PREDICTIVE ASSESSMENT OF POSTURAL RISK AND BIOMECHANICAL ANALYSIS OF MUSCULOSKELETAL DISORDER RELATED PROBLEMS OF DUMP TRUCK OPERATORS IN INDIAN SURFACE METAL MINES

Thesis

Submitted in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

by

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DECLARATION

I hereby *declare* the Research Thesis entitled **"Predictive Assessment of Postural Risk and Biomechanical Analysis of Musculoskeletal Disorder Related Problems of Dump Truck Operators in Indian Surface Metal Mines"** which is being submitted to the National institute of Technology Karnataka, Surathkal in partial fulfillment of the requirements for the award of the Degree of **Doctor of Philosophy** in **Mining Engineering** is a *bonafide report of the research work carried out by me.* The material contained in this Research Thesis has not been submitted to any University or Institute for the award of any degree.

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ABSTRACT

This study aimed to determine the postural risk among dumper operators working in Indian surface metal mines. An epidemiological study was conducted to determine the association between driving posture and Work-Related Musculoskeletal Disorders (WRMSDs). A customized self-reported questionnaire was developed to collect personal, habitual, and work-related data from the selected sample. The raw data was pre-processing and analysed using Machine Learning (ML) models, such as Random Forest (RF), Support Vector Machine (SVM), Decision Tree (DT), Gradient Boosting Machine (GBM), and Logistic Regression (LR). The performance of these models was evaluated using metrics, such as accuracy, precision, recall, F1 score, and Receiver Operating Characteristic (ROC) curve. The findings of the performance study indicated that the RF model offers better results over SVM, DT, GBM, and LR models with an accuracy of 0.71, precision of 0.75, recall score of 0.78, and F1 score of 0.76. Furthermore, the study revealed that age of the dumper operators had a significant association with WRMSDs, followed by awkward driving posture, work experience, job demand, alcohol consumption, smoking, work design, and marital status. In overall, the epidemiology study proved that the role of awkward driving posture contributes to the WRMSDs among dumper operators.

Consequently, a thorough analysis of sitting posture of dumper operators was conducted using the observation method (i.e. fuzzy RULA method). The findings showed that over 80% of dumper operators exhibited a fuzzy RULA score corresponding to 'action level two', indicating the necessity for further investigation. To investigate deeper, a study of operator’s sitting posture with respect to various job cycles (i.e. loading, hauling with load, unloading, and empty travel) was undertaken. The detailed analysis revealed relatively consistent fuzzy RULA scores ranging from 3.5 to 4.25 during dynamic operations. Conversely, during static operations, the fuzzy RULA scores fluctuated more widely, ranging from 3.25 to 4.5. This reveals that operators maintained nearly identical postures during dynamic operations, whereas their sitting postures varied more during static operations.

The Fuzzy RULA method do not consider operator’s height and weight, which is important factors contributing to WRMSDs. Therefore, a comprehensive biomechanical analysis of dumper operators was conducted using the "opensim" software package and Gait2354 human model. In this study the load on the spine, muscles, and tendons during primary climb, main

haul, right incline traverse, left incline traverse, and final climb tasks was determined. The outcome of the study showed that the load on the spinal was varying with the job cycle, with maximum load occurring during main haul (335.74N), followed by primary climb (324.30N), final climb (324.30N), right incline traverse (314.43N), and left incline traverse (304.29N). The biomechanical analysis also indicated that the muscle and tendon forces vary with job cycle. During right incline traverse, the right ERCSPN, right EXTOBL, and right INTOBL muscles experienced relatively high total forces (i.e. 41.76N, 59.99N, and 39.21N, respectively). Similarly, during left incline traverse, the left ERCSPN, left EXTOBL, and left INTOBL muscles experienced high total forces (i.e. 47.34N, 70.05N, and 51.33N, respectively).

The tendon which joins the muscles with the bone also showed the same trend. The tendons attached to the right ERCSPN, right EXTOBL, and right INTOBL muscles experienced high total force of 41.76N, 59.99N, and 39.21N, respectively during right inclined transverse. Similarly, the tendons attached to the left ERCSPN, left EXTOBL, and left INTOBL muscles experienced high total force of respectively 47.34N, 70.05N, and 51.33N when the dumper operator were performing left inclined transverse.

In general, this study showed that muscles suffers significant tensile forces when operators perform right and left inclined transverse movements. During the field study, it was observed that the operators were not wearing seat belts while operating dumpers. Because of this when navigating corners, operators encountered centripetal forces, prompting them to lean their bodies and consequently shifting the center of gravity (COG) from the center to the side. This change in COG led to tensile forces acting on the muscles and tendons connected to the spine. Hence, this study recommends for the mandatory use of seat belts by operators while operating.

Similarly, this study also disclosed that the spine undergoes significant compressive forces during the main hauling operation (i.e. the movement of the dumper between loading and unloading points). The compressive load on the spine increases with increase in Body Mass Index (BMI) of the operators. However, considering operators with lower BMIs may not be feasible due to potential recruitment bias. Hence, this study suggests to incorporate regular breaks for operators during work to mitigate ill effects on their health.

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CHAPTER 1

1. INTRODUCTION

The success of any business enterprise depends highly on its human capital. Occupational health and safety in enterprises are serious issues that have garnered government and public attention. Work safety aims to safeguard the worker's right to have safety precautions while performing work, boost national production and productivity, ensure the safety of everyone on the job, and keep the source of production safe and efficient. The duty of Corporate Social Responsibility (CSR) is the concern for the safety and health of employees to keep them motivated and engaged. The concern multiplies when the workforce is exposed to menial tasks and high-risk occupational situations, as in the mining industry.

Due to the complexity of the work environment, mining is renowned as one of the most dangerous industries in the world. Workers in mines are exposed to various risk conditions that can result in death or severe injury resulting in direct or indirect costs to employees and employers. To minimize the loss, the mining companies, government bodies, research institutes, and academics have worked over the years to prevent accidents by proposing solutions such as additional regulations, enhanced training, advanced technology, and reliable and advanced equipment.

The Mine Safety and Health Administration (MSHA) was set up to prevent mine worker's death, illness, and injury and promote safe and healthful workplaces for United State (US) miners. It works cooperatively with industry, labor, and other federal and state agencies to improve safety and health conditions for all miners in the United States. It carries out the provisions of the Federal Mine Safety and Health Act of 1977 (Mine Act) as amended by the Mine Improvement and New Emergency Response (MINER) Act of 2006. It develops and enforces safety and health rules for all U.S. mines regardless of size, number of employees, commodity mined, or extraction method. It also provides technical, educational, and other assistance to mine workers.

Based on the type of ore, MSHA classifies the U. S. mine industries into six categories (i.e., coal, metal, non-metal, stone, sand, and gravel). In 1978, during the first year of operation, MSHA reported 242 fatal accidents. Figure 1.1 clearly shows that the most of the fatal accidents occurred in coal mines, followed by metal and stone mines.

Similarly, the accidents reports were retrieved from the Directorate General of Mining Safety (DGMS) database. DGMS is an organization under the Ministry of Labour and Employment, Government of India, responsible for the enforcement of safety regulations in the mining industry. It was established in 1901 to ensure the safety and health of mine workers through the implementation of the Mines Act, 1952, and the Mines Rules, 1955. When the accident data spanning from 1901 to 2020 was referred, it showed that in total, 412 fatal accidents occurred in this period. It is evident from the Figure 1.1 and Figure 1.2 that trend in death rate in US mines and Indian mines are similar.

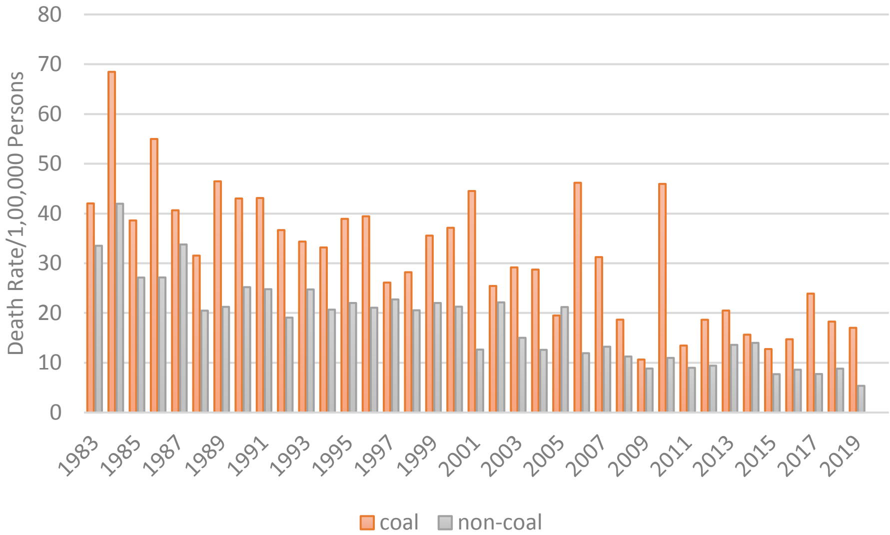


Fig. 1.1 Chart showing the trend of the fatal accident in US mines
(*source:* https://wwwn.cdc.gov/NIOSH-Mining/MMWC/Fatality/NumberAndRate)

Additionally, due to the implementation of new policies, safety practices, and industrialization, the death rate in both US and Indian mines has reduced over the year. However, the present numbers are not satisfactory. Hence, it is essential to identify the risk at each level and implement safety practices to mitigate the accident.

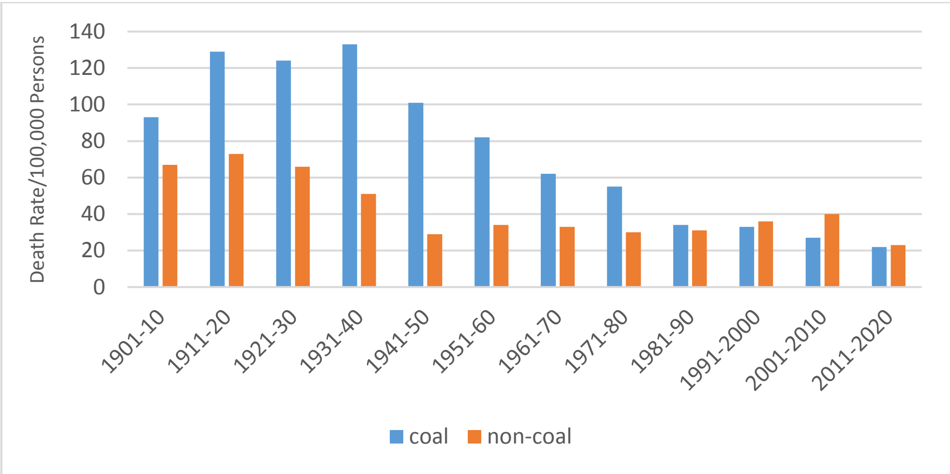


Fig. 1.2 Chart showing the trend of the fatal accident in Indian mines (1901 to 2020) (*source*: https://shorturl.at/cPZ07)

Furthermore, MSHA classifies the cause of the accident in the mining environment into eight categories (i.e., hand tools, machinery, power haulage, slip or fall of a person, fall of ground, electricity fall or rolling or sliding of rock, handling of materials). It is evident from the Figure 1.3 and Figure 1.4 that the machineries plying in the mine contributed most for the fatal accident in US and Indian. Injury prevention is most successful if the etiology of an injury is understood so that efforts can be focused more directly (Mittleman et al. 1997).

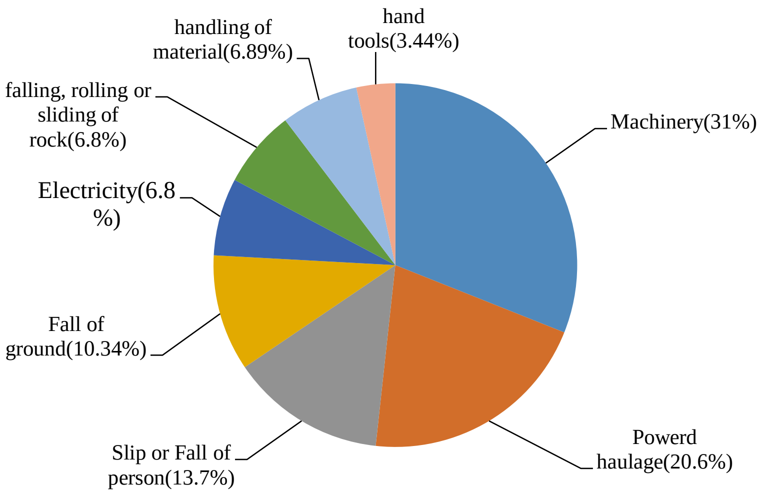


Fig. 1.3 Chart showing the percentage fatal accident and its causes in U.S. mines (*source:* https://wwwn.cdc.gov/NIOSH-Mining/MMWC/Fatality/Count)

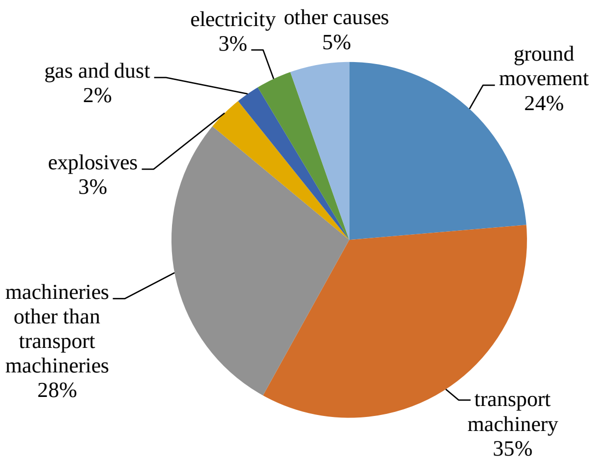


Fig. 1.4 Chart showing the percentage fatal accident and its causes in Indian mines (*source*: https://dgms.gov.in/UserView/index?mid=1362)

Previous research work showed that environment, human error, and fatigue (Orchansky et al. 2010) are the dominated risk factors that cause accidents. Further, there exist research evidence stating the significant positive association between fatigue and Work Related Musculoskeletal Disorders (Hunt et al. 1999). Hence, it can be presumed that out of many risk factors, Work Related Musculoskeletal Disorders (WRMSDs) is one of the factors which indirectly contribute to a mine accident.

1.1 Objectives of the Study

The main objectives of the research work are as follows:

1. To estimate the extent of WRMSDs problems among the dumper operators working in Indian open-cast metal mines.
2. To study the role of personal, habitual, and work-related factors of the dumper operators on WRMSDs using Machine Learning algorithm.
3. To determine the postural risk of dumper operators using a fuzzy logic-based Rapid Upper Limb Assessment (RULA) score chart.
4. To employ the K-means clustering algorithm to determine high repeated driving posture from the video footage.
5. To carry out the biomechanical analysis to assess the resultant forces acting on the spine, muscles, and tendons of the dumper operators.

1.2 Organization of Thesis

Based on the literature review and to fulfil the aim of the objectives, the thesis is structured as below.

CHAPTER 1

The introduction section covers the background of the study, proposed objectives and a brief report on organization of thesis.

CHAPTER 2

This chapter presents the detailed review of the literature pertaining to the research area such as impact of vibration exposure on Work Related Musculoskeletal Disorders (WRMSDs), the influence of posture on WRMSDs, the effects of work-related factors on WRMSDs, impact of personal factors and socio-demographic factors on WRMSDs and, also the literature pertaining to the effects of environmental factors on WRMSDs.

CHAPTER 3

This chapter addresses the technique used for the development of the custom questionnaire, the features of the case study mine selected for the data collection, and the methods employed for data preparation.

CHAPTER 4

Presents the methods and results of the univariate and multivariate analysis of the collected data.

CHAPTER 5

Presents preliminary analysis by capturing RGB images of driving postures and analysing the posture risk by means of Fuzzy Logic-Based Rapid Upper Limb Assessment Technique.

CHAPTER 6

This chapter discusses the methodology employed and outcomes of biomechanical analysis of driving postures.

CHAPTER 7

Summarises the conclusions of the research work and explores the potential scope for future work.

CHAPTER 2

2. LITERATURE REVIEW

There are a large number of studies that carried out investigation to determine the relationship between WRMSDs and related risk factors among mine workers around the globe. The resultant reports of these studies need to be organized and evaluated for a comprehensive understanding of occupational disorder. Hence this systematic review aims to

1) Identify the evidence based risk factors of Work Related Musculoskeletal Disorders among mine workers.
2) Identify the conflicts in previous studies.
3) Identify the research gaps.

The WRMSDs are syndromes which affect the musculoskeletal system of the body, such as bones, muscles, joints, and tendons. The WRMSDs are developed due to exposure of the subject to incorrect work environment (Sekkay et al. 2018). A detailed

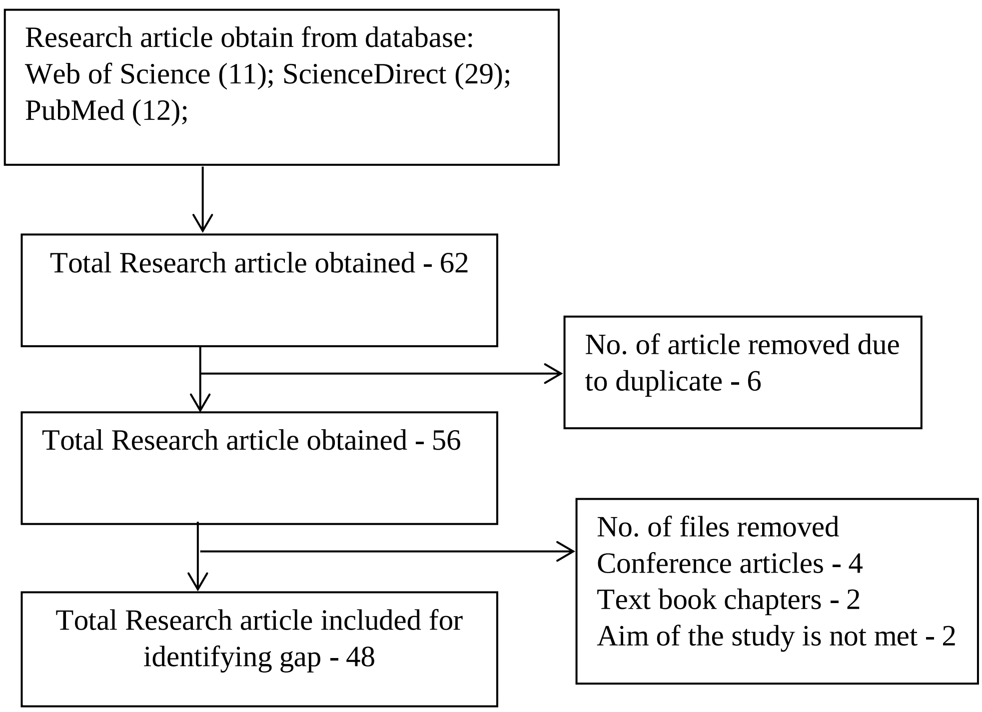


Fig. 2.1 Flow chart showing the steps involved in selection of research article

literature review was conducted for identifying the risk factors and research gap in existing literature. The Standard Preferred Reporting Items of Systematic Reviews and Meta-Analyses (PRISMA) guidelines was followed for shortlisting the research articles (Kamioka 2019; Liberati et al. 2009). An electronic search was done from the year 1998 until 2022 using ScienceDirect, PubMed, and Web of Science databases. Search terminologies such as musculoskeletal disorder, risk factors, occupational risk, mine accident etc. were used to search the research article along with the boolean operators such as AND, OR etc. Once the research article was shortlisted, they were exported to Mendeley for finding duplicated files of the research article. After removing the duplicated research articles, remaining research articles were sorted as per the published year (Figure 2.1). In total 48 research articles were identified and included for determining the research gap.

An extensive examination of the research articles revealed that research publications collected utilizing PRISMA guidelines shall be classified into five major categories as shown below:

1. Literature on effect of vibration exposure on WRMSDs
2. Literature on effect of posture on WRMSDs
3. Literature on effect of work related factors on WRMSDs
4. Literature on effect of personal factors and socio-demographic factors on WRMSDs
5. Literature on effect of environment factors on WRMSDs

2.1 Effect of Vibration Exposure on WRMSDs

In earlier investigations, the exposure to vibration appeared to be the most important physical element. Exposure to vibration has detrimental effects on the musculoskeletal system, particularly in those who drive or operate machines or equipment. In this section, all the collected literature have been grouped into three categories based on the source of vibration.

1. Vibration exposure of Heavy Earth Moving Machinery operators.
2. Vibration exposure of transport machineries operators.

3. Vibration exposure of non-transport machineries operators.

2.1.1 Vibration exposure of Heavy Earth Moving Machinery (HEMM) operators

To determine the effect of Foot Transmitted Vibration (FTV) on miners' health, Leduc et al. (2011) conducted a field study by recording FTV of the locomotive, rock breaker, lift truck, alimak raise, and jackleg drill operators using a tri-axial accelerometer. They used questionnaire administration to collect the data regarding work history, demography, and work related musculoskeletal symptoms experienced by the operators. Their study revealed that raised platforms of machines exposed the workers to vibration levels more than Health Guidance Caution Zone (HGCZ).

A similar study was performed by Eger et al. (2014) to determine the health risks associated with the FTV. They considered the operators involved in operating locomotives, jumbo drills, raise drilling platforms, and crushers. The authors of the study measured the foot transmitted root mean square (rms) acceleration using a tri-axial accelerometer and discomfort experienced by the operators using questionnaire administration. Their study showed that operators who are exposed to FTV more than 40 Hz are more prone to vibration-induced injuries.

Fieldwork was carried out by Emkani et al. (2016) to investigate the vibration exposure of HEMM operators and its association with WRMSDs by considering large data size. Using a random sampling technique, they considered 288 HEMMs operators working in the mines. The Whole Body Vibration (WBV) data and discomfort experienced by the operators were measured using vibration meters and Nordic Musculoskeletal Questionnaire (NMQ) respectively. This study reported that grader operators are exposed to high average acceleration (i.e. 2.17 m/s^2), whereas driller operators are exposed to very low vibration (i.e. 0.479 m/s^2). This study exhibited that WBV is significantly associated with neck and wrist pain.

To compare exposed and unexposed groups, Nejad et al. (2017) conducted a research by measuring the vibration exposure and its association with Lower Back Pain (LBP) among HEMM operators. The authors used a case-control (216 cases and 216 control) study design to identify the risk factors associated with LBP. They used Standardized NMQ for measuring WRMSDs of exposed and unexposed groups. The study results revealed that WRMSDs more frequently occurred among drivers than the non-drivers. Further, this study demonstrated that age, experience, exercise, and smoking are significantly related to LBP.

In another study, Barrero et al. (2019) investigated the link between WBV exposure and body part-related absenteeism. The authors collected WBV data from 11 different HEMM and absence data from the payroll of past four years. The novelty of this article lies in using the “cox regression model” for determining the relationship between WBV and leave taken by the operators. This study concluded that WBV exposure is positively and significantly associated with absenteeism.

In a field study conducted by Kumar et al. (2020), the health risk of the dumper, driller, and shovel operators exposed to Whole Body Vibration (WBV) was studied. The WBV measurement of 90 selected HEMM operators was carried out at the mine site. The authors followed ISO 2631–1/1997 guidelines for measuring vibration and health risks evaluation. They used the binary logistic regression technique to compare the health risk of dumper operators with the drill and shovel operators. This study concluded that 100 % dumper, 20 % drill, and 15 % shovel operators are likely to suffer from WRMSDs due to WBV exposure. Further, their research showed that the odds of dumper operators getting health-related problems due to WBV is 2.92 times more than drill and shovel operators.

2.1.2 Vibration exposure of transport machineries operators

An investigation was carried out in a coal mine by Mandal and Srivastava (2010) to compare the WRMSDs of dumper operators with the other workers who are not exposed to vibration. They measured the rms acceleration and body part discomfort from 40 dumper operators and 20 controls. The results of the epidemiology study indicated that along the dominant Z-axis, rms acceleration varied from 0.644 m/s^2 to 1.82 m/s^2 and 85% exposed population faced severe WRMSDs problems such as pain in the ankle (37.83%), shoulder (30%) and neck (37.5%) region compared to the control group.

In the subsequent work, Mandal and Manwar (2017) compared the WRMSDs of dumper operators exposed to WBV with the office staff of the case study mines. They considered 46 cases and 28 controls, and survey was done to determine the location and severity of body pain on a four-point scale. The authors used Chi-square statistical test to find the association between body pain and exposure. This study revealed that LBP is the most dominant WRMSD among dumper operators and is significantly associated with WBV exposure. Further, their study stated that 39 % of the exposed group suffer from severe work related musculoskeletal symptoms and they need immediate medical attention.

To investigate the effect of dumper capacity on WBV, the authors Kaviraj and Kumaraswamidhas (2018) performed a field study that measured the vibration from dumpers of different capacities. The authors measured WBV and HAV of dumper with varying capacities. This study exhibited that WBV is significantly high in the exposed group.

Vibration levels and health effects for transport and non-transport equipment in coal mines were studied by Chaudhary et al. (2020). They conducted a questionnaire survey, followed by WBV exposure measurements at the mine site. The data collected was analyzed by means of binary logistic regression model. Their study revealed that LBP risk in transport operators is 4.06 times greater than in those who operate non-transport machinery.

2.1.3 Vibration exposure of non-transport machineries operators

To address the issue of WRMSDs, Grenier et al. (2010) conducted a laboratory study to compare the ISO discomfort score obtained from WBV exposure with the reported discomfort of Load Haul Dump (LHD) operators. The authors assigned the discomfort score based on the vibration exposure at the operator's seat interface. They used the regression analysis and correlation coefficient to determine the association between predicted and subjective discomfort. The authors of the study concluded that ISO discomfort scores is poorly correlated with the reported discomfort of the LHD operators.

Similar study was performed by the authors Eger et al. (2014). They carried out the field study to examine the relationship between vibration exposure and subjective discomfort reported by Load Haul Dump (LHD) operators. They measured the vibration exposure and discomfort level of LHD operators with the help of a vibration meter and body part discomfort questionnaire. They used linear regression and correlation to determine the association between WBV and body part discomfort. This study concluded that the vibration exposure values are related to reported discomfort.

An investigation was done by Dube and Chiluba (2021) to determine the ergonomic factors that can cause low back pain among LHD truck operators. The authors considered cross-sectional study design with the sample size of 140 respondents. They found significant association between LBP and ergonomic factors, such as experience, sex, age, type and duration of shift, lifting/ handling, postures, WBV exposure, design and other psychosocial factors.

Jeripotula et al. (2020a) compared the WRMSDs among dozer operators who are exposed to WBV (i.e. 42 samples) with the subject not exposed to WBV (i.e. 22 samples). The vibration intensity and duration of 42 dozer operators and 22 controls were evaluated. To identify the extent of WRMSDs, an epidemiological study was performed. The results of the study showed that the frequency weighted rms acceleration did not exceed Exposure Limit Time (ELV) among 90% of operators, but Exposure Action Value (EAV) equivalent to an 8-hr shift was exceeded. The authors concluded that LBP, pain in the neck, shoulder, knees, and ankle was predominantly higher in the exposed group than in control group.

2.2 Effect of Posture on WRMSDs

Earlier investigation reported significant association between WRMSDs with awkward or poor postures. Based on the methods used by the various researchers for quantitating the postural risk, the research articles collected was categorised into two groups.

1. Study of postural risk using questionnaire.
2. Study of postural risk by observation.

2.2.1 Study of postural risk using questionnaire

Schutte et al. (2003) conducted a field study to determine the prevalence of WRMSDs and to identify the risk factors associated with WRMSDs among gold mine workers. A total of 1235 medical records from different gold mines, 75 records from platinum mines, and 226 records from coal mines were examined. The data about postural risk was collected from the questionnaire. The results exhibited that 16.2%, 41.3%, and 37% of workers working in respectively gold, platinum, and coal mines suffer from WRMSDs. Further, the study concluded that vibration, repetitive work, force, posture, and manual materials handling were the risk factors for WRMSDs.

Further, Moore et al. (2012) determined the appropriate postures of low seam mine workers as per their tasks and job classifications. In his study, sixty-four low seam coal miners participated, and two frequently adopted postures for each worker were analyzed. The workers were given a schematic of postures for selecting the postures taken. The study concluded that coal mine workers in low seam developed knee osteoarthritis as they took kneeling postures nearly in full flexion while performing the work.

Later in 2013, Egwuonwu et al. estimated the prevalence of WRMSDs among quarry workers and their risk pattern. In total 114 participants were asked to respond to a standard Nordic Musculoskeletal Questionnaire (NMQ). To determine the association between posture and WRMSDs, the authors performed statistical tests such as the Chi-square test for categorical data and logistic regression continuous data. This study demonstrated the significant associations between vibration, repetitive movement, posture, and WRMSDs.

One more study has been carried out by Kunda et al. (2013) to determine the prevalence of WRMSDs and their association with the posture adopted by the underground miners. The study was done with randomly chosen 500 workers performing different activities. The data was collected from a standard questionnaire, and this data was analyzed using the Statistical Package for Social Science (SPSS) software. This study's results revealed that the twelve-month prevalence of WRMSDs among underground miners is 42.6% and lower back is the most affected body part due to the poor postures and heavy lifting.

Tawiah et al. (2015) adopted a cross-sectional study design to investigate the occurrence of WRMSDs among traditional gold mine workers. They performed the cross-sectional study for collecting posture data using a modified 28-point self-administered NMQ. The collected data were analyzed using descriptive and inferential statistics. Their results indicated that 85.5% of the miners complained of WRMSDs. The authors found that LBP is the most frequently faced health problem experienced by gold miners and accidental falls, long-time posture, and work type are the risk factors associated with WRMSDs.

A comparative study was done by Sharma et al. (2016) to compare the postural demand of Side Discharge Loader (SDL) operators with respect to discomfort and WRMSDs. They evaluated the cardiac and postural strain of 12 SDL operators. The postural strain of the task was determined using a questionnaire administration. The results of the study reported postural discomfort among SDL operators as moderate to severe pain in different parts, such as hands, forearms, wrists, and ankles.

Jeripotula et al. (2020b) performed the ergonomic assessment of work-related musculoskeletal disorders among surface coal mine workers. They used standardized NMQ to collect responses from 500 randomly selected workers performing different activities. This study showed that the operators operating dumpers, dozers, graders, and electricians are most susceptible to developing WRMSDs. Their study demonstrated that neck pain is positively associated with extended static posture, bouncing, and jarring.

2.2.2 Study of postural risk by observation

In 2008 Eger et al. developed the mathematical model to predict the health risks associated with LHD operators' driving postures. The WBV, driving posture, peak, and cumulative spinal loads at the L4/L5 level during the LHD operation were estimated in this study. The average maximal and cumulative compressive force at the L4/L5 spine was 2176 N and 34 MN, respectively, for the static position. This study exhibited that vibration, postures and spinal loading are the influencing factors that can cause WRMSDs.

A comparative study was performed by the Eger et al. (2010) to analyze the driving posture, sitting position, and point of regard of the LHD operators for understanding the association with the LHD design. A LHD of 5.35 m^3 bucket capacity with several driving postures was used for the analysis. The study showed that the neck rotated more than 40 degrees for 85% of the work cycle time, and the peak compression at L4/L5 was 1843 N. This study demonstrated that the driving posture of the LHD operators depends on the ergonomic design of the LHD vehicle.

Further, Norhidayah et al. (2016) evaluated mine workers' physical risk factors associated with WRMSDs. The authors selected 18 subjects based on the Manual Material Handling (MMH) task. They evaluated each subject thrice for better reliability of the results. They found that the average Rapid Entire Body assessment (REBA) score for the MMH task is 8.24. Based on the REBA score of different body parts, the authors came to the conclusion that the neck, trunk, and upper extremities are more exposed to the physical risk factors.

One more study has been carried out in which authors Octora et al. (2018) investigated the association between WRMSDs and working postures among gold miners. In total, 53 gold mines were selected for the study, and their WRMSDs complaint and work postures were measured respectively by NMQ and REBA. The study showed that 71.7% of gold miners suffer from WRMSDs complaints in the shoulder, waist, and lower back. This study demonstrated that non-ergonomic working postures are positively correlated with WRMSDs.

A survey on the prevalence of WRMSDs among traditional underground coal mining workers was conducted by Ijaz et al. (2020). The authors collected data from 260 mine workers using NMQ and Rapid Upper limb Assessment (RULA) sheet. This study stated that the severity of pain is directly proportional to age and inversely proportional to the number of repetitions per minute. Further, study showed that all the tasks performed by the workers had a RULA score of 7, indicating that each of these postures adopted by the workers can cause health-related problems.

A study was carried out by Upadhyay et al. (2022) to investigate the combined role of awkward posture and WBV exposure on WRMSDs. The WBV was measured through frequency-weighted rms acceleration. The authors used anthropometry data and a RULA score chart for postural assessment. Further, questionnaires were used to determine the prevalence of WRMSDs. The authors used the logistic regression technique to determine the association between awkward posture and WRMSDs. Their studies revealed that most workers are seated in an awkward posture, with 54-75 percent subjected to high and medium risk of WRMSDs.

2.3 Effect of Work Related Factors on WRMSDs

Xu et al. (2012) investigated the role of occupational factors and measured the prevalence of LBP among 1573 coal miners. The prevalence of LBP was assessed using the NMQ. The logistic regression technique was used to find the association between LBP and occupational factors. The results of this study stated that 64.9% of participants reported LBP. Based on the results, the authors reported that the repetitive work, awkward postures, physical demand, and insufficient recovery time are the occupational risk factors associated with LBP.

Yue et al. (2014) investigated the contribution of psychosocial risk factors to the occurrence of WRMSDs in miners. The authors used modified NMQ to assess the prevalence of WRMSDs. In this study the logistic regression technique was used to estimate the association between psychosocial factors and WRMSDs. The study showed that the prevalence of WRMSDs was 78% among the miners. The study exhibited that the stronger associations exist between high job demands and upper limbs (odds ratio [OR] 3.05, 95% confidence interval [CI]: 1.67-5.58), neck and shoulder (OR 1.82, 95% CI: 1.05-3.16) and lower limbs (OR 1.97, 95% CI: 1.12-3.49) symptoms among miners.

Similarly, Okello et al. (2020) determined the prevalence of WRMSDs and their affecting factors among gold mine workers. The prevalence of 12 months and 24 hours WRMSDs and affecting factors were collected using questionnaires from 196 gold miners. The authors used a linear regression model with link long and robust error to determine the prevalence ratios and 95% confidence interval. The results indicated that 25% of workers reported atleast one of the work related musculoskeletal symptoms with the LBP contributing the highest. Their study revealed that the longer shifts hours (i.e. >9hr), heavy lifting, and shovelling are significantly associated with risk factors for WRMSDs.

An investigation was carried out by Annan (2020) to identify the risk factors associated with WRMSDs among mine workers. The data was collected from 180 randomly selected miners through a questionnaire survey. The author used bivariate and regression methods for the analysis. The study showed that the factors such as department type, working category, job demand, repetitive work, WBV, and Body Mass Index (BMI) are significantly associated with WRMSDs.

The research work was carried out by Jiskani et al. (2020) to investigate the influence of psychosocial factors on WRMSDs. The authors used self-administered questionnaire data collected from 252 mine workers for the analysis. The association between WRMSDs and psychosocial factors was determined using logistic regression. They found that the most common complaints reported were elbow, lower back, and knee pain and the risk of developing WRMSDs increases with job demands.

The research was performed by Balogun & Smith (2020) to study the prevalence of musculoskeletal symptoms and to identify the possible risk factors. They collected socio-demographic and work-related characteristics from 459 full-time mine workers. The authors used a questionnaire method to determine the prevalence of WRMSDs. The results of this study showed that Musculoskeletal Symptoms (MSS) of the lower back (57%), neck (38%), shoulder (38%), and knee (39%) were highly prevalent among mine workers. Their study also demonstrated that work hours per week and work type are the prominent factors leading to lower back and neck pain.

In 2021, Li et al. investigated the effects of mental health and occupational stress on WRMSDs. A total of 1675 valid questionnaires were recovered from 1800 coal miners from six companies to investigate the status of occupational stress, WRMSDs, and mental health. This study showed that the prevalence of WRMSDs was lesser in the control group than in the exposed group. This study also showed that sex, age, longer working years, shift work, education level, and monthly income are associated with WRMSDs.

2.4 Effect of Personal Factors and Socio-Demographic Factors on WRMSDs

A questionnaire study was performed by Calmels et al. (1998) to analyse the long-term effects of working conditions, post-retirement and advanced age on WRMSDs and occupational strain. They examined and evaluated the occupational strain, locomotion impairment, and functional independence of 350 subjects. The study concluded that low back, shoulder, or arm impairment and functional independence have significantly associated with occupational strain.

Later, Zejda and Stasiow (2003) studied the occurrence of osteophytes and narrowed disc spaces among the occupational working group. They used X-ray films to analyze the cervical spine of 685 samples. This data was used to analyze the suspected hand-transmitted vibration-related disorders of the study sample. The regression analysis conducted by the authors showed a significant association between age, narrowed disc spaces, and the occurrence of osteophytes.

Similarly, Bio et al. (2007) carried out a research work to identify the risk factors that causes LBP among underground gold miners. They selected 280 male miners working in underground mines using a random sampling approach. The prevalence of LBP and risk factors associated with LBP were administered through a questionnaire. The authors compared the prevalence of lower back pain among miners of different age groups, their smoking habits, and present occupations. The result of this study showed a higher prevalence of LBP among workers with a BMI greater than 23. This study revealed that the prevalence of low back pain is significantly associated with age.

The effect of psychosocial and physical risk factors on LBP and its consequence (reduced activities and absenteeism) was investigated by the Widanarko et al. (2015). The authors used questionnaires to collect data from 1294 coal miners. They placed them into one of four combination groups (i.e., high physical and high psychosocial, high physical and low psychosocial, low physical and high psychosocial, and low physical and low psychosocial). The study showed that coal miners in the high physical and psychological groups reported low back pain symptoms. Further, the authors stated that smoking, shift work, and non-permanent works are the causative factors for WRMSDs.

Aghillinejad et al. (2016) investigated the prevalence of WRMSDs in coal miners and determined its correlation with personal factors (i.e., age, experience, and BMI) of coal miners. The authors selected 505 mine workers from the study population. They collected data on WRMSDs, and demographic and work-related data using NMQ. The study found that MSS of the lumbar, knees, and low back in the previous week and during the last 12 months had a significant association with age but not BMI. The study also concluded that the prevalence of musculoskeletal symptoms in the previous week and year are significantly higher among the samples with 20 years of work experience compared to participants with work experience between 5 and 20 years.

A research work was performed by Ahmad and Alvi (2017) to determine the relationship between WRMSDs and socio-demographic factors. The authors compared the WRMSDs symptoms of 218 quarry workers and 203 comparison groups (never miners). The results of the study indicated that the prevalence of WRMSDs among the comparison group was less than quarry workers. Further, the statistical test conducted by the authors showed that age, BMI, and past injury are the risk factors associated with WRMSDs.

Further, Smith et al. (2020) predicted the health risks and musculoskeletal disorders among sand, stone, and gravel mine workers. The questionnaire data were collected from 459 stone, sand, and gravel mineworkers. They performed regression analysis to find the relationship between health factors and musculoskeletal symptoms. Their research showed that obese operators experience knee-related pain, operators who have smoking habits experience neck problems, and vigorous physical activity is positively associated with shoulder and neck pain.

The occurrences of WRMSDs and their causative factors in quarry workers were analyzed by Njaka et al. (2021). The data was collected from 226 randomly chosen samples using NMQ. The authors of the study identified the associated factors related to WRMSDs using the regression analysis technique. The results of the study showed that 89.8% of respondents had WRMSDs with LBP (83.1%) and elbow pain (45.9%) which was common in the study population. The authors concluded that BMI, age, experience, vibration exposure, working hours, and break time are risk factors associated with WRMSDs.

2.5 Effect of Environmental Factors on WRMSDs

The association of back pain with heavy lifting, low temperature, and wet clothing among mine workers was studied by Skandfer et al. (2014). The authors conducted a health survey of 3530 mine workers from four different mines. The results showed that 51% of the mine workers reported LBP in the last 12 months. Further, results showed that the adjusted odds ratio of LBP with respect to wet clothes, cold conditions, heavy lifting jobs, driving experience, and driving specific vehicles or trains were above one.

The prevalence of WRMSDs and related factors associated with perceived cold and pain was studied by Ringberg (2015). During damp and dry, the author collected the data using a questionnaire from 254 miners. The associations between the WRMSDs and exposure to cold were determined by the logistic regression analysis. The study showed that the association between WRMSDs and cold exposure was not significant.

The effect of environmental and socio-demographic factors on WRMSDs was investigated by Imran et al. (2020). The authors used subjective questionnaires with borg scale as an assessment tool to measure the importance of risk factors. The data collected from questionnaire administration was analyzed using a bivariate statistical technique. The results showed no significant association between muscle complaints and social-demographic factors, but environmental risk factors were significantly associated with WRMSDs.

In the research work performed by Yong et al. (2020), the occurrence of WRMSDs and the causative factors among coal mine workers were studied. The investigation was conducted using the job burnout scale and WRMSDs scale. The study concluded that years of service, posture, the maximum force applied, repeated movements, slip or fall incidents, temperature variations, job burnout levels, and shift work are the risk factors associated with the WRMSDs.

2.6 Summary

The comprehensive literature review focused on highlighting the risk factors associated with the WRMSDs. The research articles were shortlisted following the standardized PRISMA guidelines which resulted in a collection of 48 articles across 5 research categories (i.e., literature on effect of vibration exposure on WRMSDs, literature on effect of posture on WRMSDs, literature on effect of work related factors on WRMSDs, literature on effect of personal factors and socio-demographic factors on WRMSDs, literature on effect of environment factors on WRMSDs). Within the field of vibration analysis, an extensive review revealed that graders and drillers experience significant exposure to WBV. Their exposure showed a clear positive association with WRMSDs problems. The findings demonstrated that transport equipment operators face 4.06 times higher risk of WRMSDs compared to non-transport operators. Epidemiological studies established that occupational risk factors such as repetitive work, awkward postures, physical demands, and insufficient recovery time contribute to WRMSDs problems. Additionally, longer shift hours (i.e. >9hrs) were linked to an increased occurrence of WRMSDs. Results indicated that the adjusted odds ratio of LBP concerning wet clothes, cold conditions, heavy lifting jobs, driving experience, and operating specific vehicles or trains were consistently above one. However, there's a lack of comprehensive studies on posture, especially within the Indian context. Hence, the present study aims to assess the impact of sitting posture on WRMSDs problems among dumper operators working in Indian surface iron ore mines.

CHAPTER 3

3. QUESTIONNAIRE DEVELOPMENT, FEATURES OF THE CASE STUDY MINE AND DATA PREPARATION

In order to develop an effective questionnaire, multiple methods were used to ensure that the questions were appropriate and relevant. A thorough literature review was conducted to identify commonly used questions in the previous studies related to the research topic. Additionally, expert consultation which include ergonomist and safety expert were sought to gather insights from subject matter. Further, focus groups (dumper operators) were also consulted to gather inputs from potential respondents on the type of questions that would be most appropriate for the questionnaire. By adapting this process, the questionnaire was developed with due consideration and attention so as to ensure the questions are clear, concise, and unbiased.

The developed self-report questionnaire included questions related to the risk factors associated with WRMSDs, such as personal factors (i.e. age, work experience, marital status, and education), habitual factors (i.e. smoking, alcohol consumption, tobacco chewing, and medication use), and work-related factors (i.e. working posture, repetitive work, job demand, and work design).

To evaluate the prevalence of WRMSDs, this study utilized the standard Nordic Musculoskeletal Questionnaire (Crawford, 2007). Both questionnaires were combined to form a booklet (which is given in Appendix – 1 and 2), and was distributed among the dumper operators during the field visit.

3.1 Features of Case Study Mine

A mechanized surface mine situated in the northern part of Karnataka state was selected to study the risk factors associated with WRMSDs problems among the dumper operators population. This mine was involved in extraction of iron ore with annual production capacity of 6MTPA. The mine was working for six days per week with two shifts of eight hours per day. There were two open pits covering a total area of 62Ha.

Further, 25.61 Ha of land was utilized for infrastructure and road facilities. The mine has two dead dumps, two active dumps, and one settling pond. In total, there were 11 excavators, nine wheel loaders, 35 dumpers, two dozers, and four water tankers to extract ore from the mine site. The salient geological and mining-related information of the case study mine is shown in Table 3.1.

Table 3.1: Background of case study mine

Particulars	**Attribute**
Number of pits	2(north &south)
Total pit Area	62 Ha
Reclaimed area	23.24 Ha
Waste disposal area	40.25 Ha
Infrastructure and road area	25.61 Ha
Stack area	9.49 Ha
Yearly production capacity	6 MTPA
Current production	2.29 MTPA
Number of active dumps	2 nos.
Number of dead dumps	2 nos.
Number of settling ponds	5 nos.
Number of excavators	11 nos.
Number of wheel loaders	9 nos.
Number of dumpers	35 nos.
Capacity of dumper	31Tons
Number of dozer	2 nos.
Number of water tankers	4 nos.

3.2 Sample Selection

To obtain a representative sample for the study, a random sampling approach was adapted to select dumper truck operators who were employed in surface metal mines. Inclusion criteria were established, which required participants to have a minimum of six months of work experience in their current role and be free from significant injuries, surgeries, or absences from work exceeding two consecutive weeks due to health reasons. A total of 248 dumper truck operators met these criteria and were included in the final sample. This method ensured that sample represent the dumper population while minimizing the potential confounding factors that could influence the study results.

3.3 Data Collection

The questionnaire booklet was distributed to the selected sample of 248 dumper operators. The questionnaire booklet was administered in-person by trained research assistants, who were available to answer any questions and provide guidance if needed. Participants were assured of the confidentiality of their responses. Data collection was carried out over a period of 10 days, after which the completed questionnaires were collected and checked for completeness and pre-processing of the data was carried out Figure 3.1 shows the process involved in pre-processing of the data collected.

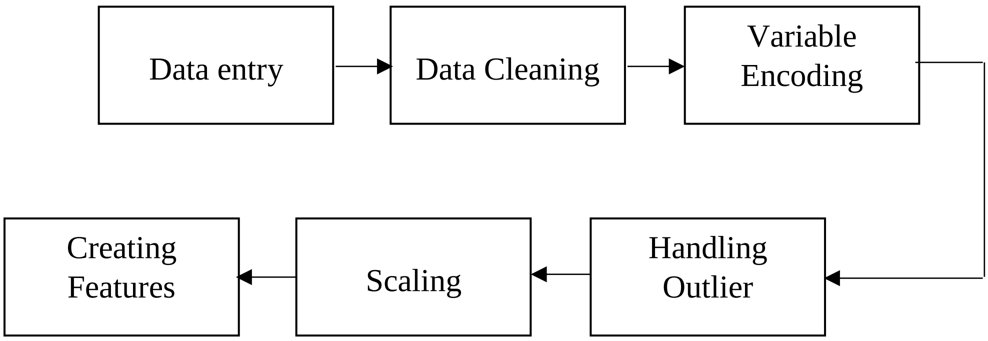


Fig. 3.1 Steps in data preprocessing

3.4 Data Pre-processing

3.4.1 Data entry

The data obtained from the questionnaire booklets were entered into a database (MS Excel) and a unique identifier was assigned to each response. To reduce errors during data entry, a double-entry method was implemented, wherein two research assistants entered the same data independently. Any inconsistencies between the two entries were resolved by carefully reviewing the original questionnaire booklet.

3.4.2 Data cleaning

The data was cleaned to identify and correct any errors in the dataset. This involved checking for missing or incomplete responses to reduce biased estimates and to increase accuracy of the statistical models. In the scientific study, one approach that had been considered for dealing with missing or incomplete data is to drop the observations or variables with missing values. However, since number of data points in the present study is relatively low, this approach could lead to the loss of important information, especially when the missing values were not randomly distributed. Hence, in this study the missing values are handled using statistical techniques, such as mean imputation and mode imputation. For the categorical variables, the mode of the variable value was determined and used for imputation of missing values. Similarly, for the continuous variables, the mean value was calculated and used to impute missing values. Further, in certain scenarios the expert knowledge was used to impute missing values. For example, medical professionals working in mine dispensary provide estimated values based on their expertise while dealing with missing variables such as age, BMI etc.

3.4.3 Categorical variable encoding

Once the dataset was cleaned the next step was encoding of categorical variables. In this study, it was observed that most of the variables in the dataset were categorical in nature, and therefore it was necessary to encode them for model building. In general, dummy coding and effect coding are two methods of encoding techniques. Dummy coding, also known as one-hot encoding involves converting each category of the categorical variable into a separate binary variable, where the presence of the category is indicated by a value of 1, and the absence by 0. In effect coding, each category is compared to the average value of all categories. Effect coding is found to be useful particularly when dealing with a large number of categories or when the categories were ordinal. Since the number of variables in this study was relatively small one-hot encoding method was employed for coding the categorical variables.

3.4.4 Handling outliers

The outliers are the observations that deviated significantly from the other observations in a dataset. These outliers could distort the statistical properties of the data, leading to biased estimates and models. Thus, it was important to use the effective strategies for detecting and handling outliers.

While handling data the outliers in the dataset can be removed my graphical method and also using mathematical functions, such as logarithmic or square root transformations. However, when mathematical functions were used to remove the outlier, there was no significant improvement in the result. Hence, this study graphical approach was used for all variable to remove the outlier. As shown in the Figure 3.2

in the graphical method the plots such as box plots, scatter plots, and histograms were drawn and the outliers were identified, and removed from the dataset.

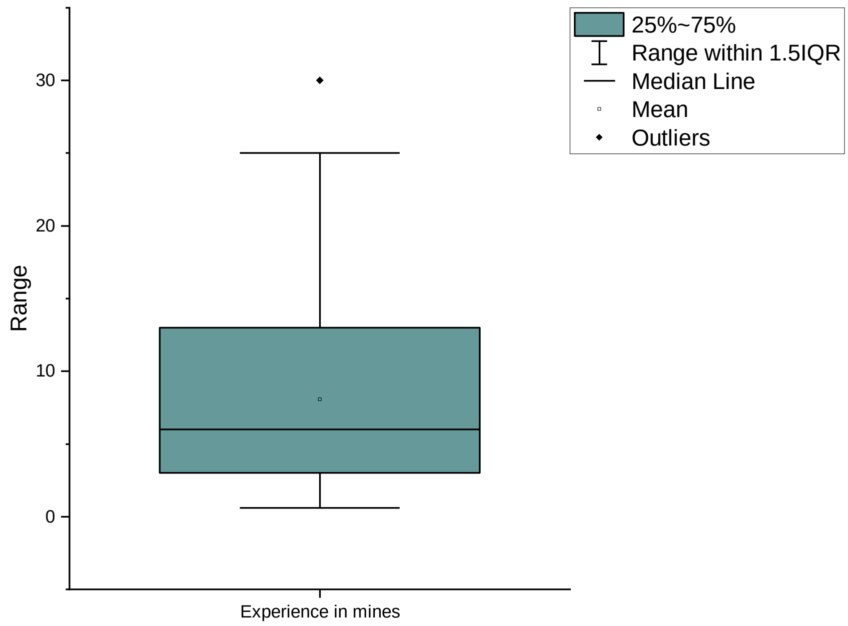


Fig. 3.2 Outlier detection using graphical method

3.4.5 Scaling

Scaling is an important step of data pre-processing in data science research. It transform the values of variables to a common scale or range. The purpose of scaling is to ensure that all variables have equal importance in the analysis and to avoid the dominance of variables with large values. Scaling is important since ML algorithm such as support vector machine are sensitive to the scale of the variables.

There are several methods for scaling variables. Some of the common methods which are extensively used are standardization, and normalization. Standardization involves subtracting the mean value of the variable from each observation and dividing it by the standard deviation of the variable. This method transforms the variable to have a mean of 0 and a standard deviation of 1. Normalization involves scaling the variable between 0 and 1. This is done by subtracting the minimum value of the variable from each observation and dividing it by the range of the variable. In this study, the dataset variables are scaled to the values between 0 and 1 using normalization method.

3.4.6 Creating features

Features are attributes or variables that describe the data and provide information that can be used to predict outcomes or classify observations. Creating features involves selecting, transforming, and engineering variables that are relevant to the research question and to the predictive model being developed.

In this study, since output variables are more than one, it was decided to merge all output variables to form a new categorical variable with the name "status of WRMSD" having two categories "with WRMSD" and "without WRMSD". The new variable is coded as ‘0’ if summation of "without WRMSD" dominate "with WRMSD" or else ‘1’ if "with WRMSD" dominate over "without WRMSD". After these steps were completed, the dataset was analyzed further through univariate analysis, data splitting, model selection, and model evaluation.

CHAPTER 4

4. UNIVARIATE AND MULTIVARIATE ANALYSIS OF RISK FACTORS

After pre-processing the data, the subsequent step involved identifying the risk factors associated with WRMSD problems in the selected population. This was accomplished through conducting both univariate and multivariate analyses of the risk factors.

4.1 Univariate Analysis

Univariate analysis is a statistical method which is used to analyse a single variable. It involves examining the distribution, central tendency, and variability of a variable to gain insights into its characteristics and to identify any patterns or trends. Univariate analysis is the first step in data analysis and will provide important information about the data, such as the range and skewness of the variable. This is achieved by determining the descriptive statistics, visual observation of the data and determining the correlation between the variables.

4.1.1 Descriptive statistics

One of the most common techniques used in univariate analysis is descriptive statistics. This involves calculating measures, such as the mean, median, mode, range, and standard deviation of a continuous variable and frequencies, percentages, fractions and/or relative frequencies for the categorical variables. The descriptive statistics of the study variables are shown in the Table 4.1.

Table 4.1: Characteristics of dumper operators

	Variable	**Response**	**Mean ± SD or n (%)**
Personal factors	Age (years)		38.47 ± 7.65
	Height (m)		1.71 ± 0.066
	Weight (Kg)		76.5 ± 10.13
	BMI		25.9 ± 3.06
	Experience in mines (years)		21.62 ± 6.32
	Education	no formal education	10(4)
		primary education	101(40.3)
		secondary education	101(40.3)

		tertiary education	36(14.5)
	Marriage Status	single	48(19.5)
		married	192(78)
		divorced	6(2.4)
Habitual factors	Medicine	yes	72(29.3)
		no	194(70.7)
	Smoking Cigarette	no	206(83.7)
		yes	40(16.3)
	Alcohol consumption	no	172(69.9)
		yes	74(30.1)
Work-related factors	Job demand	no	176(71.5)
		yes	70(28.5)
	Work design	no	220(89.4)
		yes	26(10.6)
	Repetitive work	no	172(69.4)
		yes	74(29.8)
	Awkward posture	no	224(90.3)
		yes	22(8.9)

4.1.2 Visual observation

The data distribution of the variables related to the personal factors of the study population was determined first. The trend in the educational attainment levels of the study participants were examined. Figure 4.1 shows the results which indicates that the majority of the sample completed education beyond high school, with 40.7% having completed pre-university education and 14.6% having completed a degree program. In contrast, only 4.1% of participants reported completing education till the primary level. It was also observed that 40.7% of the sample had completed education till high school. Additionally, the study found that 25.2% of the participants were single, while 71.5% were married. Only a small proportion of participants, 3.3%, reported being divorced (Figure 4.2).

Similarly, the prevalence of tobacco chewing habit among the study participants was examined and the results are shown in the Figure 4.3. The results indicated that a 42.3% of the sample, reported habit of tobacco chewing. The study participants' medical history was examined to determine the prevalence of medicine intake among the sample.

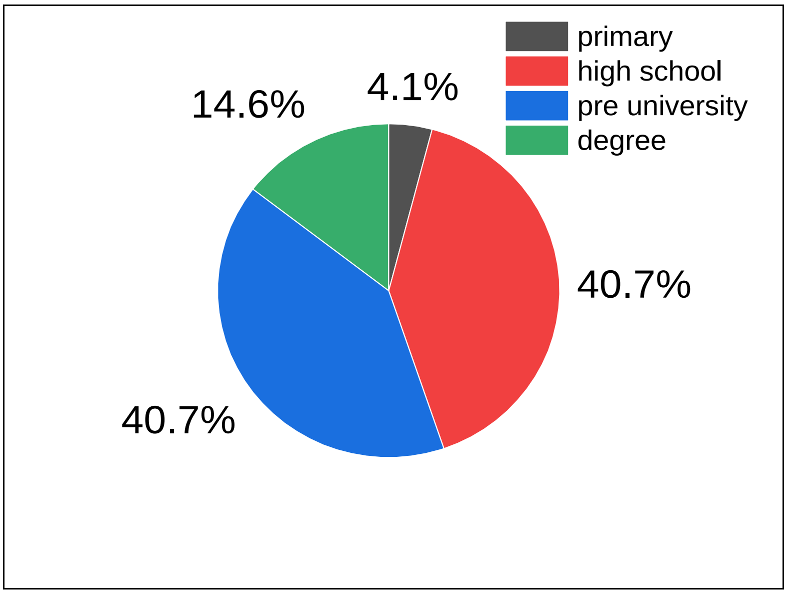


Fig. 4.1 Pie chart showing the education qualification of the dumper operators

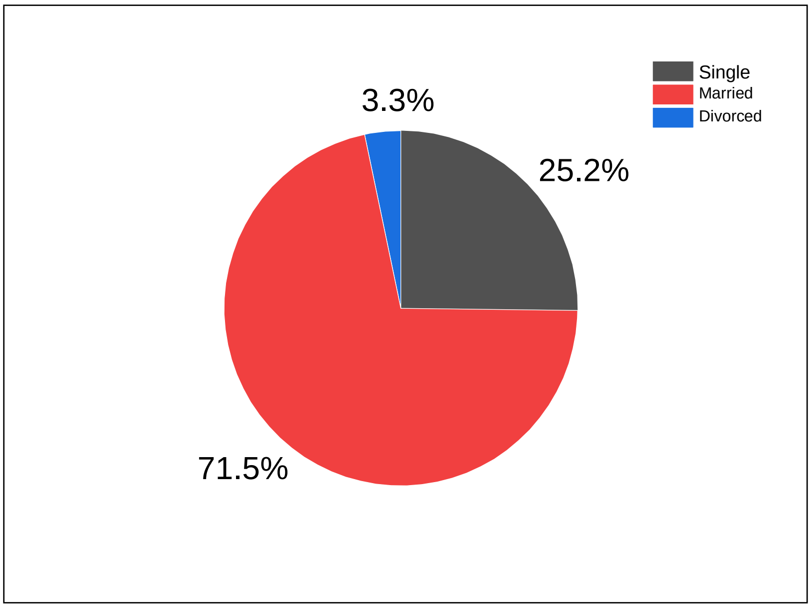


Fig. 4.2 Pie chart showing the marital status of the dumper operators

The findings as shown in Figure 4.4 revealed that 29.3% of the participants reported taking medication regularly.

During the univariate analysis of the study participants, the prevalence of smoking was examined and the results is given in Figure 4.5. These results shows that 16.3% of the sample reported being current smokers.

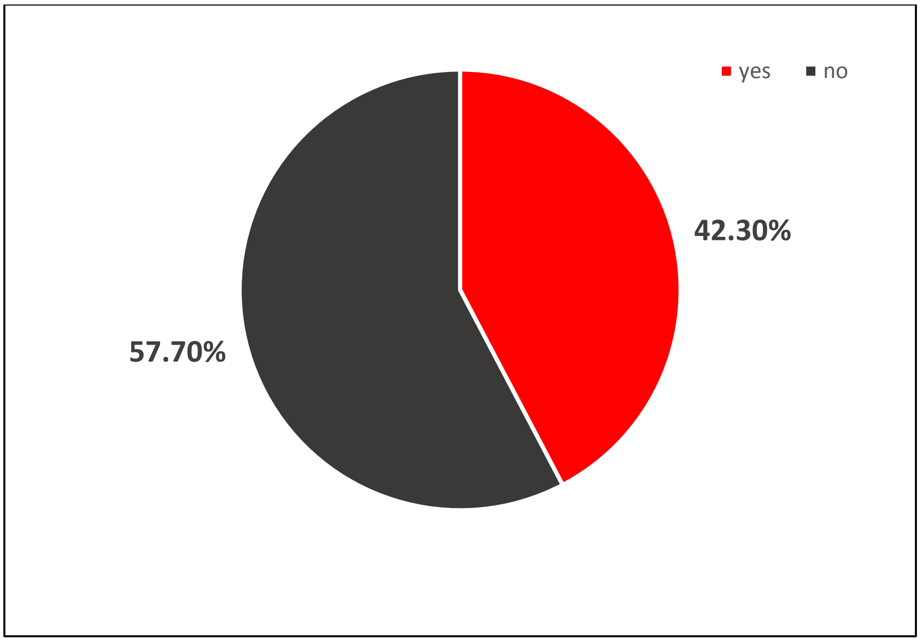


Fig. 4.3 Pie chart showing the extend of tobacco chewing habits of the dumper

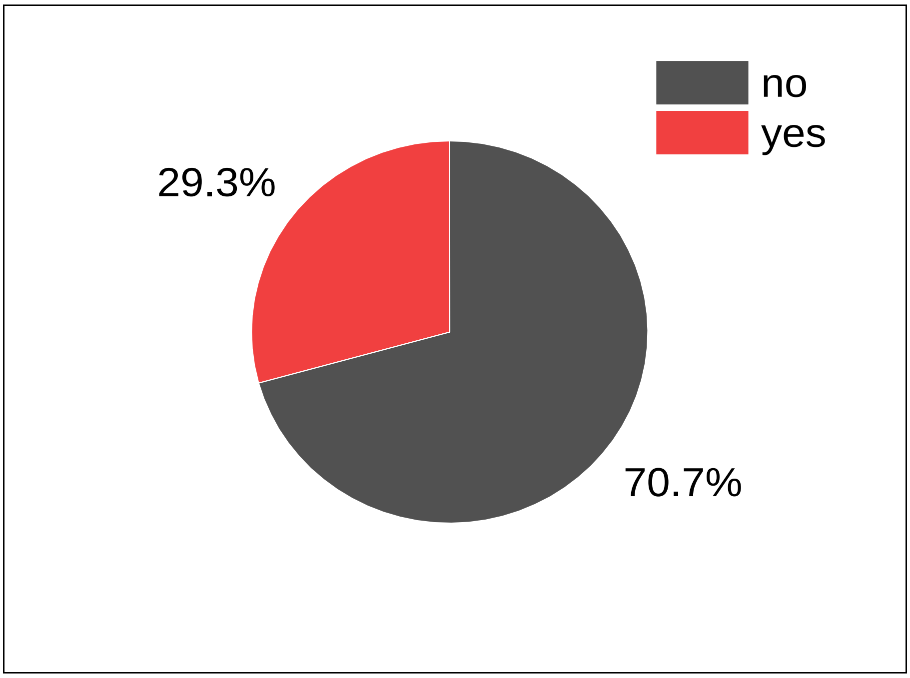


Fig. 4.4 Pie chart showing the percentage of dumper operators taking medication

Similarly, the prevalence of alcohol consumption was examined. As shown in Figure 4.6 the results indicates that 30.1% of the sample reported being drinkers.

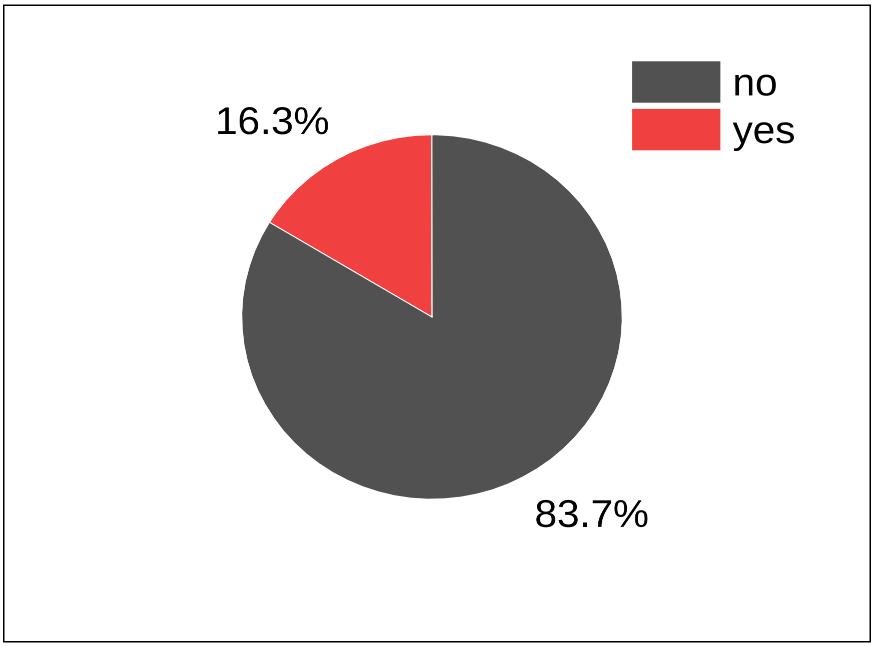


Fig. 4.5 Pie chart showing the percentage of dumper operators having smoking habits

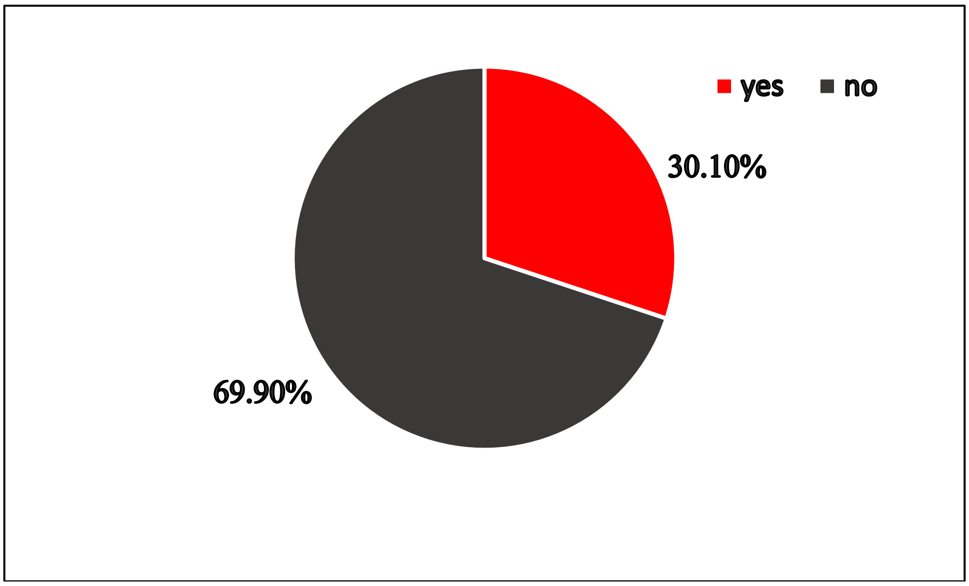


Fig. 4.6 Pie chart showing the alcohol consumption of the dumper operators

Univariate analysis of work-related factors indicates several important findings. It was found that a large majority of dumper operators (89.4%) believed that the work design was not good (as shown in Figure 4.7), while 71.5% of drivers reported that the job demand was high (as shown in Figure 4.8).

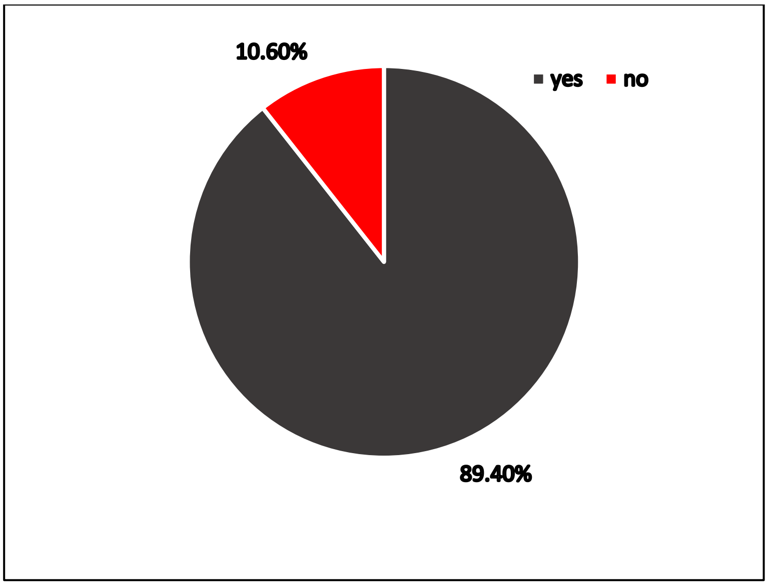


Fig. 4.7 Pie chart showing the operator's feedback on work design

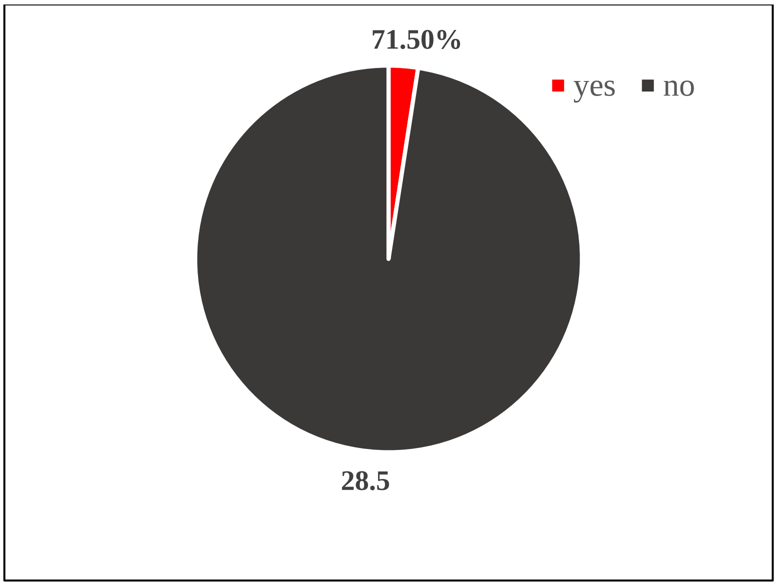


Fig. 4.8 Pie chart showing the operator's feedback on Job demand

Further, as shown in the Figure 4.9, 69.9% of the sample indicates that the operators were performing repetitive work, and a significant proportion (i.e. 91.1%) of the operators reported sitting in awkward postures as shown in Figure 4.10 during work. Graphical analysis of the data reveals that work-related factors contributing to the health and safety risks faced by dumper drivers. The findings underscore the need for further investigation for the detailed study of the risk of work-related injuries among dumper drivers.

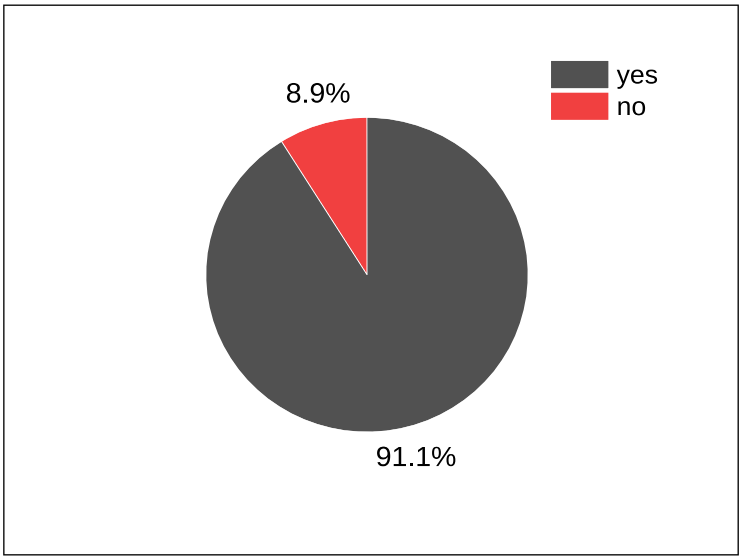


Fig. 4.9 Pie chart showing the operator’s feedback on repetitive work

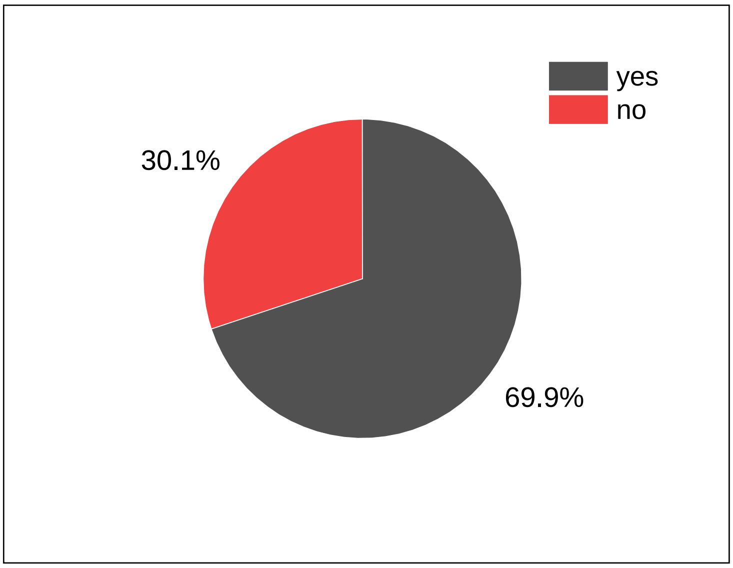


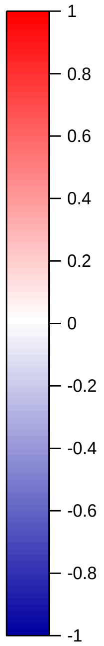
Fig. 4.10 Pie chart showing the operator’s feedback on awkward posture

4.1.3 Correlation coefficients

Correlation coefficient is often used to identify variables that are strongly associated with another independent variable. As indicated in Table 4.2, a moderate but significant correlation was found among the variables belonging to personal factors (i.e., age, experience in mines, education and marriage status). Similar trend was also observed among the variables belonging to the habitual factors (i.e., tobacco chewing, medicine intake, smoking cigarettes, alcohol consumption) and work-related factors (i.e., awkward posture, repetitive work, job demand, and work design).

Table 4.2: Correlation coefficient of the personal, habitual and work-related factors

	Age	Experience in mines	Childrens	Education	Marriage status	Tobacco chewing	medicine	smoking cigarettes	Alcohol consumption	Awkward posture	Repititive work	Job demand	Work design
Age	1	0.26	0.32	-0.34	0.18	0.019	-0.12	0.024	-0.15	0.097	0.0048	0.13	-0.14
Experience in mines	0.26	1	0.22	-0.16	0.21	0.15	0.043	-0.071	-0.052	-0.049	0.044	-0.13	-0.088
Childrens	0.32	0.22	1	-0.15	0.23	-0.051	0.081	-0.13	0.033	-0.1	-0.22	-0.19	-0.052
Education	-0.34	-0.16	-0.15	1	-0.18	0.08	0.0068	-0.062	0.015	-0.16	-0.15	-0.024	0.12
Marriage status	0.18	0.21	0.23	-0.18	1	0.082	0.07	0.063	0.0044	0.024	-0.032	0.025	0.046
Tobacco chewing	0.019	0.15	-0.051	0.08	0.082	1	0.57	0.024	0.52	-0.095	0.049	0.12	-0.027
medicine	-0.12	0.043	0.081	0.0068	0.07	0.57	1	0.1	0.51	-0.076	-0.032	-0.049	-0.047
smoking cigarettes	0.024	-0.071	-0.13	-0.062	0.063	0.024	0.1	1	-7.8E-4	0.094	0.14	0.16	-0.0082
Alcohol consumption	-0.15	-0.052	0.033	0.015	0.0044	0.52	0.51	-7.8E-4	1	-0.081	0.11	0.097	-0.053
Awkward posture	0.097	-0.049	-0.1	-0.16	0.024	-0.095	-0.076	0.094	-0.081	1	0.29	0.37	0.26
Repititive work	0.0048	0.044	-0.22	-0.15	-0.032	0.049	-0.032	0.14	0.11	0.29	1	0.37	0.24
Job demand	0.13	-0.13	-0.19	-0.024	0.025	0.12	-0.049	0.16	0.097	0.37	0.37	1	0.25
Work design	-0.14	-0.088	-0.052	0.12	0.046	-0.027	-0.047	-0.0082	-0.053	0.26	0.24	0.25	1



4.2 Multivariate Analysis

4.2.1 Study design

As discussed in the earlier chapter to conduct the multivariate analysis 248 dumper operators were selected from the case study mine those who meet the inclusion criteria (such as age between 18 and 56 years, at least 6 months of professional driving experience) and exclusion criteria (such as no history of injuries). Data was collected using a standard Nordic (Kuorinka et al. 1987) and custom questionnaire (which is given in Appendix – 1 and 2).

The collected data after pre-processing (i.e., data entry, data cleaning, categorical variables encoding, handling outliers, data scaling, and feature creation) was split into training (80%) and testing (20%) datasets. The ML models (such as Logistic Regression (LR), Support Vector Machine (SVM), Decision Tree (DT), Gradient Boosting (GB), and Random Forest (RF)) were then developed and validated with the help of training and testing datasets.

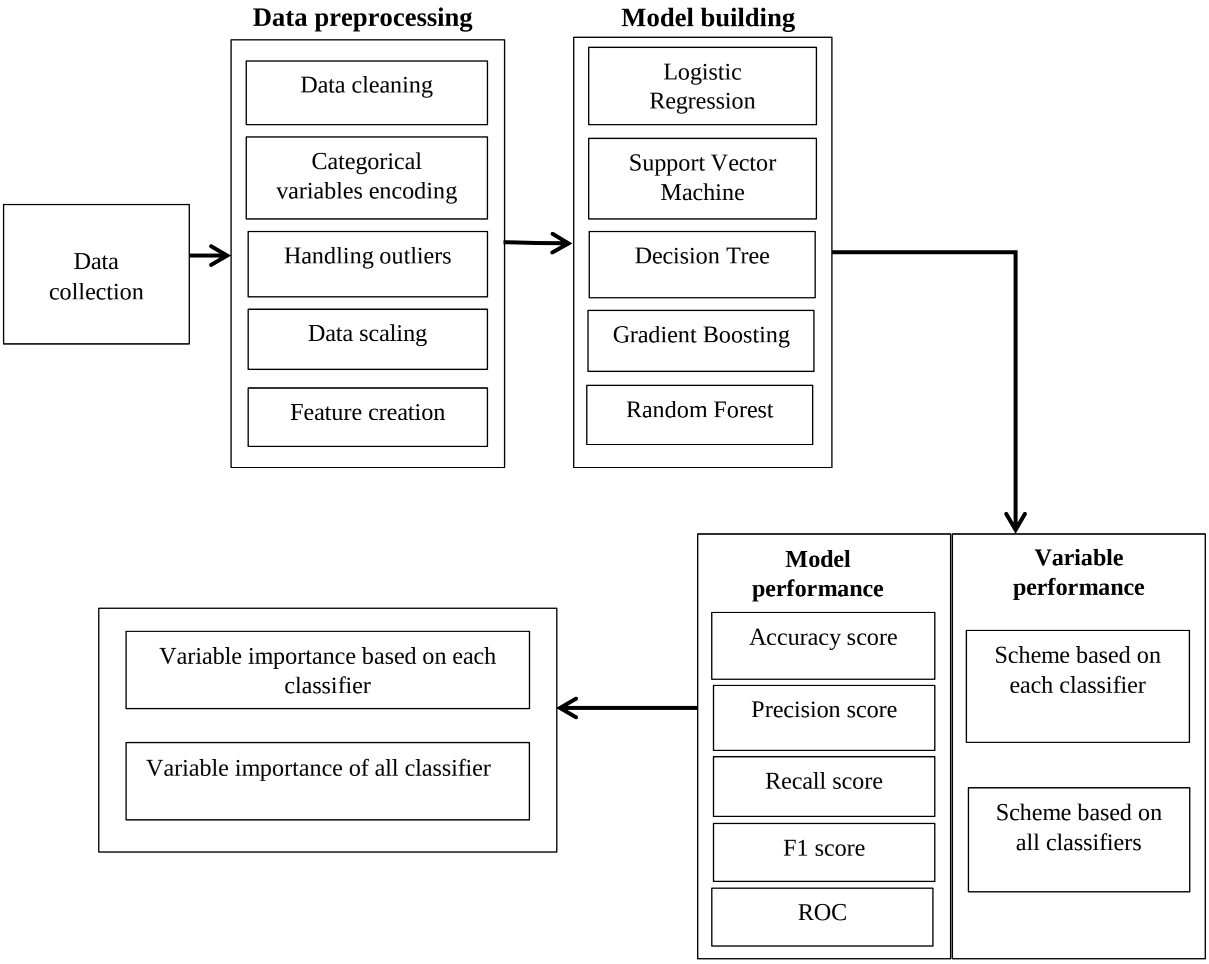


Fig. 4.12 Study design to determine the risk factors associated with WRMSD among dumper operators population

The data analysis was done with the help of scikit-learn Python library and the best fit model for predicting the WRMSDs among the dumper operators was determined based on the model's accuracy, precision, recall score, F1 score, and area under the Receiver Operating Characteristic curve (ROC). The flow chart of the study design is shown in the Figure 4.12.

4.2.2 Results and Discussion

This study demonstrated the importance of the risk factors based on the model coefficient (in the case of LR and SVM) and feature importance scores (in the case of DT, GBM, and RF). Similarly, the best model for predicting the WRMSDs among the dumper operators was determined based on the model's accuracy, precision, recall score, F1 score, and area under the Receiver Operating Characteristic curve (ROC).

4.2.2.1 Logistic Regression

Logistic Regression (LR) is a statistical model used for the analysis of classification problems. According to the Table 4.3, 'experience in mines', 'medicine', and 'work design' had a negative impact on the WRMSD. On the other hand, the 'age', 'smoking cigarettes', 'alcohol consumption', 'marriage status, 'awkward posture', and 'job demand' positively impacted the outcome. The most significant coefficient was observed was awkward posture (0.82), alcohol consumption (0.58), medicine (-0.87), and job demand (0.47), indicating that these variables have the most substantial influence on the WRMSD.

As given in the Table 4.4, when the performance of the LR model was evaluated on the test dataset, it showed that the model had an accuracy of 0.64, a precision score of 0.69, a recall score of 0.66, and an F1 score of 0.68. This accuracy score indicates that the LR model correctly predicted the target class for 64% of the instances, which is a moderate level of performance. The precision score of 0.69 suggests that the model correctly predicted the target class for 69% of the time when it made a positive prediction. However, the recall score of 0.66 indicates that the model could only identify 66% of the instances that belongs to the target class. The F1 score, (a balanced measure of precision and recall) of 0.68, suggests that the model's overall performance is moderate, with a scope for improvement in correctly identifying all instances of the target class.

4.2.2.2 Support Vector Machine

Similar to LR, in the Support Vector Machine (SVM), the most positive and significant coefficient was associated with alcohol consumption (1.15) followed by awkward posture (1.03), and job demand (0.59), indicating that these variables have the strong and positive influence on the WRMSDs. Further, experience in mines (-0.41), medicine (-1.17), work design (-0.18), and marriage status (-0.08) were found to have a negative impact on the WRMSDs (Table 4.3).

The SVM model performance was evaluated with accuracy, precision, recall, and F1 score metrics. As given in the Table 4.4 the SVM model achieved an accuracy of 0.64, a precision score of 0.76, a recall score of 0.54, and an F1 score of 0.63. The relatively high precision score compare to LR model indicates that the model is better at identifying true positives than avoiding false positives. However, the recall score is lower, showing that the model misses a significant number of actual positive cases. The F1 score suggests that the model's overall performance is moderate.

4.2.2.3 Decision Tree

The Decision Tree (DT) is a tree-like structure, where each internal node represents an attribute test, each branch represents the output of the test, and each leaf node corresponds to a category. In this study, the DT algorithm was trained on the training dataset using Gini impurity as the splitting criterion and default parameters of the scikit-learn library. The DT was developed with a maximum depth of 4. As given in Table 4.1 the age (0.42), experience in mines (0.21), and job demand (0.079) were the most significant risk factors associated with WRMSD. When the model was tested using the test dataset, it achieved an accuracy of 0.63, a precision score of 0.72, a recall score of 0.77, and an F1 score of 0.74, which is given in Table 4.4. The recall score is the highest among all the evaluation metrics, indicating that the DT model is good at identifying the true positives. The precision score is also relatively high, indicating that the model is effective at avoiding false positives. The F1 score is a balanced measure of precision and recall, and designator that the model's overall performance is good.

4.2.2.4 Gradient boosting

The Gradient Boosting (GB) model was obtained by training the various weak classifiers for the same training data set and then merging these classifiers to create a stronger final classifier. The goal is to optimize classification results through multiple iterations and address the weaknesses by combining weak classifiers.

Table 4.3: Feature importance/rank obtained from LR, SVM, DT, GB, and RF models

Rank	Machine learning models									
	LR		SVM		DT		GB		RF	
	Variable		Variable		Variable		Variable		Variable	
1	Age	1.02	Age	1.42	Age	0.42	Age	0.36	Age	0.42
2	Medicine	-0.87	Medicine	-1.17	Experience in mines	0.21	Experience in mines	0.27	Experience in mines	0.29
3	Awkward posture	0.82	Alcohol consumption	1.15	Job demand	0.079	Awkward posture	0.14	Job demand	0.09
4	Alcohol consumption	0.58	Awkward posture	1.03	Awkward posture	0.077	Alcohol consumption	0.09	Awkward posture	0.08
5	Job demand	0.47	Smoking cigarettes	1	Medicine	0.072	Medicine	0.05	Medicine	0.05
6	Smoking cigarette	0.42	Job demand	0.59	Alcohol consumption	0.057	Smoking cigarettes	0.033	Smoking cigarettes	0.05
7	Work design	-0.19	Experience in mines	-0.41	Marital status	0.027	Job demand	0.032	Alcohol consumption	0.04
8	Experience in mines	-0.13	Work design	-0.18	Smoking cigarettes	0.027	Work design	0.02	Work design	0.02
9	Marital status	0.015	Marital status	-0.08	Work design	0.021	Marital status	0.01	Marital status	0.01

The results showed that age (0.36), experience in mines (0.27), and awkward posture (0.14) are the most prominent risk factors associated with WRMSDs as given in Table 4.3. The results given in the Table 4.4 reveals that the GB model have an accuracy of 0.61, and its precision score, recall score, and F1 score are 0.77, 0.72, and 0.75, respectively. The precision score is higher than the recall score, indicating that the model is better at correctly identifying true positive cases than avoiding false negative ones. However, the F1 score, which considers precision and recall, suggests that the GB model's overall performance is fair.

4.2.2.5 Random Forest

RF is an algorithm that combines bagging ensemble learning theory with a random subspace approach. RF generates many decision trees for the random data at training time. Each tree provides a classification, and the RF chooses the classification with the most votes.

As given in Table 4.3, the RF model ranked age (0.42), work experience (0.29), and job demand (0.09) as the critical parameters that are associated with the WRMSDs. Further, Table 4.4 indicates that the RF model has an accuracy of 0.71, a precision score of 0.75, a recall score of 0.78, and an F1 score of 0.76. The model performed well in accuracy and precision, indicating that it correctly classified a high percentage of positive samples. The recall score reveals that the model also identified a significant number of true positives, although it may have missed some positive samples. The F1 score indicates that the RF model's overall performance is moderate.

4.2.2.6 Comparing the performance of ML models

In this study, the Receiver Operating Characteristic curve (ROC) was used to compare the performance of five different ML algorithms. The Figure 4.13 shows that the ROC curve of the RF model has highest area (0.82), followed by GB (0.79), DT (0.76), SVM (0.73), and LR (0.69). These results suggest that RF is the most accurate algorithm for the present dataset.

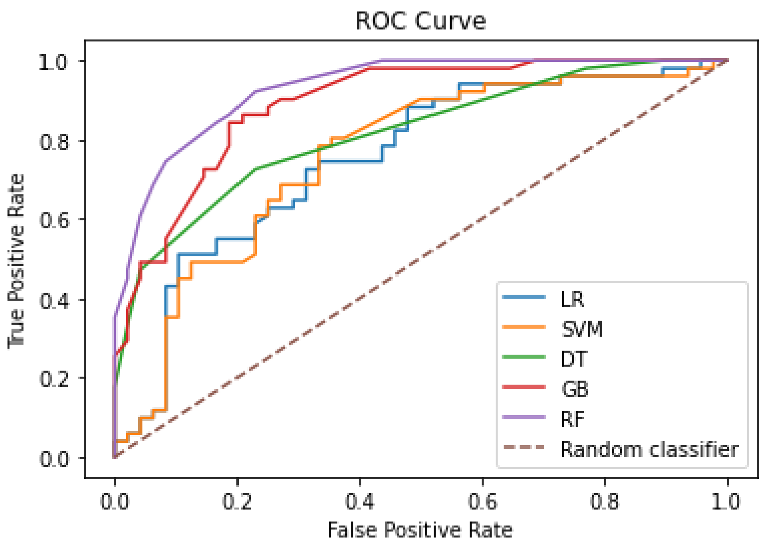


Fig. 4.13 Area under ROC for the LR, SVM, DT, GB, and RF models

As indicated in the Table 4.4, while comparing the performance metrics, the RF model had relatively high metric values compared to the other models. There are several possible explanations for why RF performed better than the other algorithms. RF is a non-parametric algorithm; it does not make any assumptions about the data distribution. This makes it more robust to noise and outliers in the data. Furthermore, RF is an ensemble algorithm, where it combines the predictions of multiple decision trees. This helps to reduce the variance of the predictions and improve the overall accuracy.

Table 4.4: Comparison of ML model performance

	LR	**SVM**	**DT**	**GB**	**RF**
Accuracy	0.64	0.64	0.63	0.61	0.71
Precision	0.69	0.76	0.72	0.77	0.75
Recall	0.66	0.54	0.77	0.72	0.78
F1 score	0.68	0.63	0.74	0.75	0.76

4.2.2.7 Mean rank of the risk factors

The rank of the risk factors is highly dependent on the ML model used. The mean rank of the risk factors was determined to get a generalized idea about the importance of the risk variables. As indicated in Table 4.5 the age is highly associated with WRMSDs, followed by awkward posture, experience in mines, job demand, alcohol consumption, smoking cigarettes, work design, and marriage status.

Table 4.5: The mean rank of the risk factors associated with the WRMSD

ML Models		LR	SVM	DT	GB	RF	Mean rank
Feature importance rank	**Age**	1	1	1	1	1	1
	Work experience	8	8	2	2	2	4.4
	Smoke cigarettes	6	5	8	6	6	6.2
	Alcohol consumption	4	3	6	4	7	4.8
	Marital status	9	9	7	9	9	8.6
	Work design	7	7	9	8	8	7.8
	Job demand	5	6	3	7	3	4.8
	Awkward posture	3	4	4	3	4	3.6
	Medicine	2	2	5	5	5	3.8

4.2.3 Reliability of the questionnaire data

The stability and consistency of the questionnaire data over time were assessed by re-administering it to a subset of the sample after a 9-month interval. A total of 20% of the participants were selected to participate in the retest. By comparing the responses at Time 1 and Time 2, the consistency of the measurements over the extended period was tested. The result indicated a strong (ranging from 0.82 to 0.91) and statistically significant correlation between the responses to the items of the custom questionnaire at Time 1 and Time 2.

CHAPTER 5

5. POSTURAL ANALYSIS USING FUZZY LOGIC-BASED RAPID UPPER LIMB ASSESSMENT TECHNIQUE

Figure 5.1 depicts the flow chart outlining the study design to determine the fuzzy logic based Rapid Upper Limb Assessment (RULA). The study consists of sample selection, data collection, fuzzification, and defuzzification.

5.1 Data Collection

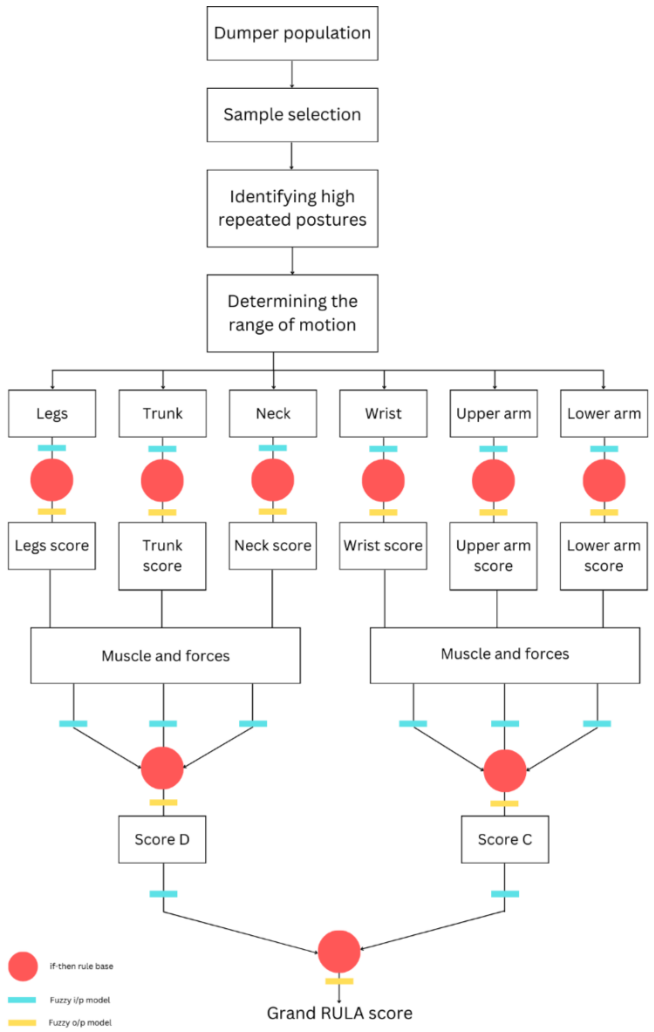


Fig. 5.1 Study design for calculating fuzzy RULA score

Initially the operators were briefed about the purpose of the study in the local language. A digital camera (Nikon D5600) was installed inside the dumper cabin to record the driver’s driving posture in sagittal plane. The dumper operators were instructed to continue their normal work and their driving posture was recorded while performing different job cycle. The recorded footage was manually examined, and highly repeated driving postures were extracted. Further, the Range of Motion (ROM) of different body parts (i.e. upper arm, lower arm, wrist, neck, trunk and legs) was measured from the image using ImageJ software package. Figure 5.2 shows the typical posture of the operator during loading operation.

Fig. 5.2 A typical posture adopted by the dumper operator while performing the loading operation

5.1.1 Fuzzification and defuzzification of the first layer

The fuzzification involves converting the input parameters into membership values ranging from 0 to 1. Figure 5.3 shows the fuzzy model to convert neck angle to membership values. It comprises of two fuzzy models: input and output. The fuzzy input model converts the neck angle into a membership value with the help of four sets of membership functions. The first membership function (i.e. trapezoidal membership function) of the input model converts the angle of extension (i.e. backward bending) into a membership value. The second and third membership functions (i.e. triangular membership functions) convert neck angles between 0 to 10 degrees and 10 to 20 degrees, respectively, into corresponding membership values. Similarly, the fourth membership function (i.e. trapezoidal membership function) converts neck angle greater than 20 degrees into membership values.

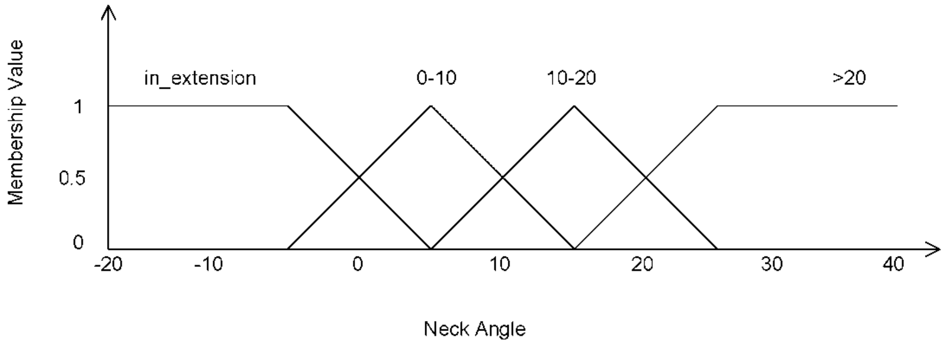


Fig. 5.3 Fuzzy input model for the neck

Similar to the fuzzy input model, the fuzzy output model was developed that converts membership values obtained for the fuzzy input model into the risk score. The input and output fuzzy models are interconnected through four sets of if-then rules (i.e. if the neck angle is within the range of 0 to 10 degrees, the neck score will be 1. If it is between 10 and 20 degrees, the neck score will be 2. If it exceeds 20 degrees, the neck score will be 3. In case of backward bending the neck score will be 4.). The fuzzy input model, fuzzy output model, and if-then rules were coded in MATLAB, such that when the ROM of the neck is given as input the fuzzy interface system gives neck score as output (as shown in Figure 5.4).

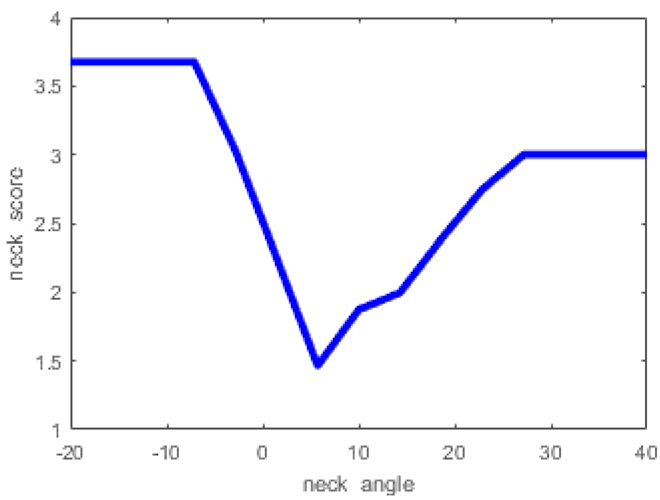


Fig. 5.4 Graph showing the relationship between the neck angle and neck score

In a similar way, the risk scores for the other body parts were also calculated. After calculating risk scores for all the body parts, the adjustment values, such as muscle and forces score, were added using the standard RULA score sheet.

5.1.2 Fuzzification and defuzzification of the second layer

The second layer consists of two fuzzy interface system, which were developed using Table A and Table B of the standard RULA chart. The output of the first layer of the fuzzy interface system was given as input to the second layer. The first fuzzy interface system of second layer uses 144 sets of if-then rules (which were created using Table A of the standard RULA score chart) and the risk scores of the upper arms, lower arms, and wrist to generate appendicular region score as output (as shown in Figure 5.5). Similarly, the second fuzzy interface system of second layer uses 72 sets of if-then rules constructed using Table B of the RULA score chart and risk scores of the neck and trunk to produces an axial region score as output.

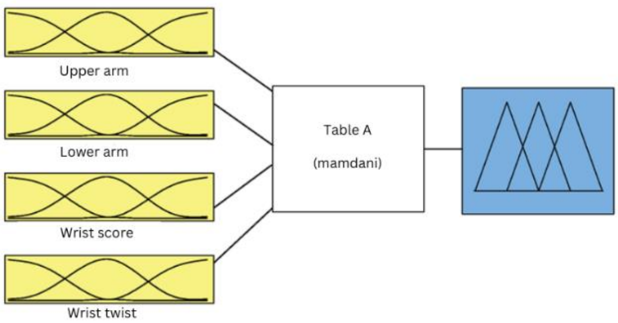


Fig. 5.5 Fuzzy interface system constructed using Table A of the RULA score sheet

5.1.3 Fuzzification and defuzzification of the third layer

As shown in Figure 5.6, the final score was calculated by adjusting the axial and appendicular score obtained from the second layer and then giving it as input to the third layer of the fuzzy interface system. The third layer of the fuzzy interface system uses axial and appendicular region score along with 56 sets of if-then rules to compute the grand RULA score.

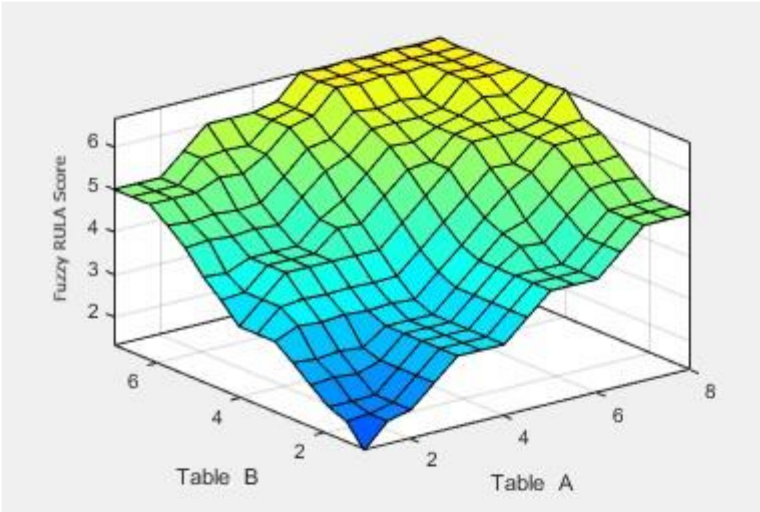


Fig. 5.6 Fuzzy interface system constructed using Table C of the RULA score sheet

5.2 Fuzzy RULA Scores for Static and Dynamic Operations

To determine the postural risk of the dumper operators, the most commonly repeated postures of 15 operators were selected for the analysis. A total of 60 frequently repeated postures (i.e., 15 postures during loading, 15 postures during loaded travel, 15 postures during unloading, and 15 postures while traveling without any load) were identified from the observations of 15 dumper operators. Table 5.1 gives the ROM, RULA score and Fuzzy RULA score of dumper operators during various job cycles.

Table 5.1 ROM of various body parts, RULA score and Fuzzy RULA score of seated posture of dumper operators

	Operators	Upper Arm Angle (in deg)	Lower Arm Angle (in deg)	Wrist Angle (in deg)	Neck Angle (in deg)	Trunk Angle (in deg)	RULA Score	Fuzzy RULA Score
Loading	Operator 1	44.96	80.10	8.30	13.81	33.49	4	3.98
	Operator 2	75.08	148.97	3.53	30.91	21.20	3	3.55
	Operator 3	37.61	128.90	24.83	4.22	35.50	3	3.57
	Operator 4	37.10	84.46	7.18	4.51	32.12	3	3.50
	Operator 5	61.72	143.38	29.15	15.19	30.75	4	4.61
	Operator 6	30.46	115.70	62.69	2.79	33.50	3	3.95
	Operator 7	54.28	131.23	23.47	12.94	45.18	2	4.40
	Operator 8	72.44	130.32	41.14	25.79	30.20	4	4.61
	Operator 9	43.22	77.51	12.72	2.52	28.20	3	3.99
	Operator 10	41.98	93.44	20.22	10.12	29.92	4	3.75

	Operator 11	79.79	122.83	8.13	21.84	27.59	3	3.99
	Operator 12	83.16	108.10	41.99	20.49	22.91	4	3.88
	Operator 13	51.10	108.84	36.09	5.65	36.69	4	3.47
	Operator 14	46.58	118.40	19.63	6.67	36.32	3	3.56
	Operator 15	40.52	109.74	4.94	3.83	36.99	3	3.65
Loaded travel	Operator 1	80.14	109.11	11.84	16.84	31.49	5	4.04
	Operator 2	64.87	101.89	16.49	5.81	34.61	4	3.85
	Operator 3	33.79	108.06	19.12	1.29	34.38	3	3.99
	Operator 4	43.15	113.63	17.22	8.39	31.51	3	3.67
	Operator 5	28.32	114.49	38.96	26.35	29.10	3	3.99
	Operator 6	46.16	102.67	37.97	8.67	31.90	3	3.69
	Operator 7	45.31	111.32	14.00	20.97	33.22	3	3.99
	Operator 8	60.61	124.92	11.41	16.33	31.76	4	4.02
	Operator 9	80.72	123.32	1.68	27.95	27.37	4	3.99
	Operator 10	85.92	123.02	4.45	20.57	38.68	3	3.99
	Operator 11	41.70	111.74	34.68	9.41	36.22	4	2.99
	Operator 12	58.24	121.40	28.29	20.40	32.73	4	4.61
	Operator 13	45.90	127.44	21.74	11.77	36.33	3	3.88
	Operator 14	29.90	110.93	3.47	2.51	34.50	4	3.99
	Operator 15	41.05	93.89	23.75	0.34	36.09	3	3.99
Unloading	Operator 1	29.68	111.62	23.45	14.13	21.19	3	3.16
	Operator 2	32.82	18.89	6.36	62.88	10.20	3	2.58
	Operator 3	34.21	46.10	28.91	11.75	18.08	3	2.80
	Operator 4	59.52	93.58	42.36	20.68	18.53	3	3.60
	Operator 5	54.07	117.64	9.53	23.38	30.20	3	3.99
	Operator 6	82.25	113.88	29.33	31.74	25.61	4	4.60
	Operator 7	43.50	136.21	26.94	4.54	30.14	2	3.50
	Operator 8	31.52	118.76	45.57	0.77	34.52	4	3.99
	Operator 9	55.92	127.51	16.24	17.67	39.73	4	4.29
	Operator 10	37.33	104.30	114.96	12.00	39.80	3	3.89
	Operator 11	35.30	86.77	36.19	5.25	40.07	3	3.42
	Operator 12	37.46	109.09	61.55	13.25	42.03	3	3.95
	Operator 13	64.42	143.85	45.02	2.87	27.28	5	4.53
	Operator 14	69.41	122.36	76.67	18.76	41.82	4	3.99
	Operator 15	38.30	102.06	24.78	12.04	38.10	3	3.90
Empty travel	Operator 1	65.89	56.42	31.00	94.30	47.58	4	4.57
	Operator 2	78.68	114.99	2.72	14.14	41.19	4	3.98
	Operator 3	77.24	109.64	3.92	4.37	33.98	3	3.53
	Operator 4	38.10	105.24	27.82	8.69	41.96	3	3.71
	Operator 5	49.86	120.41	23.29	5.92	38.26	4	3.49
	Operator 6	64.97	144.87	35.03	7.78	31.95	3	4.21
	Operator 7	38.61	117.09	20.59	7.26	34.58	5	3.61

	Operator 8	46.19	131.28	12.75	12.97	39.42	4	3.94
	Operator 9	80.83	111.29	3.16	18.25	30.44	3	3.99
	Operator 10	52.57	75.44	54.08	9.02	25.95	4	3.68
	Operator 11	46.59	103.53	23.06	30.21	43.55	4	3.99
	Operator 12	51.10	116.62	153.62	21.55	26.85	4	3.99
	Operator 13	93.35	116.87	1.12	8.85	32.07	3	3.72
	Operator 14	82.91	130.95	34.11	22.86	27.54	4	4.61
	Operator 15	31.52	118.76	45.57	0.77	34.52	4	3.99

As indicated in Table 5.1, 48 (i.e. 80 %) driving postures of dumper operators having the fuzzy RULA score between 3 and 4. This score corresponds to action level two i.e. low risk of WRMSDs as per standard RULA chart. It recommended that there is a need for further investigation and a change in sitting posture may be required to prevent potential WRMSDs issues in the near future.

Similarly, 12 (i.e. 20 %) driving postures of the dumper operators reported the fuzzy RULA score more than 4. This indicates that the operators are exposed to medium risk of WRMSDs and hence there is a need to change the sitting posture of operators as soon as possible to prevent them from WRMSDs. Figure 5.7 shows the fuzzy RULA score for different job cycle of dumper operators. It reveals that the mean fuzzy RULA score

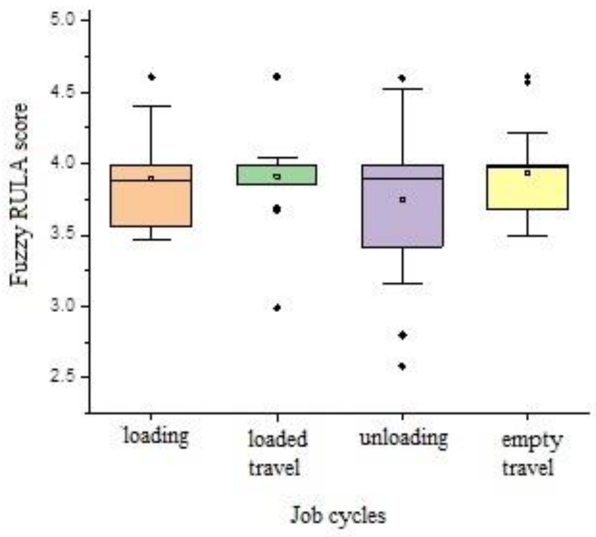


Fig. 5.7 Fuzzy RULA score for loading, full load travel, unloading and empty travel of dumper operators

is relatively higher during dynamic operations (i.e. while loaded travel and empty travel) compared to static operations (i.e. during loading and unloading). In addition, the interquartile range in case of dynamic operation is very small, which illustrates that the fuzzy RULA score remains consistent throughout the dynamic operations (i.e. the body maintains at relatively stationary position during full load and empty travel tasks). However, for static operations the interquartile range is large, which implies that the fuzzy RULA score exhibit more variation (i.e. the operators tend to sit in distinct postures while engaging in loading and unloading).

5.3 Comparison of Standard RULA Score with the Fuzzy RULA Score

5.3.1 Correlation analysis

A correlation analysis was conducted to examine the relationship between the RULA score obtained from the standard RULA and the fuzzy RULA methods. This analysis shown that the correlation between the two RULA scores was moderate, as the Pearson Correlation Coefficient was 0.315 (the range for moderate correlation is 0.3 to 0.8), but it was statistically significant, as p was 0.026 (correlation is considered as significant when $p < 0.05$). From Table 5.1 it is evident that the restricted range of RULA scores (i.e. 2 to 5) and influence of outliers contributed to the moderate correlation between the two methods of RULA score.

5.3.2 Bland-Altman Analysis

To further assess the agreement and disagreement between the two methods (i.e. Standard RULA score and fuzzy RULA score), Bland-Altman analysis was performed. Figure 5.8 shows the Bland-Altman Plot between the standard RULA score and fuzzy RULA score. The mean of difference between the standard score and fuzzy RULA score was -0.38, with a standard deviation of 0.65. The limits of agreement were determined as -1.66 to 0.88. As depicted in Figure 5.8, approximately 93% of the differences between the two methods were within the range, whereas only 7% of the data points were outside the mean difference line. Further, the Bland-Altman plot reveals that the majority of the data points were near to the mean line, which indicates that the variability between the two methods is minimal and fuzzy RULA method can be used as alternative method to determine postural risk.

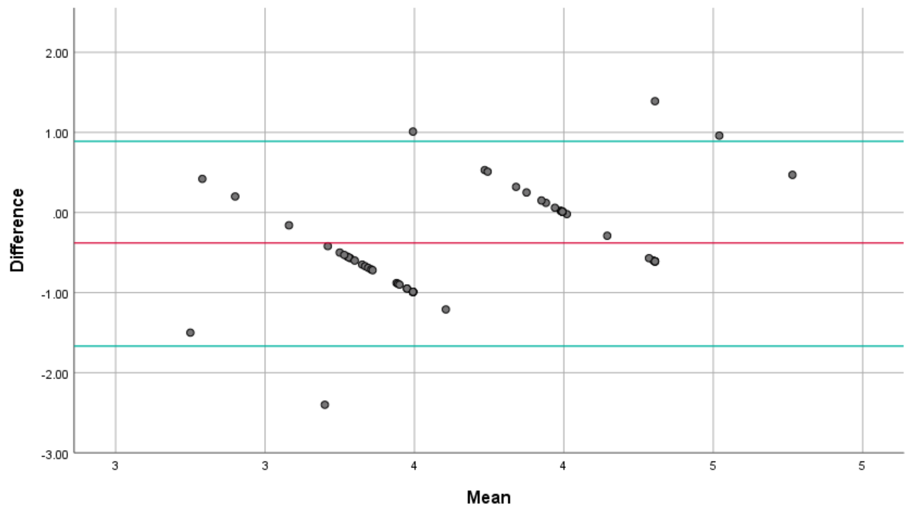


Fig. 5.8 Bland-Altman Plot measuring the agreement between the traditional RULA method and fuzzy RULA method

While the standard RULA and fuzzy RULA methods are valuable tools, they have limitations. These methods primarily focus on the posture of the operators and do not account for individual factors, such as body weight and height. Since these factors can also significantly contribute to the risk of WRMSDs, incorporating body weight and height into the analysis is crucial for a more in-depth assessment. In this regard, a detailed study has been carried out through biomechanical analysis of sitting posture of the dumper operators.

CHAPTER 6

6. BIOMECHANICAL ANALYSIS OF THE DUMPER OPERATOR'S DRIVING POSTURE

The study design for the calculation of biomechanical forces acting on the musculoskeletal system (i.e. spinal cord, muscles and tendons) is showed in the Figure 6.1. It includes selection of mine site, sample selection, data collection, determining the high repeated posture, developing the biomechanical model of driving posture and seat using the OpenSim software package, and finally calculation of biomechanical forces.

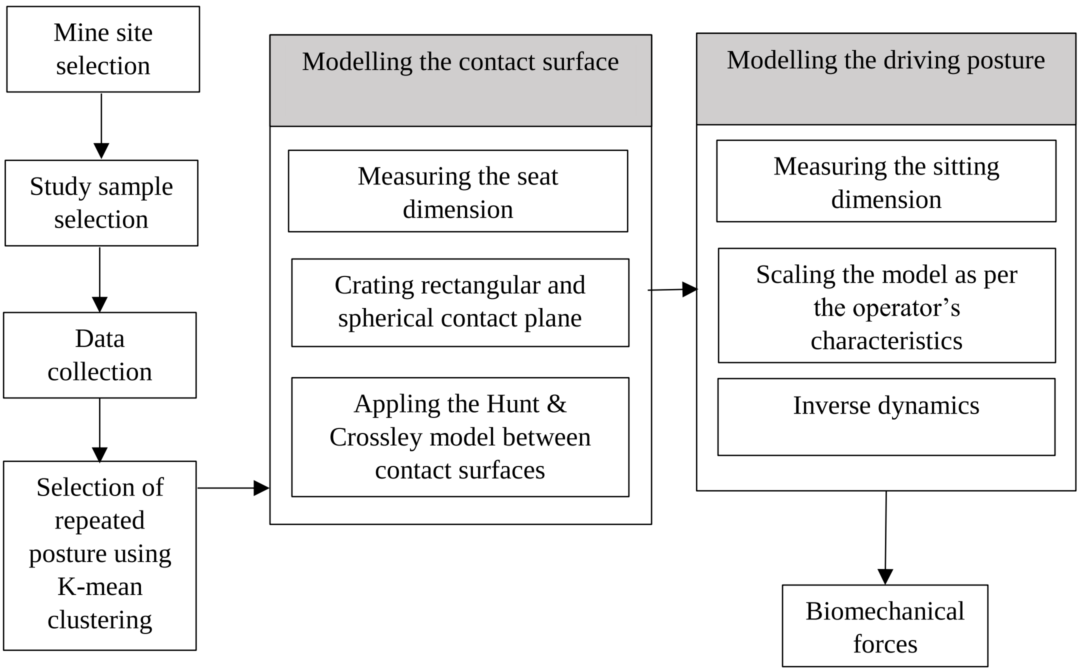


Fig. 6.1 Flow chart for calculation of biomechanical forces

6.1 Sample Selection and Data Collection

The iron ore mine which was selected for the preliminary analysis was also considered for the biomechanical analysis of dumper operator's posture. Out of 262 dumper operators, three dumper operators were randomly selected. The operators were selected in such a way that they will encompass three Body Mass Index (BMI) categories (i.e., underweight (BMI<18.5), healthy (18.5<BMI<24.9), and overweight (BMI>25)).

These operators were between 18 to 55 years age, with minimum 6 months of professional driving experience, and without any history of injuries. The operators were briefed about the purpose of this study to all the operators in the local language. A digital camera (Nikon D5600) was installed inside the dumper cabin to record the driver's driving posture in sagittal plane. The dumper operators were instructed to continue their normal work and their driving postures were recorded while performing primary climb (i.e. movement of the dumper inside the pit from the excavation point to main haul road in inclined upward direction), main haul (i.e. movement of the dumper inside the pit on the horizontal haul road), right incline traverse (i.e. cornering the dumper in left direction inside the pit), left incline traverse (i.e. cornering the vehicle in right direction inside the pit), final climb (i.e. movement of the dumper from the pit to the surface in inclined upward direction) at the rate of 24 frames per second.

6.2 Selection of Repeated Posture Using K-mean Clustering Algorithm

The video footage of operators performing the primary climb, main haul, right incline traverse, left incline traverse, and final climb were collected. To minimize bias in identifying repeated postures, an image clustering algorithm was used instead of manual analysis. The RGB frames for every 5 seconds were extracted from the video footage using the openCV Python library. Based on the similarity of these frames during each job cycles, they were grouped into clusters using the K-means clustering algorithm. One image from the largest cluster of each job cycle was selected for biomechanical analysis of the sitting posture.

6.3 Modelling of Driving Posture

The biomechanical forces acting on the spinal cord, muscles and tendons of the dumper operators were determined analytically by means of OpenSim software package. Figure 6.2 depicts the standard postures of operators recreated utilizing the Gait2354 human body model. The 3D musculoskeletal model (i.e. Gait2354) comprising of 12 body parts, 12 body joints and 54 muscles with 23 degrees of freedom was selected for the biomechanical study. The default model was 1.8 m tall and weighed 75.16 kg.

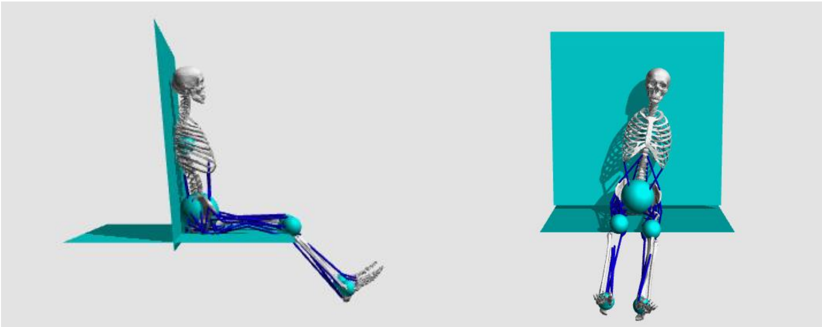


Fig. 6.2 Scaled Gait2354 model of the dumper operators in sitting posture

6.4 Modelling of Driving Seat

The seat was modelled using the contact surface feature to simulate the sitting arrangement of the dumper. The two contact planes (i.e. vertical and horizontal) were used to mimic the orientation of an actual seat. Further, the "Hunt Crossley force" model was used to determine the contact forces between the Gait2354 model and the seat.

6.5 Calculation of Biomechanical Forces

The biomechanical forces were calculated by extracting joint angles from the repetitive posture with the ImageJ software. This data was used to readjust the Gait2354 model to accurately represent the sitting posture. Further, the model was scaled as per the anthropometric data of the operator. The scaled model was used to determine the biomechanical forces, such as force acting on the spinal cord, muscle and tendon (Fig. 6.3) using inverse dynamics.

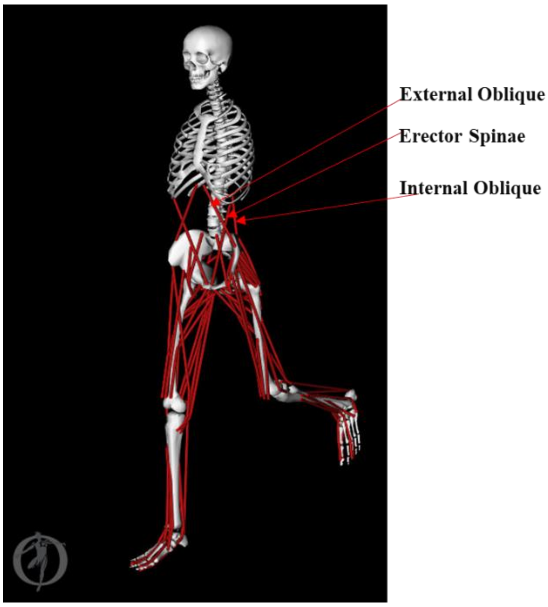


Fig. 6.3 Gait2354 model modelled with External Oblique, Erector Spinae and Internal Oblique muscle

6.5.1 Biomechanical forces during various job cycles

The load on the spine of the dumper operators were analysed according to the job cycle and BMI. Table 6.1 gives the spinal load and moment experienced by the dumper operators while performing various job cycles. The highest spinal load on vertical direction was experienced during the main haul (i.e. F_y = 335.74 N). Similarly, the highest moment was experienced in x-axis during the right (i.e. 40.11 Nm) and left (i.e. -48.52 Nm) inclined transverse job cycle.

Table 6.1: Spinal load acting on the healthy dumper operators during job cycles

	Spinal load (N)			Moment (Nm)		
Job Cycle	**F_x**	**F_y**	**F_z**	**M_x**	**M_y**	**M_z**
Primary Climb	86.89	324.30	0	0	0	-37.53
Main Haul	0	335.74	0	0	0	-10.07
Right Incline Traverse	0	314.43	117.72	40.11	3.41	-9.11
Left Incline Traverse	0	304.29	-141.89	-48.52	-4	-8.57
Final Climb	86.89	324.30	0	0	0	-37.53

Table 6.2 shows the passive, active and total forces acting on the muscles during various job cycles. This study revealed that Erector spinae muscle (ERCSPAN) was subjected to high active forces (i.e. 24.9 N) in all job cycles. The right External abdominal oblique (EXTOBL) and left internal abdominal oblique (INTOBL) muscles were subjected to high passive forces especially during the right transverse (i.e. 51.40 N, 30.6 N), whereas left EXTOBL and right INTOBL was subjected to high muscular force during left transverse (i.e. 61.96 N, 43.17 N). As indicated in the Table 6.2 the total muscle forces were highest during the right and left transverse but relatively low during primary, final climb and main haul.

The tendon forces acting on the ERCSPN, EXTOBL, and INTOBL muscles during the primary climb, main haul, right incline traverse, left incline traverse, and final climb job cycles were also studied. The results as seen in the Table 6.3 suggested that the tendon forces were highest on the right ERCSPN (i.e. 41.76 N), right EXTOBL (i.e. 59.99 N) and left INTOBL (i.e. 39.21 N) during right incline traverse. Whereas, during left inclined traverse the left ERCSPN, left EXTOBL and right INTOBL were subjected high tendon forces of 47.34N, 70.05N, and 51.33N respectively. The analysis also showed that the tendon forces are more evenly distributed between the right and left sides during the primary (i.e. 9.02 N), main (i.e. 8.99 N) and final climb (i.e. 9.02 N).

Table 6.2: Passive, active and total force acting on the ERCSPN, EXTOBL, and INTOBL muscles while performing various job cycle

	Passive Force (N)						**Active Force (N)**						**Total Force (N)**					
Job Cycle	**ERCSPN**		**EXTOBL**		**INTOBL**		**ERCSPN**		**EXTOBL**		**INTOBL**		**ERCSPN**		**EXTOBL**		**INTOBL**	
	R	**L**	**R**	**L**	**R**	**L**	**R**	**L**	**R**	**L**	**R**	**L**	**R**	**L**	**R**	**L**	**R**	**L**
Primary Climb	0	0	18.01	0	0	0	24.99	24.99	8.9	8.9	8.99	8.99	24.99	24.99	26.80	26.80	9.02	9.02
Main Haul	0	0	18.12	0	0	0	24.99	24.99	9.01		9.01		24.99	24.99	26.80	26.80	8.99	8.99
Right Incline Traverse	16.87	0	51.40	4.5	0	30.63	24.89	24.91	8.60	8.62	8.64	8.63	41.76	24.97	59.99	13.48	8.65	39.21
Left Incline Traverse	0	22.51	3.15	61.96	43.17	0	24.98	24.97	8.31	8.31	8.31	8.32	24.98	47.34	12.18	70.05	51.53	8.58
Final Climb	0	0	18.014	0	0	0	24.99	24.99	8.9	8.9	8.99	8.99	24.99	24.99	26.80	26.80	9.02	9.02

Note: ERCSPN: Erector spinae; EXTOBL: External abdominal obliques; INTOBL: Internal abdominal obliques

Table 6.3 Tendon force acting on the healthy dumper operators during various cycle

Tendon Force (N)						
Job Cycle	**ERCSPN**		**EXTOBL**		**INTOBL**	
	R	**L**	**R**	**L**	**R**	**L**
Primary Climb	24.99	24.99	26.80	26.80	9.02	9.02
Main Haul	24.99	24.99	26.80	26.80	8.99	8.99
Right Incline Traverse	41.76	24.97	59.99	13.48	8.65	39.21
Left Incline Traverse	24.98	47.34	12.18	70.05	51.53	8.58
Final Climb	24.99	24.99	26.80	26.80	9.02	9.02

Note: ERCSPN: Erector spinae; EXTOBL: External abdominal obliques; INTOBL: Internal abdominal obliques

6.5.2 Biomechanical forces acting on the dumper operators of various BMI

When analysis was done based on the BMI of the operators it was observed that the force acting on the muscle and tendon remained almost same. However, there was gradual increase in the spinal loading with increase in BMI of the operators. The Figure 6.4 shows that variation of spinal load (y-axis) during various job cycle and BMI.

The highest force was observed in the overweight operators during the main haul (402.01 N). The lowest spinal load was observed in the operators belonging to the underweight category during the right inclined transverse job cycle. Similar trend was also observed for the bending momentum acting on the spinal (as shown in Figure 6.5).

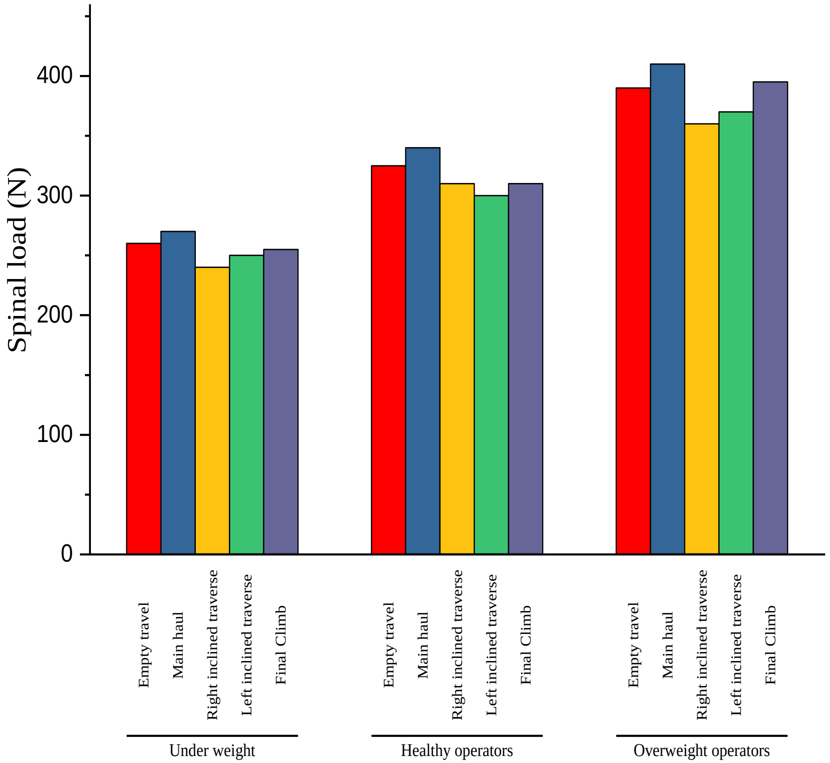


Fig. 6.4 Load acting on the spinal of the dumper operators

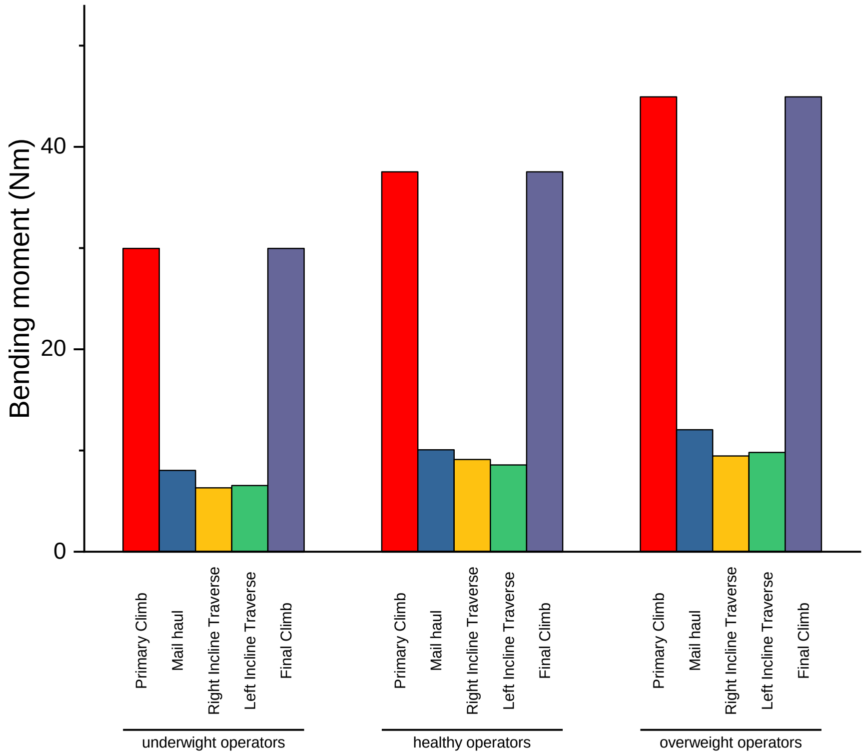


Fig. 6.5 Bending moment on the spinal of the dumper operators

CHAPTER 7

7. CONCLUSIONS AND SCOPE FOR FUTURE WORK

7.1 Conclusions

This research work aimed to determine the postural risk of the dumper operators working in Indian surface mines. To confirm the influence of driving posture on WRMSDs an epidemiology study was conducted. A custom self-reported questionnaire was developed and data was collected with respect to personal factors, habitual factors, and work-related risk factors of the dumper operators. The raw data was pre-processed to ensure its quality and these data were analysed using ML models. Five ML models, such as RF, SVM, DT, GBM, and LR were used for the analysis. The performance of ML models were measured using metrics, such as accuracy, precision, recall, F1 score, and ROC. The performance study shown that the RF model outperformed compared to SVM, DT, GBM, and LR models with the accuracy of 0.71, precision of 0.75, recall score of 0.78 and F1 score of 0.76. The results of the this study showed that age is highly associated with WRMSDs, followed by awkward driving posture, work experience, job demand, alcohol consumption, smoking cigarettes, work design, and marital status. As a whole, this study revealed that the awkward driving posture is one of the parameters that cause WRMSDs problems in dumper operators.

Hence, the postural analysis of dumper operators (i.e. sitting posture) was carried out using the observation method (i.e. fuzzy RULA method). The results of the study indicated that more than 80% of driving postures of dumper operators had fuzzy RULA score corresponding to ‘action level two’ which point out the need for further investigation, and also recommends for the change in sitting posture to prevent potential WRMSDs. In addition, the study indicated that if the dumper operators continue to work in their current sitting posture, they may develop WRMSDs in the near future. In this regard, a detailed study was carried out to analyse the sitting posture of the operators during the different job cycles (i.e. loading, hauling, unloading, and empty travel). The results revealed that the fuzzy RULA score was relatively consistent and varied between 3.5 and 4.25 during dynamic operation. Similarly, during the static operation the fuzzy RULA score was varying in a wider range (i.e. between 3.25 and 4.5). This means during dynamic operation the operators were sitting in almost same postures, whereas their sitting posture varying during static operation.

Fuzzy RULA method can be used only for the preliminary analysis. It does not consider the operators height and weight which are the important factors that contribute to the WRMSDs. Therefore, a detailed biomechanical analysis of dumper operators was conducted using Gait2354 human model. In this analysis, the load acting on the spine, muscle and tendon was determined, which is depicted in Figure 6.1. In this analysis, the sitting postures of the operators during the primary climb, main haul, right incline traverse, left incline traverse, and final climb were considered.

As observed in the Table 6.1, the spinal load is dependent on the job cycle (i.e. primary climb, main haul, right inclined transverse, left inclined transverse and final climb) performed by the dumper operators. The spine was subject to the maximum load during main haul (i.e. 335.74N) followed by primary climb (i.e. 324.30N), final climb (i.e. 324.30N), right inclined transverse (i.e. 314.43N) and left inclined transverse (i.e. 304.29N). Similarly, the Table 6.1 indicates that the force acting on the muscles and tendons is depending on the job cycle performed by the dumper operators. The right ERCSPN, right EXTOBL, and right INTOBL muscles experienced relatively high total force (i.e. 41.76N, 59.99N, and 39.21N, respectively) during right inclined transverse. Similarly, the left ERCSPN, left EXTOBL, and left INTOBL muscles experienced high total force (i.e. 47.34N, 70.05N, and 51.33N, respectively) when dumper operators perform left inclined transverse.

The tendon which joins the muscles with the bone also showed the same trend. The tendons attached to the right ERCSPN, right EXTOBL, and right INTOBL muscles experienced high total force of 41.76N, 59.99N, and 39.21N, respectively during right inclined transverse. Similarly, the tendons attached to the left ERCSPN, left EXTOBL, and left INTOBL muscles experienced high total force of respectively 47.34N, 70.05N, and 51.33N when dumper operators were performing left inclined transverse.

In general, WRMSDs occur when the muscular and skeletal systems experience stress. This study demonstrated that muscles are subjected to relatively high tensile forces when operators perform right and left inclined transverse movements. Maintaining poor or awkward postures can lead to muscle fatigue, as certain muscles are overworked to hold the body in position. This can cause discomfort and pain, particularly in the back, neck, shoulders, and legs. Pain and discomfort from poor posture can reduce concentration and productivity, as individuals may find it difficult to focus on tasks when they are physically uncomfortable. Prolonged exposure to poor postures can lead to chronic pain conditions, such as lower back pain, neck pain, or repetitive strain injuries like carpal tunnel syndrome. This pain can become persistent and debilitating, affecting daily activities and quality of life.

During the field study, it was observed that the operators drove the dumpers without wearing seat belts. While cornering, operators experienced centripetal forces and tilt their bodies, causing the centre of gravity (COG) of the body to shift from the centre to the side. This shift in COG resulted in tensile force on the muscles and tendons attached to the spine. Hence, this study recommends mandatory wearing of seat belts for the operators while driving.

Similarly, the results of the study reveals that the spine is exposed to high compressive forces during the main haul. The compressive load on the spine increases with increase in BMI of the operators. Selecting operators with lower BMI may not be a viable alternative as it could introduce recruitment bias. Therefore, this study recommends implementing periodic breaks for dumper operators during work shift to minimize the health effects.

7.2 Scope for Future Work

1) This study can also be conducted on other HEMM operators to determine the health risks.
2) This study focused on HEMM operators working on surface mine. Future iterations of work may explore the health risks faced by HEMM operators in underground mines.
3) To reduce the need for manual intervention during postural analysis, a sensor-based study can be conducted to replicate posture more precisely.

4) Further studies may be carried out to determine the effectiveness of wearing seat belt while operating dumpers.

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APPENDIX 1

<table>
<tr><td rowspan="4">Dumper Data</td><td>Name of the Mine:</td><td>ID Number:</td><td>Dumper Number:</td></tr>
<tr><td>Make:</td><td>Dumper Model:</td><td>Vehicle age:</td></tr>
<tr><td colspan="3">In the past one year how many times truck has broken down? ______</td></tr>
<tr><td colspan="3">For past, six months how many times trucks have gone to maintenance?____</td></tr>
<tr><td rowspan="10">Personal Factors</td><td colspan="3">What is your age?</td></tr>
<tr><td colspan="3">From past how many years you are into driving?</td></tr>
<tr><td colspan="3">How many years of work experience do you have in mines?</td></tr>
<tr><td colspan="3">How many years of work experience do you have in this company?</td></tr>
<tr><td colspan="3">What is your education level?
□No formal education □Primary education □Secondary education
□Tertiary education</td></tr>
<tr><td colspan="3">Do you have any health problems?
□Yes □No</td></tr>
<tr><td colspan="3">Do you take medicine?
□Yes □No</td></tr>
<tr><td colspan="3">Do you Smoke?
□Yes □No</td></tr>
<tr><td colspan="3">Do you have drinking habit?
□Yes □No</td></tr>
<tr><td colspan="3">Have you worked with injury?
□Yes □No</td></tr>
<tr><td rowspan="9">Social Factors</td><td colspan="3">What is your marital status?
□Single □Married □Divorced □Widow/widower</td></tr>
<tr><td colspan="3">What is your family size?</td></tr>
<tr><td colspan="3">What do you do in leisure time?
□ Hobbies:
□ Physical Exercise
□ Sports
□ none</td></tr>
<tr><td colspan="3">On an average how many times do you involve in Hobbies/Exercise/ sports activities?
□ 1-2 times/quarter
□ 2-3 times/month
□ 1-2 times/week
□ More than 3 times/week
□ Never</td></tr>
<tr><td colspan="3">Do you think your work design is poor?
□Yes □No</td></tr>
<tr><td colspan="3">Does your work requires high job demand?
□Yes □No</td></tr>
<tr><td colspan="3">Do you feel that you are doing repetitive work?
□Yes □No</td></tr>
<tr><td colspan="3">Do you feel that your work posture is awkward?
□Yes □No</td></tr>
<tr><td colspan="3">How many hours do you sleep?</td></tr>
</table>

	What is your monthly Income?
	How many hours do you work everyday?
	How many minutes of break do you take everyday?
	What is your body shape? 1)mesomorph 2)ectomorph 3)endomorph
	Whether break time provided by the company is sufficient for you? □Yes □No
	Have you undergone any awarness program on driving posture? □Yes □No

APPENDIX 2

Musculoskeletal Discomfort Form (Based on the Nordic Questionnaire (Kourinka et al. 1987)) **Employee ID:**____________________

Job/Position: ___________________________ Gender: M F Age: _______ Height: ____ ft.____ in. Weight: ____________
How long have you been doing this job? ___years ___ months How many hours do you work each week? _____

How to answer the questionnaire:

***Picture*:** In this picture you can see the approximate position of the parts of the body referred to in the table. Limits are not sharply defined, and certain parts overlap. You should decide for yourself in which part you have or have had your trouble (if any).

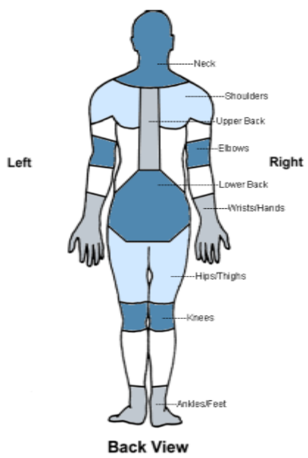

***Table*:** Please answer by putting an "X" in the appropriate box - one "X" for each question. You may be in doubt as to how to answer, but please do your best anyway. Note that column 1 of the questionnaire is to be answered even if you have never had trouble in any part of your body; columns 2 and 3 are to be answered if you answered yes in column 1.

To be answered by everyone	**To be answered by those who have had trouble**	
Have you at any time during **the last 12 months** had trouble (ache, pain, discomfort, numbness) in:	Have you at any time during the **last 12 months been prevented from doing your normal work** (at home or away from home) because of the trouble?	Have you had trouble at any time during **the last 7 days?**
Neck ☐ No ☐ Yes	☐ No ☐ Yes	☐ No ☐ Yes
Shoulders ☐ No ☐ Yes, right shoulder ☐ Yes, left shoulder ☐ Yes, both shoulders	☐ No ☐ Yes	☐ No ☐ Yes
Elbows ☐ No ☐ Yes, right elbow ☐ Yes, left elbow ☐ Yes, both elbows	☐ No ☐ Yes	☐ No ☐ Yes
Wrists/Hands ☐ No ☐ Yes, right wrist/hand ☐ Yes, left wrist/hand ☐ Yes, both wrists/hands	☐ No ☐ Yes	☐ No ☐ Yes
Upper Back ☐ No ☐ Yes	☐ No ☐ Yes	☐ No ☐ Yes
Lower Back (small of back) ☐ No ☐ Yes	☐ No ☐ Yes	☐ No ☐ Yes
One or Both Hips/Thighs ☐ No ☐ Yes	☐ No ☐ Yes	☐ No ☐ Yes
One or Both Knees ☐ No ☐ Yes	☐ No ☐ Yes	☐ No ☐ Yes
One or Both Ankles/Feet ☐ No ☐ Yes	☐ No ☐ Yes	☐ No ☐ Yes

LIST OF PUBLICATIONS

Sl. No.	Title of the paper	Authors (in the same order as in the paper. Underline the Research Scholar's name)	Name of the Journal, Vol. No., Pages	Month and Year of Publication	Category
1	Structural equation modelling of work related musculoskeletal disorders among dumper operators.	<u>Mohith Bekal Kar,</u> Mangalpady Aruna, Bijay Mihir Kunar	Scientific Reports http://dx.doi.org/10.1038/s41598-023-40507-9	August, 2023	1
2	Risk factors associated with work-related musculoskeletal disorders among dumper operators: A machine learning approach	<u>Mohith Bekal Kar,</u> Mangalpady Aruna, Bijay Mihir Kunar	Clinical Epidemiology and Global Health http://dx.doi.org/10.1016/j.cegh.2023.101438	October, 2023	1
3	Fuzzy Logic-Based Rapid Upper Limb Assessment: A Novel Approach to Evaluate the Postural Risk of Dumper Operators.	<u>Mohith Bekal Kar,</u> Mangalpady Aruna, Bijay Mihir Kunar	Journal of The Institution of Engineers (India): Series C http://dx.doi.org/10.1007/s40032-023-00986-1	August, 2023	1
4	An Analytical Hierarchy Approach for Studying the Impact of Human Error, Environmental Factors, and Equipment Failure on Mine Accidents: A Case Study in India	<u>Mohith Bekal Kar,</u> Mangalpady Aruna, Bijay Mihir Kunar	International Journal of System Assurance Engineering and Management http://dx.doi.org/10.1007/s13198-023-02232-4	January, 2024	1
5	Postural analysis of dumper operators and construction workers-a case study	Bijay Mihir Kunar, Mangalpady Aruna, <u>Mohith Bekal Kar</u>	Journal of Mines, Metals & Fuels https://doi.org/10.18311/jmmf/2021/28525	June, 2021	1

* Category: 1: Journal paper, full paper reviewed 2: Journal paper, Abstract reviewed 3: Conference/Symposium paper, full paper reviewed 4: Conference/Symposium paper, abstract reviewed 5: others (including papers in Workshops, NITK Research Bulletins, Short notes etc.)

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PUBLICATIONS

1. **Kar, M. B.**, Aruna, M., & Kunar, B. M. (2023). Structural equation modelling of work related musculoskeletal disorders among dumper operators. *Scientific Reports*, *13*(1), 14055.
2. **Kar, M. B.**, Aruna, M., & Kunar, B. M. (2023). Risk factors associated with work-related musculoskeletal disorders among dumper operators: A machine learning approach. *Clinical Epidemiology and Global Health*, *24*, 101438.

3. **Kar, M. B.**, Aruna, M., & Kunar, B. M. (2023). Fuzzy Logic-Based Rapid Upper Limb Assessment: A Novel Approach to Evaluate the Postural Risk of Dumper Operators. *Journal of The Institution of Engineers (India): Series C*, *104*(5), 1047-1055.
4. **Kar, M. B.**, Aruna, M., & Kunar, B. M. (2024). An analytical hierarchy approach for studying the impact of human error, environmental factors, and equipment failure on mine accidents: a case study in India. *International Journal of System Assurance Engineering and Management*, 1-7.
5. Mihir Kunar, B., Aruna, M., & **Bekal Kar, M.** (2021). Postural analysis of dumper operators and construction workers – a case study. *Journal of Mines, Metals and Fuels*, *69*(6), 180–185. https://doi.org/10.18311/jmmf/2021/28525