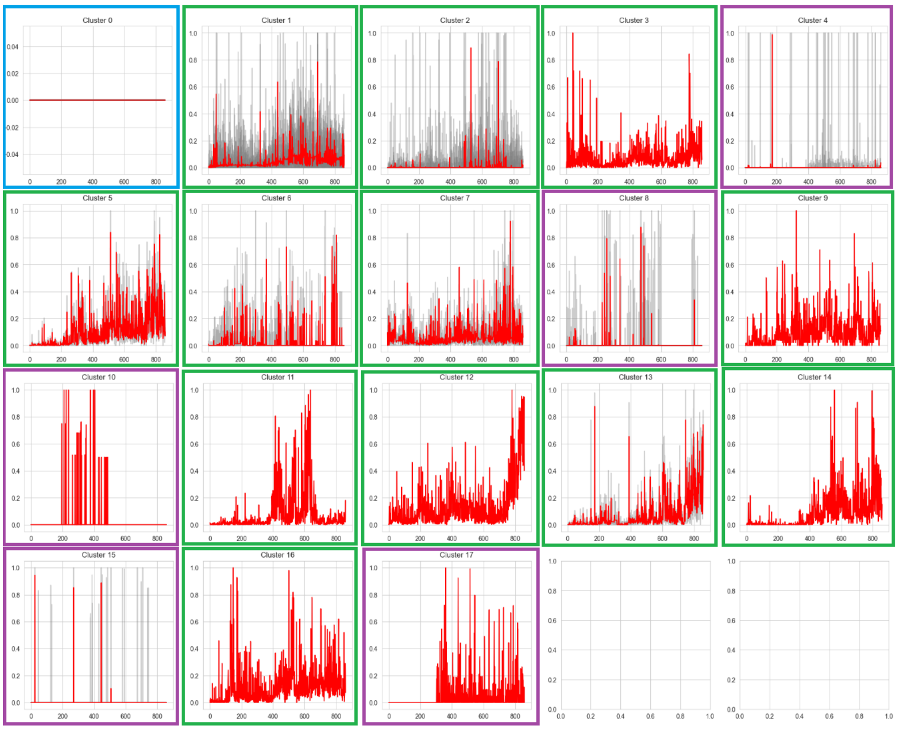


Figure 15: Clusters derived from K-means clustering

4.4 Phase 1 - Time Series Clustering

For the exploratory analysis of the dataset, time series clustering is used to identify patterns within the data from the different departments. The initial dataset obtained from the modeling process consisted of 676,582 submissions made by 23,207 employees across 302 departments. The goal of the time series clustering was to discover the different styles of employee engagement among these departments. In particular, we aimed to identify groups of departments that exhibited steady or increasing trends in employee engagement reporting, thereby selecting meaningful departments for further statistical analysis. As explained in Section 3.3, two different approaches were employed for time series clustering: Self-Organizing Map (SOM) and K-means clustering enhanced with Principal Component Analysis (PCA).

Figure 14 illustrates the clusters generated by SOM, while Figure 15 presents the results from the K-means clustering. In both figures, the grey lines represent the individual trends of the departments, whereas the red lines depict the overall derived trend for each cluster. As it can be observed, SOM identified 25 clusters, while the K-means clustering produced 17 clusters, with the latter number deemed optimal based on the departmental distribution. When looking at the overall trend lines, it can be seen that part of the clusters show consistent reporting over the full time period (e.g., SOM cluster 24), whereas others show irregular or no reporting trends (e.g., SOM cluster 1).

Figure 16 presents the distribution of the departments among the clusters for both clustering methods. It is evident that each method yielded a predominant cluster containing the majority of departments: cluster 21 in SOM with approximately 74% coverage, and cluster 0 in K-means with around 70% coverage. Notably, neither of these dominant clusters revealed any significant reporting trends. The distribution among the remaining clusters was more balanced, with each cluster containing a relatively small number of departments.

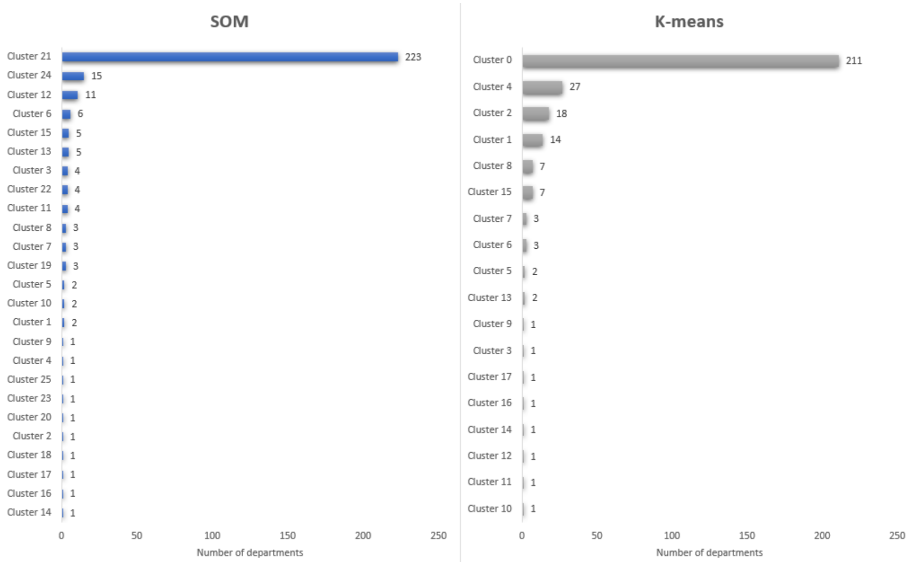


FIGURE 16: Distribution of departments among clusters

Upon examining the trend lines, the clusters were categorized into three groups: (1) consistent engagement and (2) inconsistent or (3) no engagement, as indicated by the color boxes in Figure 13. This classification was performed based on the 75th percentile of the overall reporting trend, where clusters with a value above 0 were assigned to the first group and the other clusters to the second group. For the SOM method, this decision threshold identified clusters 12 and 24 as showing consistent engagement, while for K-means this was observed in clusters 1, 2, 3, 5, 6, 7, 9, 11, 12, 13, 14 and 16. Finally, the departments which belonged to a consistent engagement cluster in both K-means and SOM were selected for further analysis, resulting in the identification of 17 departments with a total of 576,596 submissions out of 676,582. These 17 departments, comprising only 5% of the total number of departments, accounted for 90% of the total submissions and 80% of the unique submitters.

4.5 Phase 2 - Correlation Testing

In Phase 2, we conducted a correlation analysis to assess both the direction and strength of the relationship between occupational safety indicators and employee engagement, testing the first two hypotheses. A correlation matrix was generated for each department, comparing the EE indicators with the OHS indicators. An example of the correlation matrix for department 8 is shown in Figure 17. For this department, the correlations range from 0.18 to -0.53, with a predominance of negative correlation coefficients. The strongest correlations were observed for overall incidents and particularly for those with low severity. Ergo injuries exhibited the highest positive correlations, while LIFE and restricted injuries did not show significant correlations.

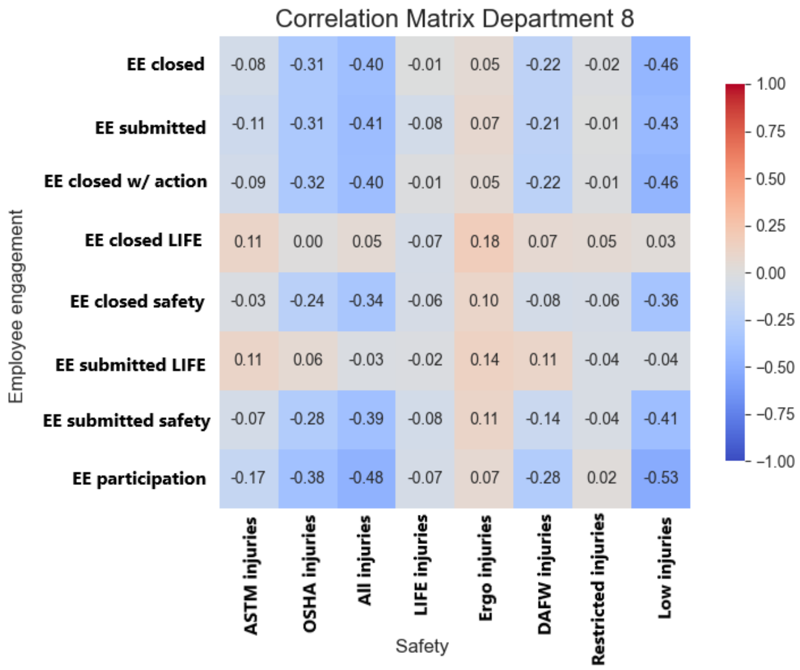
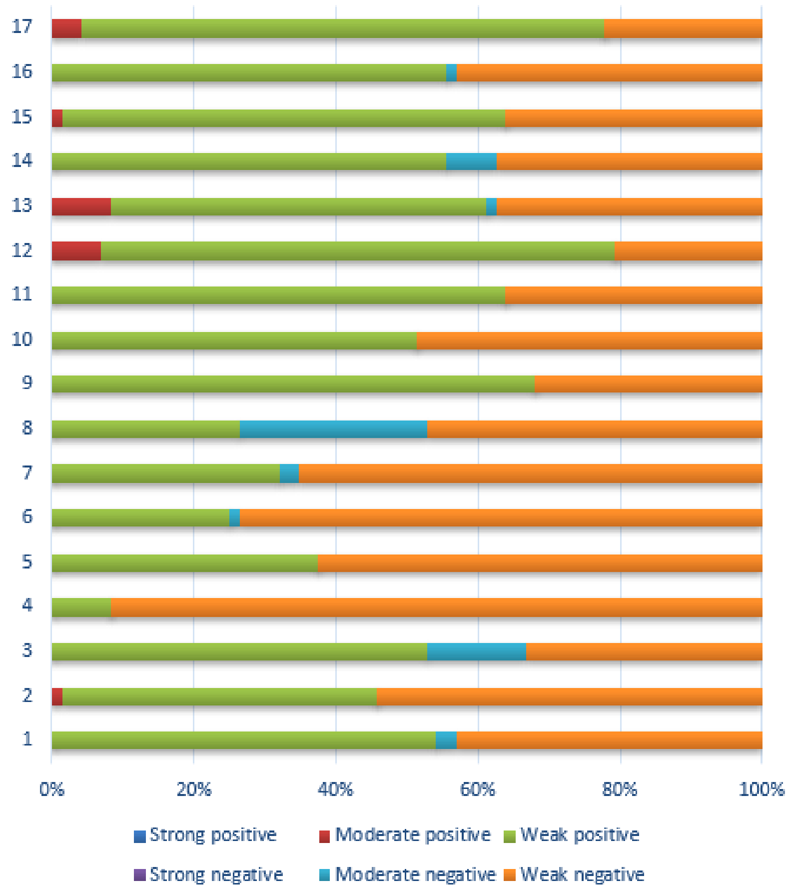


FIGURE 17: Correlation matrix between EE indicators and OHS indicators for department 8.

The correlation matrix for each department has been summarized and categorized into weak, moderate, and strong correlations, as described in Section 3.4.1. Figure 18 illustrates the distribution of correlation relationships identified for each department. The results vary across departments, with weak positive and weak negative correlations being the most common. Notably, department 4 exhibits the highest number of negative correlations, while department 17 shows the strongest positive correlations. Department 8 has the most moderate correlations, all of which are negative, followed closely by department 3.

FIGURE 18: Correlation results per department



The results from Figure 17 and 18 only show the correlation results at lag 0, meaning that the employee engagement and the injury indicators are compared at the same point in time. Cross correlation was applied to get a deeper understanding of how the relationship between the two different types of indicators evolves over time. Figure 19 illustrates a cross correlation function plot, highlighting the moderate negative correlation between closed employee engagement and low injury rates, as initially identified in Figure 17. The plot shows that the correlation remains negative across all lags, indicating a consistent inverse relationship between employee engagement and injury numbers. Specifically, a moderate negative correlation is observed between lags -9 and 4, with the strongest correlation occurring at lag 0. Furthermore, The correlation is statistically significant at the 95% confidence level between lag -13 and lag 10. Additionally, the negative lags of the CCF capture the relationship between future employee engagement and current injury numbers. It can be observed that when employee engagement leads, the number of injuries consistently reduces, whereas when employee engagement lags behind injury numbers, the correlation coefficient increases, but remains negative overall.

The cross-correlation analysis was performed for each department, comparing employee engagement and occupational health and safety indicators, resulting in 64 experiments per department. The overall findings revealed that the most substantial negative correlations occurred in employee engagement indicators with closure. The strongest correlations were found between the EE closed and injuries under the ASTM and OSHA categories, with 13 out of 17 departments exhibiting a moderate negative correlation. Department 7 showed the strongest correlation, with a coefficient of -0.6. In contrast, the EE participation feature displayed the weakest correlations. Interestingly, the correlation patterns for each employee engagement feature remained relatively consistent, regardless of the specific safety indicator analyzed. However, significant variations emerged when the data was analyzed by department. For example, departments 8, 3, and 17 exhibited a more pronounced negative correlation across all experiments. Similarly, departments 9, 10, 11, 13, and 15 showed weaker negative correlations, while other departments displayed only weak or negligible correlations.

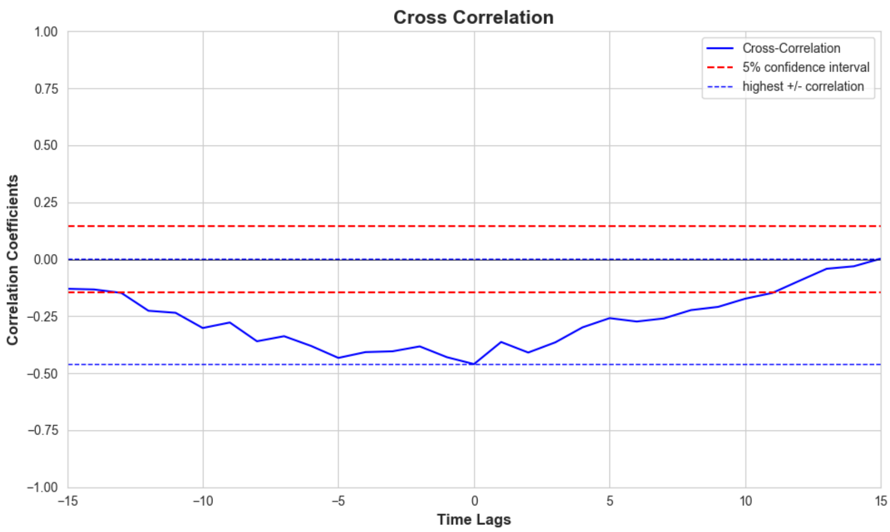


FIGURE 19: Cross correlation between closed EE and low injuries for department 8.

4.6 Phase 2 - Causality Testing

For causality testing, the Granger hypothesis was evaluated for various pairwise combinations of indicators. This approach was implemented across a series of experiments, each designed to explore various facets of employee engagement in relation to distinct leading indicators of occupational safety. In our analysis, X represents a measure of employee engagement, while Y corresponds to an indicator of occupational safety, where both X and Y are selected from Table 3. Specifically, an experiment was conducted to determine whether an employee engagement indicator Granger-causes an occupational safety indicator, resulting in a total of 64 experiments. Each experiment, such as "submitted employee engagement Granger-causes ASTM injuries" was performed across 17 departments, which were selected as explained in Chapter 4.4.

The overall findings from these experiments indicate a significant influence of employee engagement indicators in predicting occupational safety indicators. Figure 20 illustrates

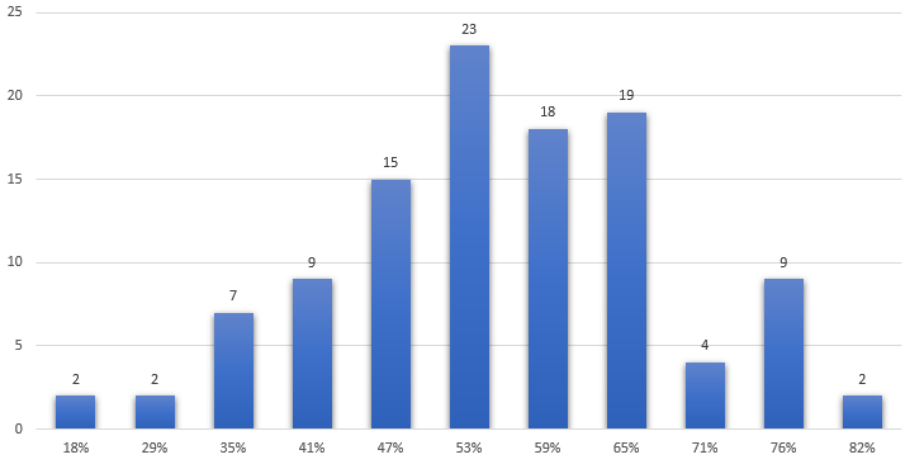


FIGURE 20: Numbers of experiments demonstrating Granger causality

the number of experiments that successfully passed the Granger causality test at a 95% confidence level, plotted against the percentages of the departments. A notable observation is the variability in results across the different experiments. Some experiments demonstrated strong Granger causality across most departments, while others showed significance in only a few. The majority of experiments exhibited Granger causality in a range between 47% and 65% of the departments. On the higher end of the spectrum, two experiments exhibited Granger causality for 14 out of 17 departments (82%), nine experiments for 76%, and four for 71%. These experiments consistently indicated strong Granger causality across the departments and were often related to severe injuries. Among the 15 experiments with a higher success rate than 70%, six showed Granger causality for OSHA-related injuries, three for ASTM injuries, four for low-severity injuries, and one for restricted injuries. Furthermore, employee engagement indicators that involved implementation with action exhibited the highest predictive power for these safety indicators. Conversely, employee engagement indicators that were submitted without follow-up actions were positioned on the opposite side of the spectrum, where Granger causality was observed in less than 20% of the departments.

A final important observation on causality is that certain departments consistently exhibited Granger causality across a majority of the experiments, while others showed minimal significance. As depicted in Figure 21, departments 1, 3, 4, and 6 displayed Granger causality in in 89 - 91% of the experiments, whereas departments 10 and 15 showed causality in only 29% and 36% of the experiments, respectively. This variation underscores the differing impact of employee engagement across departments.

4.7 Phase 3 - Feature Engineering, Validation and Selection

In phase 3, the goal was to quantify the impact of specific employee engagement factors on occupational safety outcomes. This investigation involved an extensive feature engineering process, in which the data set was enriched by applying time series techniques, including the creation of lags, rolling windows, and expanding windows, as explained in Section 3.5.1. In the context of our case study, we introduced lags ranging from 1 to 15 weeks to determine the time at which the implementation of employee suggestions fully impacts occupational health and safety. The decision on the number of lags was guided

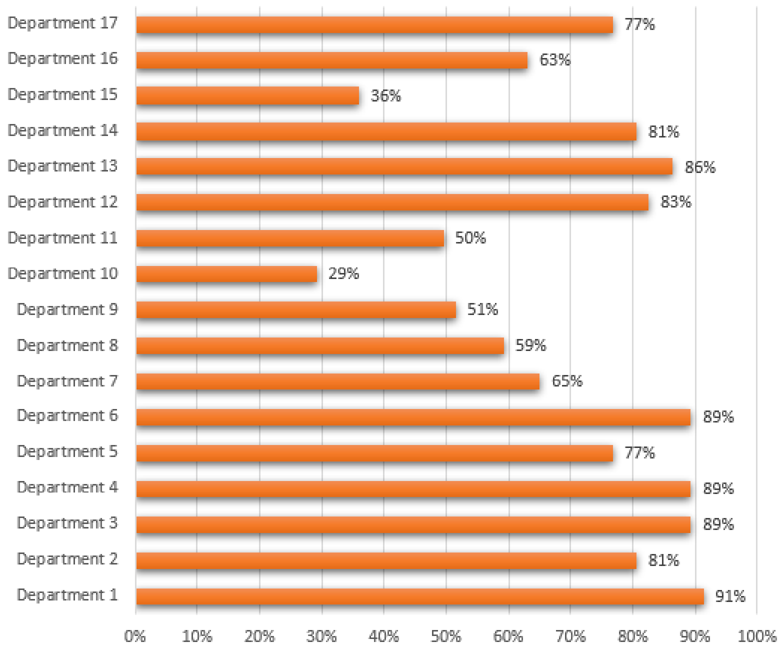


FIGURE 21: Departments rate for passing causality test

by the causality results which indicated that the causality was strongest around 15 weeks. For the calculation of the windows features, both the mean and variance functions were applied. The process of feature engineering resulted in a total of 179 features.

To evaluate the significance of these features, Ordinary Least Squares (OLS) regression analysis was conducted. The validation process confirmed that 81% of the features had a statistically significant impact on occupational safety indicators, although the extent of this impact varied across features. The critical differentiating factor among these features was the R-squared value indicating the proportion of variance in the dependent variable (safety indicator) that is predictable from the independent variables (employee engagement indicators). For incidents classified as high severity, particularly those falling under the ASTM and OSHA regulatory frameworks, the features associated with the actual implementation of employee engagement suggestions demonstrated the highest R-squared values, ranging from 0.85 to 0.8. This suggests a strong predictive relationship between these implemented employee suggestions and the occurrence of severe safety incidents. Moreover, features with higher lag values (e.g., 15, 14, 13) exhibited the strongest correlations, indicating that the impact of employee engagement on safety outcomes emerges after a certain period of time. The subsequent lags followed in a descending order of correlation strength, further highlighting the temporal dynamics at play.

On the other hand, a different pattern was observed while analyzing low severity safety incidents. In this case, features related to the submission of employee engagement initiatives focused specifically on safety concerns showed the highest R-squared values. Interestingly, for these features the lags were ranked from 1 to 15 in terms of importance following the exact reverse order compared to the high severity events associated with ASTM and OSHA. The feature selection results in a total 17 most important features which were further used for linear regression. It is important to note that the most important features are different with regard to every safety indicator.

4.8 Phase 3 - Linear Regression

To develop the linear regression model, the most significant features identified in Section 4.7 were utilized to fit the safety indicators. To ensure that the model was generalizable to the entire organization, data from the different departments were integrated into one dataset. Figure 22 presents the performance of the linear regression model with regard to the safety indicators. A robust model is characterized by a high R-value and a low Mean Squared Error (MSE). The figure shows that the highest R-value was obtained for ASTM injuries (0.6) followed by LIFE injuries (0.5), whereas the lowest MSE was associated with LIFE injuries (0.28) followed by ASTM injuries (0.34). These results suggest that employee engagement features are most effective in predicting these two safety outcomes. Conversely, the model struggled most with predicting OSHA Injuries (R=0.04, MSE=0.72) and low-severity injuries (R=0.07, MSE=0.71).

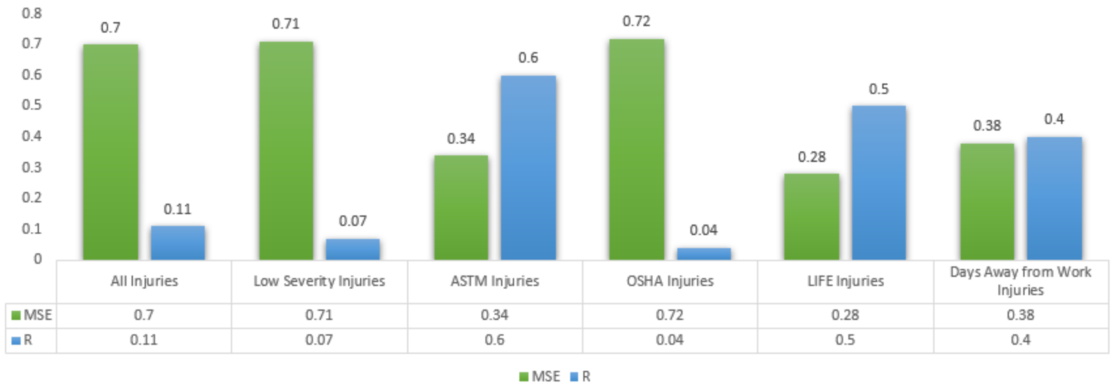


Figure 22: Linear regression results per safety indicator

Table 4 provides a detailed analysis of the most significant features for each occupational safety indicator. The table shows the weight of each feature as calculated during the model fitting process. It can be observed that the weights of these features vary considerably, with both positive and negative values observed. Moreover, the importance of the features depends on the safety indicator. Overall, it is evident that employee engagement, particularly when analyzed with a 15-week lag using an expanding window approach, is an important feature for most safety indicators. Furthermore, the closed employee engagement consistently displays a negative coefficient, suggesting that as the implementation of employee engagement increases, the number of severe injuries decreases. In contrast, the submitted feature for the same expanding window is also significant across multiple departments but shows positive coefficients. In general, employee engagement submissions tend to show positive coefficients, though some negative coefficients are observed, especially when the lag period extends. It is also noteworthy that many key features are related to LIFE-submitted employee engagements.

From the perspective of safety indicators, the importance of specific features varies. For high-severity injuries (ASTM), employee engagement closure has a strong influence on the output, with coefficients reaching -14.37 and -7.75, respectively, the largest by far. A similar pattern is observed for all injuries and low-severity injuries, where total submissions over various lags emerge as significant. For the submitted feature over a 15-week expanding window, the coefficients are positive (2.58, 2.48), while the same submissions focused on safety exhibit negative coefficients (-0.37, -0.39). Regarding LIFE injuries, the significant features have relatively low weights, indicating minimal influence on the safety outcome. For OSHA and days away from work, similar results are observed, where the LIFE submissions carry substantial weight, but the coefficients alternate between positive and negative across different lags.

Table 4: Weights of features selected for predicting safety indicators. "-" indicates that the feature was not selected as important for the safety indicator.

Employee Engagement Feature	**All Injuries**	**Low Severity Injuries**	**ASTM Injuries**	**OSHA Injuries**	**LIFE Injuries**	**Days Away Injuries**
EE closed - lag 15 expanding window	-2.3	-2.15	-14.37	-	2.8E+01	-
EE closed - lag 14 rolling window	-	-	-7.75	-	-	-
EE closed - lag 14	-	-	-0.96	-	-	-
EE submitted - lag 15 expanding window	2.58	2.48	0.02	-	2.8E+01	0.26
EE submitted LIFE - lag 15 expanding window	0.01	0.05	-	0.36	1.12E-02	-
EE submitted LIFE - lag 1 rolling window	0.56	0.19	1.32	-0.06	-	-
EE submitted LIFE - lag 2 rolling window	-0.61	-	-0.78	-	-	-
EE submitted LIFE - lag 3 rolling window	0.21	-0.13	-	-	-	-
EE submitted LIFE - lag 8 rolling window	-0.5	0.27	-	-	-	-
EE submitted LIFE lag 10	-	-	-	-	-	-0.52
EE submitted LIFE lag 11	-	-	0.19	-	-	0.43
EE submitted LIFE lag 12	-	-	-0.33	-	-	-0.34
EE submitted LIFE lag 13	-	-	-0.06	-	-	0.12
EE submitted LIFE lag 14	-	-	0.18	-	-	-0.08
EE submitted LIFE lag 15	-	-	0.12	-	-	0.12
EE submitted safety - lag 15 expanding window	-0.37	-0.39	5.6	-	-1.57E-02	1.12
EE submitted safety - lag 1 rolling window	-	-0.16	-0.43	-	-	-

Chapter 5

Stakeholder Validation

This chapter presents the findings from stakeholder validation, representing phase 4 of the SEED-DM methodology. The main objective of this phase is to validate the results of the case study and to assess the reliability and applicability of SEED-DM in organizational settings. Through this validation process, we aim to confirm the robustness of the methodology and identify areas for improvement. To accomplish this, semi-structured interviews were conducted with a diverse group of stakeholders involved in employee engagement initiatives and workplace safety promotion at various organizational levels. As highlighted in the review of the literature (Section 2.2.2), qualitative research has been an effective approach, providing practical insights into how employee participation impacts occupational safety. This qualitative approach complements the quantitative analysis in the previous phases, making the overall methodology more comprehensive. Ultimately, this phase aims to strengthen the practical value of SEED-DM, ensuring its ability to provide evidence-based outcomes in occupational health and safety.

A total of five in-depth interviews were conducted, with the interviewees covering a range of roles within the organization. Two participants held specialist positions, meaning they work closely with front-line employees and have direct insight into day-to-day safety practices. Two others participants occupied managerial roles, overseeing employee engagement efforts across multiple departments, thereby providing a broader organizational perspective. The final interview was conducted with a director, responsible for high-level strategic management of employee engagement initiatives within the leadership team. This stratified sampling was performed to capture a holistic view of how employee engagement initiatives are perceived and implemented at various levels in the organization.

The interviews were structured around three main objectives: first, to gather the opinions of the participants on the proposed hypotheses and their personal experiences with employee engagement; second, to obtain feedback on the research findings, particularly with respect to their alignment with real world practices; and third, to receive suggestions for refining the methodology. By using a semi-structured format, the interviews allowed for flexibility, enabling participants to discuss unanticipated insights while still addressing key themes critical to the goals of this study. The questions were crafted to be both exploratory and comparative, facilitating the comparison of responses across various organizational roles. The following questions were used to guide the interviews:

- **Overall experience.** *How do you experience employee engagement to have an impact on the occupational safety?*

- **Overall experience.** *How strong do you feel about the proposed hypotheses of the methodology?*
- **Overall experience.** *What do you think are the biggest drivers within employee engagement which influence workplace safety?*
- **Feedback on results.** *To what extent do the experimental results align with your experience?*
- **SEED-DM Refinement.** *What suggestions do you have for refining the methodology?*

5.1 Overall Experience

All interviewees perceived employee engagement as a valuable initiative with substantial potential benefits, particularly with respect to occupational safety. They noted that employees become increasingly aware of safety hazards and start to actively engage in addressing safety concerns. This heightened awareness fosters a more conscious approach to safety practices, ultimately leading to improved occupational health and safety outcomes. Furthermore, all interviewees strongly supported the first two hypotheses, affirming a clear relationship between employee engagement, occupational incidents, and their severity.

However, the responses were divided regarding the third hypothesis, which stated that employee engagement would reduce the number of occupational incidents. Most interviewees expressed skepticism, suggesting that although engagement enhances awareness of occupational hazards, it may actually lead to an increase in reported incidents, particularly those of lower severity. They argued that heightened awareness also results in greater identification and reporting of such incidents, which in itself is a great development. In contrast, there was unanimous agreement with the fourth hypothesis, emphasizing that the ultimate goal of employee engagement should focus on reducing the severity, rather than the frequency, of occupational incidents. The goal of occupational health and safety initiatives is to create a great capacity which helps reduce the severity of occurring accidents.

When asked about the key drivers of employee engagement, two primary factors emerged: leadership advocacy and prompt action. Interviewees highlighted the critical role of operational leadership in advocating for employee engagement. They asserted that leadership must actively champion the importance of engagement for employees to feel motivated and committed to these initiatives. Once employees motivated to engage in safety practices, it is essential that they also feel their contributions are valued and impactful. Leadership dvocacy, coupled with acknowledgment of employees' efforts, are vital initial steps in fostering meaningful engagement. However, these steps must be followed by prompt, visible actions on employee suggestions to demonstrate that their engagement leads to tangible outcomes. Therefore, leadership advocacy and timely action are considered the most crucial elements for driving successful employee engagement and achieving measurable improvements in occupational health and safety.

5.2 Feedback on Results

The discussion of the results revealed key insights closely related to the organizational context. Firstly, the finding that only a fraction of the departments in the organization accounts for nearly all employee engagement highlights the need to expand participation across the workforce. This suggests a critical need for leadership to encourage broader employee involvement in organizational initiatives. Furthermore, the results were generally in agreement with the stakeholders' practical experiences and expertise, without raising any concerns that would challenge the validity of the findings. The positive correlations between employee suggestions and occupational incidents, particularly those of low severity, supports their initial assumption that increased submissions enhance awareness and reporting of such events. Notably, certain forms of employee engagement that influence low-severity injuries are actions that can be performed directly by frontline workers. For example, simple preventive measures such as cleaning a wet floor to reduce the likelihood of slips or ensuring that equipment is stored properly to prevent accidental cuts can significantly decrease the number of minor injuries. These actions, taken instantly by employees, contribute to the overall reduction in injuries, particularly low-severity ones. This proactive approach is one of the key principles advocated in the organization's safety program: encouraging employees not only to report safety concerns, but also to take immediate corrective actions where possible.

The disparities in correlation between employee engagement and organizational safety across the different departments were largely anticipated. Our findings reveal that the most significant decrease in these injuries results from the effective implementation of recommended measures, though several weeks are typically required before their impact becomes evident. The interviewees indicated that the actions with the greatest effect often involve large-scale engineering controls and comprehensive risk reduction campaigns. However, these initiatives frequently necessitate considerable time due to the complexity of planning, design, collaboration, and execution. Nonetheless, the organization remains focused on minimizing the delay between identifying safety concerns and implementing corrective actions, striving to expedite the realization of these safety improvements.

The correlation results between employee engagement and departmental differences were largely anticipated. It was generally acknowledged that employee engagement interacts with other variables, the most prominent being leadership. For instance, in department 8, where a strong negative correlation was observed, the responsible specialist explained that employee engagement is deeply embedded in the department's culture. Leadership in this department prioritizes safety, dedicating substantial time to addressing employee suggestions and encouraging active participation. Consequently, employees consistently focus on safety, even during production downtime, addressing concerns they can resolve themselves. Moreover, their proactive efforts are acknowledged and rewarded by the leadership. Another interviewee emphasized the maturity of leadership as a key variable, noting that frequent changes in leadership can hinder efforts to foster sustained employee engagement. In addition, the risk profile of each department is another important factor to consider. Departments with generally low-risk activities tend to experience fewer and less severe injuries, where employee-led initiatives have a substantial impact. In contrast, departments engaged in higher-risk activities require more comprehensive interventions, such as engineering modifications, equipment upgrades, or extended safety programs, to effectively reduce injury rates.

5.3 SEED-DM Refinement

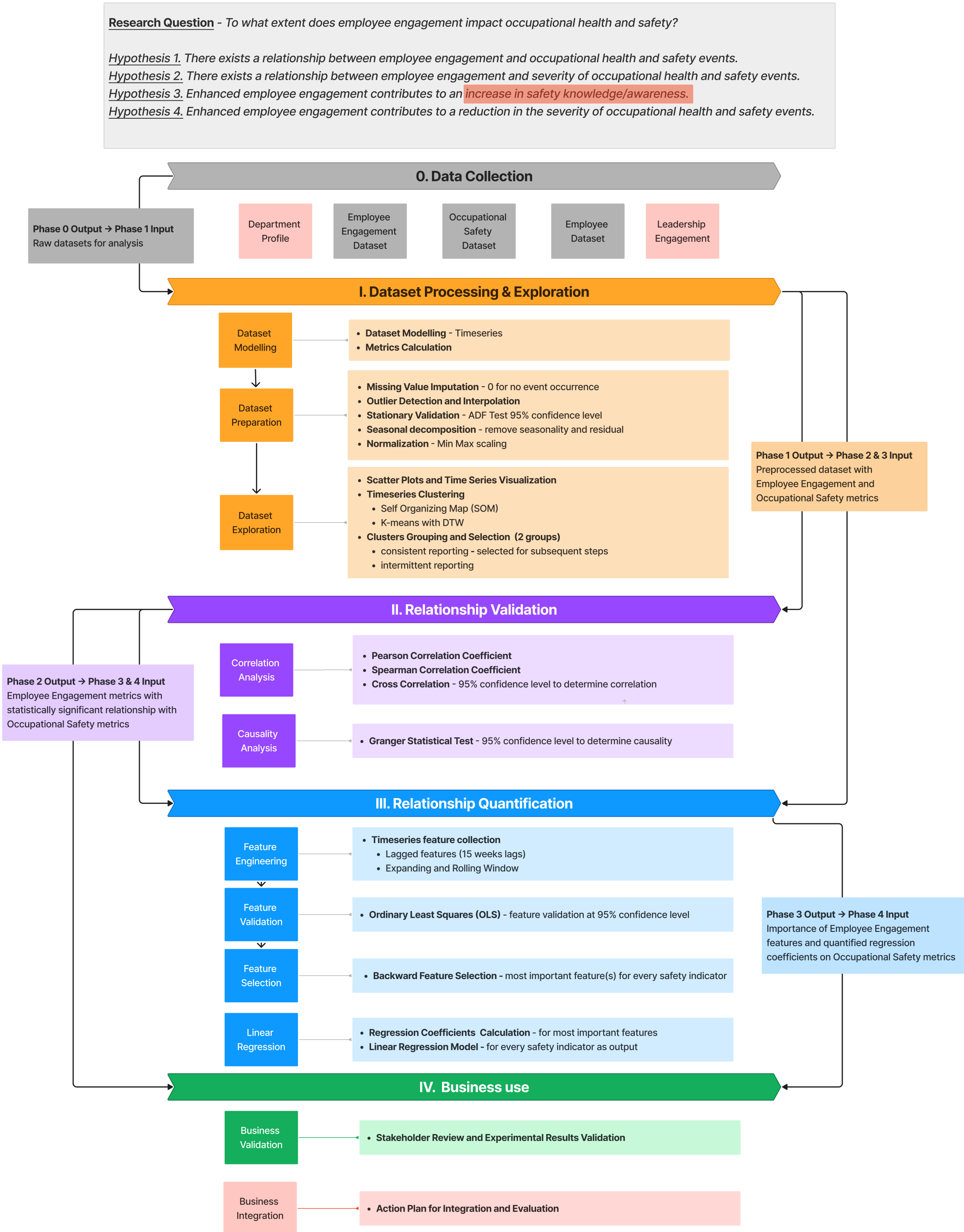
Based on the feedback and insights gathered during the interviews, several opportunities have been identified to refine SEED-DM to better align with practical experience. These suggested refinements are illustrated in Figure 23 and are discussed further in this section.

As identified from the participants experience in practice, the effectiveness of employee engagement initiatives is closely tied to the active participation of leadership. Therefore, a primary focus for enhancing employee engagement should be on fostering leadership advocacy and involvement. However, operational leaders often prioritize productivity, output, and cost reduction, which can limit their engagement in safety-related activities. Interviewees revealed optimism that SEED-DM could strengthen engagement initiatives and secure leadership buy-in. Presenting data results to leadership offers evidence that engagement efforts positively influence operations goals. An effective enhancement to SEED-DM would be to expand Phase 4 by incorporating additional steps for sharing results with operations, offering concrete plans for adopting employee engagement strategies, and demonstrating their impact on their teams.

Regarding the third hypothesis, practitioners expected employee engagement to increase safety awareness, potentially resulting in increased incident reporting. While employee engagement clearly benefits occupational safety, measuring the frequency of low-injury incidents over time may not serve as the most effective indicator. Instead, the hypothesis could focus on assessing the safety knowledge and awareness that employees are expected to gain through active engagement.

SEED-DM currently focuses exclusively on integrating employee engagement and safety data. However, both experimental results and stakeholder feedback indicate that additional factors could influence the overall impact of employee engagement on occupational health and safety. Incorporating these variables into the dataset and analysis can provide greater context to the results. Two key insights emerged from the feedback: first, understanding the targets that leadership sets for employee engagement and the emphasis they place on this initiative is essential. This knowledge will help validate the observation that departments with strong leadership support are generally more successful in enhancing employee engagement. Second, it is essential to consider the operational aspects within each department, particularly the risk profiles and types of activities performed. By integrating these factors into the analysis, we can develop a more comprehensive understanding of the dynamics at play and their effects on the outcomes.

FIGURE 23: SEED-DM proposal for refinement. The suggested refinements are highlighted in red boxes in Hypothesis 3, Phase 0 and Phase 4.



Chapter 6

Discussion

This chapter discusses the methodology developed and the results obtained from its application in the real-world case study. The design of the SEED-DM methodology was informed by the literature review and the answers to the sub-research questions. The literature review encompassed a wide range of studies focused on occupational safety indicators and methodologies that assess the impact of organizational practices on these indicators. These studies spanned various countries and industries, offering both global and sector-specific perspectives. Covering research from 1996 to 2022, the review provides a comprehensive overview of the evolution of occupational health and safety research over time.

Regarding safety indicators (SRQ1), the literature review identified an extensive list of measures, highlighting a clear shift in research focus from lagging indicators to leading indicators. While leading indicators are more proactive, they present challenges in standardization and measurement consistency. In contrast, lagging indicators, which are reactive, allow for trend monitoring and benchmarking. Given that SEED-DM relies on quantitative and statistical methods, lagging indicators were deemed more appropriate for studying the relationship between employee engagement and occupational safety outcomes. By examining a wide range of lagging indicators from the literature, our methodology also enables a comprehensive comparison with other studies.

In exploring the methods used to assess the relationship between organizational practices and occupational safety (SRQ2), two primary approaches were identified: statistical analysis and regression models. When combined, these methods offer valuable insights into how organizational practices (independent variables) influence safety outcomes (dependent variables). Furthermore, a number of studies relied exclusively on qualitative research, such as interviews with employees and leadership, to capture their perspectives. In our methodology, we integrated all of these three methods - statistical, regression and qualitative analysis - to provide a comprehensive overview on the impact of employee engagement on occupation safety. By doing so, we not only build on existing research but also enrich it by correlating operational data from reporting systems with insights gathered from stakeholders.

Looking at the results of the case study, in phase 1 of the methodology, the time series clustering analysis revealed that a small number of departments exhibited a consistent trend in reporting employee engagement. Despite the dataset comprising 302 departments, only 17 consistently demonstrated high levels of engagement, accounting for approximately

90% of the total submissions. This finding was surprising given the size of the dataset. Nevertheless, it aligns with the existing literature and the insights provided by the interviewed stakeholders. The stakeholders emphasized that fostering employee engagement within an organizational culture is a complex process, requiring key elements such as leadership encouragement, recognition of employee input, and timely follow-up on employee suggestions. These observations further support the conclusions of Homan [47] which highlights the crucial role supervisors play in promoting employee engagement. Supervisors must ensure that employees feel heard, valued and empowered to make meaningful contributions. In addition, stakeholders stressed that leadership must recognize that employee engagement is not a separate initiative separate from organizational goals of productivity, efficiency, and cost reduction. Instead it serves as an important enabler of these objectives. Once leadership embraces employee engagement as a core component of organizational culture, then it can significantly influence positive outcomes, particularly in the domain of occupational safety. Henceforth, to strengthen this leadership component in the SEED-DM methodology, the refinement proposed integrating concrete action plans for employee engagement and as well measuring to the impact of leadership targets on the effectiveness of employee engagement.

Hypothesis 1 and 2 were addressed in phase 2 of our methodology, which focused on the relationship between employee engagement and the occurrences and severity of occupational safety events, respectively. To this end, the methodology used a set of statistical techniques that examine the correlation and causality between the variables. The majority of experiments demonstrated a causal relationship across most departments at a significance level of 95%, with the strongest causality observed in the context of severe injuries, such as those classified as ASTM and OSHA. While these results are predominantly positive, it is important to note that the results varied across the departments. For example, during the causality testing, a number of departments demonstrated a causal link for 89-91% of the experiments, whereas other showed causality in only 29-36% of the cases. Likewise, the results varied across departments for the correlation tests. These findings suggest that employee engagement alone may not be sufficient to significantly impact safety outcomes, but there may be other factors playing a complementing role. As mentioned during stakeholder validation, the risk profile of each department's operational activities is a crucial factor. In low risk departments, employee engagement can help to address immediate issues and lead to rapid improvements. However, in high risk departments, a more comprehensive approach is required from the organization to achieve substantial safety improvements.

Hypothesis 3 was examined in phase 3 of the methdology, stating that employee engagement would lead to a reduction in occupational health and safety incidents. Analyzing the factors contributing to these injuries, it was found that employee engagement reporting, specifically in relation to safety and LIFE initiatives, had the greatest impact. Two notable trends emerged when examining the temporal dynamics of these engagements. Firstly, when employee engagement was assessed with a one-week lag, a significant reduction in the number of low-severity injuries was observed. Stakeholders indicated that this decrease could be attributed to front-line workers taking immediate actions to address these safety concerns, which are often manageable by the employees themselves. Examples given of such actions included cleaning wet floors and properly storing equipment to minimize the risk of falls, slips, and cuts. Secondly, when expanding the observation window to a 15-week lag, the submissions instead demonstrated a positive association with the total number of low-severity injuries. This finding was in line with the practical experience from stakeholders, who believed that employee engagement increases awareness and involvement, in turn leading to more diligent reporting of workplace incidents. This outcome is encouraging, as it promotes a proactive approach to safety and aligns with the literature on leading safety indicators discussed in Section 2.2.1.

Hypothesis 4 was addressed in Phase 3, stating that employee engagement leads to a reduction in the severity of occupational injuries. Both our experimental results and stakeholder validation provided strong support for this hypothesis. During the feature engineering and selection processes, it became evident that employee engagement, particularly when paired with the implementation of actions, significantly contributes to reducing injury severity. The weights in the linear regression model indicated that while actions in general reduced the overall occurrence of injuries, the highest impact was observed for severe injuries classified under ASTM standards. In comparison to lower-severity injuries, the impact of engagement was most pronounced after a time lag of 14 to 15 weeks. Insights gained from stakeholder interviews further clarify that the interventions most effective at reducing severe injuries often involve engineering controls, equipment upgrades, or the introduction of risk mitigation programs and specialized training. These measures typically require a considerable period for full implementation. However, these findings underscore the complexity of the relationship between employee engagement and occupational safety, suggesting that while engagement can improve safety, the timing and specific nature of engagement activities are crucial in determining their efficacy. This insight is essential for organizations seeking to improve safety outcomes through targeted engagement strategies, emphasizing the importance of both the type of engagement and the timing of its deployment.

Upon reviewing the results of the linear regression analyses, it became evident that the generalizability across all models is still limited. The models demonstrated the best performance for ASTM and LIFE severity injuries, as indicated by both low Mean Squared Error (MSE) and high R-squared values. In contrast, the models for predicting the other safety indicators achieved less optimal results. This observation summarizes the findings from previous phases of the research and stakeholder validation, highlighting the ongoing difficulty in isolating the impact of employee engagement on occupational safety. The challenge is compounded by the presence of numerous potential confounding factors. Isolating the effect of a single variable in research poses significant methodological difficulties due to the inherent complexity of real-world data [79]. Confounding variables, such as the risk profile of various departments, leadership, implementation of actions can influence both the independent and dependent variables.

6.1 Limitations and Implications for Future Work

While both the stakeholder validation and the case study application yield positive results, there are opportunities for further work on both the methodology and its practical implementation. First, as highlighted in the stakeholder validation in Section 5.3, several suggestions were made for refining the methodology. During the stakeholder validation, several factors were identified that may influence both employee engagement and occupational health and safety. These factors, which were not accounted for in the current methodology, represent an important avenue for future research. Investigating these aspects in future studies could lead to a more comprehensive model that integrates various influences on workplace safety. Ultimately, a deeper exploration of these dynamics could enhance the ability to predict and improve workplace safety through a more nuanced understanding of the relationships between engagement, safety, and other contributing factors.

While the case study yielded promising results, it also revealed several limitations that warrant consideration for future applications of SEED-DM. First, the data sample used in this study was relatively limited. Specifically, the analysis is based on approximately 200 time points (weeks) for a department with consistent reporting on employee engagement and injury rates. Notably, only 17 departments were included in Phase 1 and 2, and it was observed that not all departments provided the complete 200 data points due to later onset of employee engagement reporting. Extending the time lags further reduced the available data points, thereby potentially limiting the robustness of the impact analysis over time. Moreover, working with time series data posed inherent challenges. Temporal dependence, characterized by autocorrelation, complicates modeling efforts since past values influence future observations. Ensuring data stationarity is another critical challenge, as many time series models assume stationary data, requiring transformations or differencing to stabilize mean and variance. Additionally, noise and outliers can distort patterns and affect model accuracy. While SEED-DM addressed seasonality, autocorrelation, and outliers, these adjustments also resulted in a reduced dataset size.

The application Phase 1 and 2 of the methodology was limited to departments exhibiting consistent patterns of employee engagement. While this focus provides valuable insights into how sustained engagement impacts occupational safety, it also suggests areas for further exploration. Specifically, including departments with intermittent or absent employee engagement could yield a more comprehensive understanding of the relationship between engagement and workplace safety. Applying SEED-DM to the other trends would allow researchers to assess whether sporadic or non-existent engagement correlates with differing safety outcomes and to identify potential variables that influence engagement patterns. Expanding the scope to include these trends could offer a more nuanced view of how varying levels of engagement affect safety and potentially reveal underlying factors that contribute to or detract from effective safety practices. Furthermore, this broader analysis could help determine whether certain engagement thresholds are necessary for achieving optimal safety outcomes or if other organizational factors might mediate or moderate this relationship.

Finally, the challenge of isolating the effect of employee engagement in this study highlights the complexity of the task. While techniques used in SEED-DM, such as statistical and regression analysis, are beneficial, they may not fully capture the nuances of differentiating the impact of employee engagement from other influencing factors. A more rigorous approach, such as a controlled experimental design, could enhance internal validity by establishing a clearer cause-and-effect relationship between employee engagement and safety outcomes. This design would involve manipulating engagement levels in a controlled environment to observe their direct effects on safety indicators. Such an approach would strengthen causal inferences and minimize biases related to generalizability. Applying SEED-DM in these conditions would contribute to a more robust understanding of the mechanisms through which engagement influences safety.

Chapter 7

Conclusion

Occupational health and safety significantly impact both employee well-being and organizational performance. While the importance of employee engagement in fostering a safer work environment is widely recognized, much of the existing research relies on subjective metrics, leaving a gap in empirical evidence. This study addresses this gap by investigating the relationship between employee engagement and occupational health and safety using operational data from a manufacturing organization. To achieve this, we developed SEED-DM, a data-driven methodology that tests four hypotheses to evaluate the strength of the relationship between employee engagement and both the frequency and severity of occupational safety incidents. Our methodology was grounded in a literature review and employs statistical tests (correlation and causality), linear regression, and stakeholders interviews. We applied SEED-DM in a case study, where the results showed a positive impact of employee engagement on occupational safety outcomes, indicated by both correlation and causality. Additionally, we discovered a specific relationship involving low-severity incidents, where employee engagement initially demonstrated a negative correlation with the number of safety incidents, but shifted to a positive correlation over a longer time frame. This finding aligns with expert insights suggesting that higher engagement leads to increased awareness and reporting of safety issues, ultimately resulting in improved safety outcomes. Furthermore, our analysis indicated that employee engagement, particularly when combined with proactive safety initiatives, significantly reduces injury severity. This effect is most pronounced after approximately 15 weeks, highlighting the time required for the design and implementation of effective safety interventions. Finally, from our case study and the stakeholder interviews we identified several opportunities for enhancing SEED-DM. For example, the variations in results across departments suggested that external factors may influence both employee engagement and safety outcomes. Hence, we propose incorporating additional context in the analysis, such as departmental risk profiles and leadership objectives, to gain a better understanding of related factors that can influence the results. Furthermore, stakeholders expressed interest in expanding the practical application of this methodology by integrating employee engagement strategies within organizations. Through our work, we contributed to the existing literature by proposing a generalizable data-driven methodology for evaluating the impact of employee engagement on occupational safety. Moreover, we provided empirical evidence in support of this relationship by means of a case study. Finally, our findings offer practical insights for organizations to promote employee engagement at the leadership level and emphasize the importance of timely safety actions.

Appendix A

Quality Assessment Evaluation

Paper	QC1	QC2	QC3	QC4	QC5	Score
[15]	1	1	1	1	1	5
[21]	1	1	1	1	1	5
[29]	1	0	1	1	1	4
[12]	1	1	1	1	0	5
[25]	0	1	1	1	0	3
[16]	1	1	0	0	1	3
[52]	1	0	0	1	1	3
[17]	1	1	1	1	1	5
[47]	1	0	1	0	0	2
[30]	1	0	1	0	1	3
[20]	1	1	1	0	0	3
[14]	1	1	1	0	0	3
[48]	1	0	1	0	0	2
[43]	0	0	1	0	0	1
[32]	1	0	1	0	0	2
[33]	1	0	1	1	1	4
[46]	1	0	0	1	0	2
[34]	1	0	0	1	1	5
[39]	1	0	1	1	1	4
[36]	1	0	1	1	0	3
[37]	1	0	0	1	0	2
[80]	1	0	0	0	0	1
[44]	1	0	1	1	1	4
[27]	1	0	1	1	1	4
[81]	1	0	0	0	0	1
[19]	1	0	0	0	1	2
[82]	1	0	0	0	0	1
[26]	1	1	1	0	0	3
[83]	1	0	1	0	0	2
[84]	1	0	0	0	0	1
[10]	1	0	0	0	0	1
[85]	1	0	0	0	0	1
[86]	1	1	0	0	0	2
[35]	1	1	1	1	1	5

[28]	1	1	1	0	0	3
[42]	1	0	0	0	0	1
[41]	1	0	1	0	1	3
[87]	1	0	0	0	0	1
[88]	1	0	0	0	0	1
[27]	1	1	1	0	0	3
[11]	1	0	0	0	0	1
[48]	0	0	1	0	0	1
[54]	0	0	1	0	0	1
[89]	1	0	0	0	0	1
[90]	1	0	0	1	0	2
[22]	1	0	1	0	0	2
[91]	1	0	1	0	0	2
[23]	1	1	1	0	1	4
[92]	1	0	1	0	1	3
[45]	1	0	1	1	0	3
[49]	1	0	0	0	0	1
[50]	1	0	0	0	0	1
[51]	1	0	0	0	0	1
[84]	0	0	1	0	0	1
[24]	1	1	0	0	1	3
[93]	1	1	0	0	0	2
[94]	1	0	1	0	0	2
[95]	1	0	0	0	0	1
[96]	1	0	0	0	0	1
[97]	1	0	0	0	0	1
[98]	1	0	0	0	0	1
[99]	1	0	0	0	0	1
[100]	1	0	0	0	0	1
[101]	1	0	0	0	0	1

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