Journal of Risk, Insurance, and Safety
DOI: 10.18311/JRIS.1.1.2026.1-12
ISSN: XXXX-XXXX | Vol 1(1), 2026 | pp. 1-12

Investigation into the Effectiveness of Fatigue Management Systems for Reducing Incidents in the Surface Mine

Aditya Martha Wijaya[1]*, Ashis Bhattacherjee[2], Nearkasen Chau[3], Ashish Kumar[4], Boris Albijanic[1], Ping Chang[1], Jianwei Cheng[5] and Apurna Ghosh[1]*

[1]Department of Mining Engineering and Metallurgical Engineering, Western Australian School of Mines (WASM), Curtin University, Kalgoorlie, WA 6430, Australia; apurna.ghosh@curtin.edu.au
[2]Department of Mining Engineering, Indian Institute of Technology, Kharagpur - 721302, West Bengal, India
[3]National Institute of Health and Medical Research (INSERM), Paris Sud University, Paris Descartes University, F-75679 Paris, France
[4]School of Advanced Engineering, University of Petroleum and Energy Studies, Dehradun - 248007, Uttarakhand, India
[5]China University of Mining and Technology, Xuzhou, Haidian - 100083, China

Abstract

In this study, personal and impersonal factors, such as family conditions, experience, training, work location, fatigue status detection, residential status, and supervision, will be investigated as predictors of injury within a causal analysis framework. The data are taken from a surface coal mining in Indonesia, and a statistical model defined as Structural Equation Modelling (SEM) will be simulated to determine the significance of the factors causing the incident occurrence. The methods to obtain the data from the heavy equipment operator are by using two approaches: qualitative data by on-the-spot input answer, and quantitative data by sleep length detection using a smartwatch. Then, the path diagram model was developed that shows the causal relationship between the factors in a surface mine incident model. The surface mine incident modelling in this study results in a Confirmatory Factor Analysis (CFA). The CFA based on the best fit path diagram obtained in this study reveals that Emotional Condition (EC) has a positive direct effect on the injury (γ=0.20, $p<0.05$), driving confidence has a positive direct effect on the injury (γ=0.12, $p<0.05$), and level of fatigue has a significantly positive direct effect on the injury (β=0.40, $p<0.05$). Among the measurement of the response variables Y, fatigue level (observed by the length of sleep or sleep disorder) has the greatest loading effects on injury (β=0.40, $p<0.05$). Based on the causal analysis result, the level of supervision has an inverse moderate indirect effect on the injury tendency, with the loading factor value of -0.31 by passing the fatigue level path. Moreover, work risk has a moderately significant indirect effect on the injury tendency, with the loading factor value of 0.34 by passing the fatigue level path. These results indicate that the mitigation measure related to fatigue is urgently needed. As a new state-of-the-art to support the Fatigue Management System (FMS) in the mine site, the smartwatch, as a personal sleep length detector for heavy equipment operators, shows satisfying results to represent the sleep length in real-time accurately.
Major Finding: *Fatigue was identified as the most significant factor influencing workplace injuries among heavy equipment operators in surface mining operations.*

Keywords: *Causal Relation, Confirmatory Factor Analysis, Fatigue, Smartwatch, Structural Equation Modelling*

Received: 13.03.2026; **Revised:** 19.06.2026; **Accepted:** 20.06.2026

1. Introduction

Road traffic incidents represent a major global safety concern, causing approximately 1.35 million deaths each year[1]. In the mining sector, vehicle-related incidents are a particularly significant category of

*Author for correspondence

harm. In Western Australia, traffic incidents contribute 42 out of 51 injuries as reported in the Monthly Safety and Health Snapshot[2]. Moreover, Incident and Injury Statistics 2019-20[3] showed that in surface mining, the vehicle or mobile plant rollover became the most significant number of fatalities than any other category (3 out of 13), as shown in Table 1. It indicates that a traffic management plan becomes one of the essential issues to reduce the incident rate. The Government of Western Australia regulates the traffic management in mining by the Traffic Management Fundamentals Audit Guide[4]. This guidance regulates the traffic management in the mine operation, including the systems, vehicles, and people, to ensure traffic management safety in mining.

Table 1. Number of fatalities in 2015-2016 to 2019-2020 by type of (DMIRS, 2020)[3]

Category		Number of fatalities
Underground	Exposure to environmental heat	1
Surface	Vehicle or mobile plant rollover	3
	Caught by the machine	2
	Fall from height	2
	Caught by or between objects	1
	Fall while getting on or off the vehicle	1
	Sting from an insect	1
	Struck by an object	1
Exploration	Exposure to environmental heat	1
Total		13

Apart from fatalities, the vehicle-related factor caused serious injuries in the mine operations. According to Jones *et al.*[5], vehicle-related injury becomes one of the eleven most prominent factors in Western Australia, as can be seen in Table 2.

Table 2. The number of serious injuries is the determining factor[5]

Cause of injury	Serious injury number
Overexertion	240
Stepping/miss-stepping	76
Struck by an object	71
Caught between	63
Trip and fall	61
Vehicle-related	46
Recurrence	37
Bodily contact	30
Fall from height	12
Fall from a vehicle	12
Other	9

While traffic management becomes one of the factors affecting the incident rate, factors affecting operators and workers' situational awareness, such as fatigue, are also a crucial factor. Research confirms that chronic fatigue, acute sleepiness, and irresponsible driver behaviour increase the risk of traffic incidents and lead to severe injuries[6].

Fatigue is one of the top five contributory factors, based on the Monthly Safety and Health Snapshot for the Western Australian mineral sector[2]. Most of them (9 of 20 incidents) were related to sleep or microsleep conditions. Currently, the prevention of fatigue is limited to roster management and break periods during work. Research found that sleep patterns an impact on fatigue[7]. In the digital era, sleep patterns can be examined by digital electronic devices. The sleep behaviour pattern can be measured by using a smart watch[8] to obtain data on whether the operator has enough sleep. Ricchio *et al.*[9] found that the smartwatches show high reliability for monitoring tracking steps and heart rate. The result showed that the smartwatch was relatively accurate, with a level of

error of 2-6% in tracking steps and 6-11% in heart rate measurement.

The risk management guidelines already regulate the employee working hours in the Code of Practice[10], but are not specific in terms of sleeping time.

This study focuses on investigating the role of fatigue and related psychosocial and operational factors in contributing to injury occurrence among heavy equipment operators in surface mining operations. The research hypothesises fatigue as a critical safety concern in mining environments due to its influence on concentration, reaction time, situational awareness, and decision-making ability during equipment operation. In addition to fatigue, the study also examines the influence of EC, driving confidence, supervision, and work risk on occupational injury occurrence. Based on the findings, the study proposes a fatigue management approach aimed at improving operator fitness assessment before work activities. The proposed approach includes a sleep detection and monitoring process to evaluate whether operators have obtained sufficient sleep and are physically and mentally fit to operate heavy equipment safely. Operators identified with insufficient sleep or signs of fatigue may undergo further examination before being permitted to work.

To analyse the complex relationships among the studied variables, SEM is employed as the primary statistical technique. SEM is selected because it provides a comprehensive framework for examining both direct and indirect relationships between observed and latent variables[15]. Observed variables refer to measurable indicators such as sleep duration, work location, and supervision level, whereas latent variables include constructs such as fatigue level, EC, and work risk, which cannot be measured directly. The SEM approach enables the identification of causal relationships and the evaluation of how multiple personal, psychosocial, and operational factors collectively contribute to workplace injuries. The scope of this study is limited to surface mining operations and focuses specifically on heavy equipment operators. The study serves as an initial step toward developing a comprehensive fatigue management and injury prevention framework for improving occupational safety and operational reliability in open-pit mining environments.

2. Methodology

2.1 Study Site and Subjects

The case study is based on a surface coal mine in Kalimantan Island, Indonesia. The mine location can be seen in Figure 1. The number of heavy equipment operators involved in the mine is approximately 165 persons, subject to change due to the production target fluctuation (Pamapersada Nusantara ABKL District, 2021). On average, the mine produced 2.5 million tons of coal and 25 million bank cubic meters of overburden per annum. Basically, the operator will do their work



Figure 1. Mine location of the study in Indonesia[12].

either at the pit or on the hauling road. There are two residential options for the operator, either in camp or non-camp.

In the present study case, the sample size is 165 operators with eight different variables[11]. According to Memon *et al.*[13], a sample between 160 and 300 valid observations will be suited in SEM analysis.

2.2 Study Design

The research focuses on examining the relationships among fatigue, EC, supervision, work risk, driving

confidence, and workplace injuries. A quantitative research approach was adopted, and data were collected from heavy equipment operators working in a surface mining environment. SEM was employed as the primary analytical technique to examine both direct and indirect relationships among the observed and latent variables. SEM was selected because of its capability to simultaneously analyse multiple causal relationships and evaluate complex interactions between psychosocial, operational, and fatigue-related factors affecting workplace safety. The study also involved the development of a fatigue management framework aimed at improving operator fitness assessment prior to work activities.

2.2.1 Methodology

The study starts from the problem identification based on the current state of the topic. The next stage is the construction of objectives and the formulation of hypotheses. After that, a literature review was carried out to find out the theoretical basis and research gaps to find solutions to the problems. Then the research method carried out is in the form of case studies and historical data of the research objects. After the data is obtained from the field, a hypothesised model is constructed using LISREL software. In this study, six models were constructed in LISREL, and the best-fit model was chosen. After the best-fit model is determined, the significance evaluation of the factors that affect the injury is examined. The details of the methodology can be seen in Figure 2.

To monitor the sleep duration and sleep patterns of heavy equipment operators, wearable smartwatches available in the commercial market were utilised. The study proposes the use of smartwatch-based monitoring as part of a fatigue management approach for evaluating operator fitness before work activities. Among the available devices, the Xiaomi Mi Band 4 was selected for the experimental design due to its low cost, wide market availability, and acceptable measurement performance. Previous research has shown that a similar device, the Mi Band 3, demonstrated relatively low error rates in step detection and heart rate monitoring[12], supporting its suitability for fatigue-related monitoring applications.

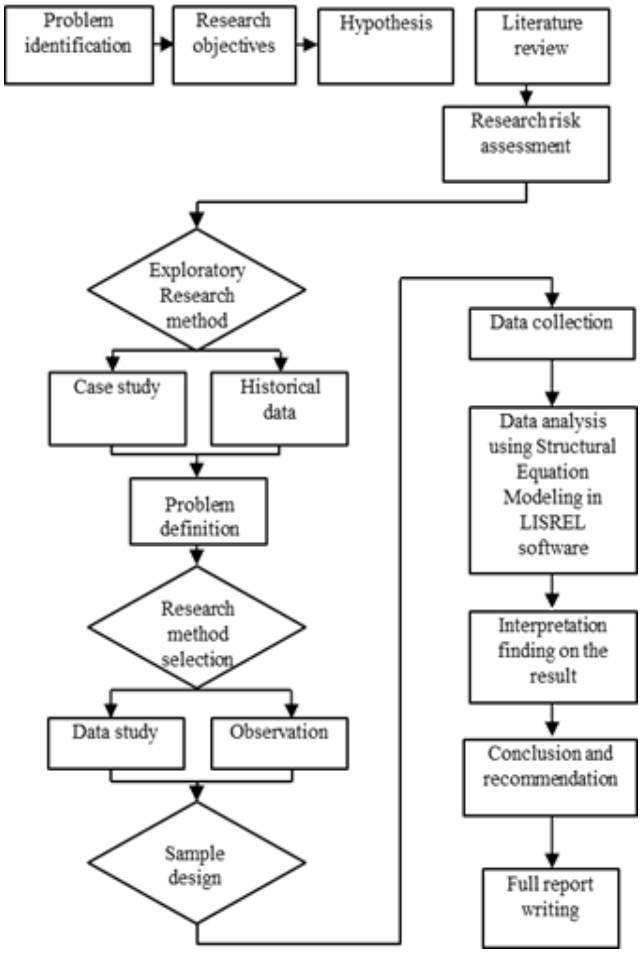


Figure 2. Research methodology.

In this study, the smartwatch was used to automatically monitor sleep-related parameters through heart rate sensing and activity tracking functions. The device records the duration of sleep as well as interruptions during sleep, including the number of times a person wakes up throughout the sleeping period. These indicators are important for evaluating sleep quality and identifying potential fatigue conditions that may affect worker alertness and operational performance.

For the experimental procedure, the participant was required to wear the smartwatch continuously during sleep. The real data recording that has been conducted by using a smartwatch can be seen in Figure 3. Due to its ability to represent real-time sleep length detection, it is possible to apply it in the mining industry. Tibbitts[14] concluded that sleep for a length of around eight hours

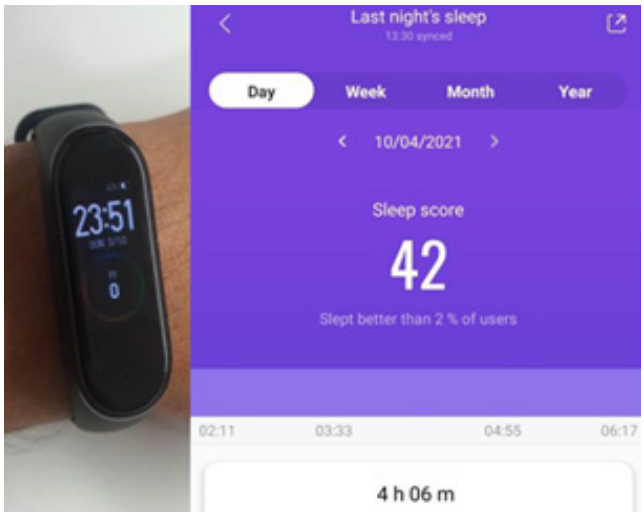


Figure 3. Smartwatch detection of the sleep pattern.

is needed to maintain mental and physical health, or between four and ten hours, which can be the basis for the length of a person's sleep hours to be declared adequate sleep.

2.2.2 Data Collection

In accordance with the objectives of this study, data were collected from the coal mining site of Pamapersada Nusantara, ABKL District[11], Indonesia, in 2021. The study involved a sample of 165 heavy equipment operators. The recorded sleep duration of the operators was classified into three categories: less than five hours, between five and seven hours, and more than seven hours. Some employees resided in company-provided accommodation located approximately 40 kilometres from the mine site, while others lived in their own homes near the mining area. Several factors that may contribute to fatigue were considered in the study, including insufficient sleep, illness, and personal or family-related issues. The fatigue classification was

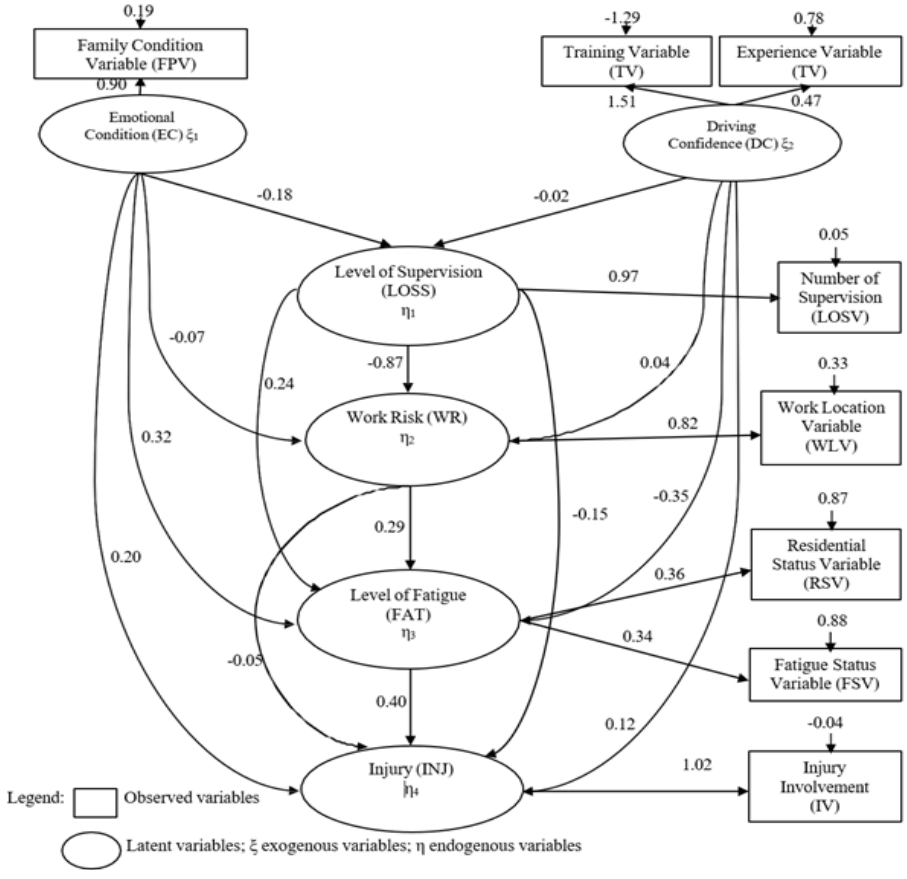


Figure 4. The best-fit model indicates the loading factor value by the LISREL simulation.

determined based on the number of hours slept on the previous day as well as during the preceding two days. Employee experience was measured according to the length of service within the company, assuming that employees with longer service periods possess greater operational experience. The dataset also included information regarding the training received by heavy equipment operators, as operators are generally qualified to operate more than one type of equipment unit. In addition, work location was considered as a variable, representing whether employees primarily worked in the pit area, on haulage roads, or across both locations. There are two types of variables as described[15]:

- Observed or measured variables

This data is directly measurable. This includes the data on the length of sleep, residential status, and details of the hours of sleep.

- Latent variables

This data cannot be measured directly, including fatigue and family problems data.

Based on the data collection, the latent variable can be constructed from observed factors in a complex system[16]. The hypothetical factor enhances the understanding of the most important factor to improve in terms of mine safety.

3. Results

The result analysis is divided into two sections: Confirmatory Factor Analysis (CFA) and SEM. SEM in this study was conducted using LISREL software.

3.1 Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) is a multivariate statistical technique used to verify whether the observed variables adequately represent the underlying latent constructs proposed in a research model. Unlike Exploratory Factor Analysis (EFA), which explores possible factor structures, CFA is theory-driven and is used when the researcher has a predefined relationship between variables and constructs based on literature, theory, or prior studies. The CFA process begins with the development of a measurement model in which observed variables (survey items) are assigned to specific latent constructs. After data collection, the model is analysed using statistical software. The analysis estimates factor loadings, which indicate the strength of the relationship between each observed variable and its corresponding construct[17].

In the present study, the model consists of both exogenous latent variables and endogenous latent variables associated with workplace fatigue, supervision, work risk, and injury occurrence among heavy equipment operators in surface mining operations. In this model, the latent construct EC was measured using the observed variable Family Condition Variable (FPV). Similarly, the latent construct Driving Confidence (DC) was measured through the Training Variable (TV) and Experience Variable (TV). The endogenous latent constructs included Level of Supervision (LOSS), Work Risk (WR), Level of Fatigue (FAT), and Injury (INJ). These constructs were measured using different observed indicators, including Number of Supervision (LOSV), Work Location Variable (WLV), Residential Status Variable (RSV), Fatigue Status Variable (FSV), and Injury Involvement (IV), respectively. The CFA model was designed to examine whether these observed variables adequately represented the theoretical constructs proposed in the study.

Table 3 shows the description of variables.

Table 3. The variables and their description

Variable	Description
Emotional Condition $\xi 1$	Family condition input by the operator
Driving Confidence $\xi 2$	Length of work (experience) and training involvement
Level of Supervision $\eta 1$	Number of supervisions
Work Risk $\eta 2$	Work location (In-pit or haulage)
Level of Fatigue $\eta 3$	Residential status and fatigue detection status
Injury $\eta 4$	Injury involvement during work

3.2 Structural Equation Modelling (SEM)

The structural equation model is defined by a path diagram to represent the relationship among the contributing factors and the type of data that has been collected. After that, the LISREL simulation was used to describe the relationship between the factors. Ghosh and Bhattacherjee[18] showed that the LISREL model shows the advantage of estimating the direct and indirect factors incorporated into the model. Moreover, it allows us to explain the complex system relationship using a single model. Six different path models were constructed to obtain the best result of the statistical parameter. Figure 4 shows the best-fit model simulation by using LISREL that determined by the exogenous variables (ξ) and endogenous variables (η). The statistical fit parameter comparison that consists of RMSEA (Root Mean Square Error of Approximation), GFI (Goodness of Fit Index), AGFI (Adjusted Goodness of Fit Index), NFI (Normed Fit Index), NNFI (Non-Normed Fit Index), IFI (Incremental Fit Index), and p- value. According to Rigdon (1996), RMSEA is a good option to determine the fit of a research model to yield interpretable indicators and to provide a basis for future theory development in the confirmatory context that is used in this study[19]. The summary of the statistical parameter can be seen in Table 4.

Table 4. The best-fit model statistical parameter summary and suggested value

Fitness statistical parameter	Best fit model (Figure 4)	Suggested value
RMSEA	0.09*	< 0.10
GFI	0.98*	> 0.90
AGFI	0.89**	> 0.85
NFI	0.95*	> 0.90
NNFI	0.83	> 0.90
IFI	0.97*	> 0.90
pvalue	0.048***	< 0.05

*Good fit according to Medsker *et al.*[20]

** Acceptable fit according to Akinci[21]

*** Statistically significant according to Wasserstein & Lazar[22]

Table 5. Direct effect of variables on Injury Tendency (INJ)

Latent variable	Path coefficient to Injury Tendency (INJ)
Emotional Condition (EC)	0.20
Driving Confidence (DC)	0.12
Level of supervision (LOSS)	-0.15
Work risk (WR)	0.24
Fatigue level (FAT)	0.40

Table 6. Path coefficient and the t-statistic of the structural models

	Exogenous Variables				Endogenous Variables	
	Variables	**1a. Emotional condition**	**1b. Driving confidence**	**2. Level of supervision**	**3. Work risk**	**4. Level of fatigue**
	Level of Supervision (2)	-0.18(-1.87)	-0.03(-0.58)			
Endogenous Variables	Work Risk (3)	-0.07(-1.29)	0.04(1.73)	-0.87(-12.94)		
	Level of Fatigue (4)	0.32(5.06)	-0.35(-9.34)	0.24(3.34)	0.29(3.26)	
	Injury (5)	0.20(2.10)	0.12(-1.76)	-0.15(-1.36)	-0.05(-0.47)	0.40**(0.76)

* t values are in parentheses, generated from LISREL

** statistically significant according to Gorsuch[24]

Based on the standardised solution, the level of fatigue has the greatest path coefficient among all variables and has a positive impact; thus, this variable should be examined carefully in the mine. The indirect effect is defined as the difference between the total and direct effects[23]. The summary of the direct path coefficient from each latent variable to Injury Tendency (INJ) can be seen in Table 5. Table 6 shows the direct path coefficient and the t-statistic of the structural models.

In addition, the summary of the indirect effect from each latent variable to Injury Tendency (INJ) by the calculation adopted from Joreskog and Sorbom[23] can be seen in Table 7.

Table 7. Indirect path coefficient to Injury Tendency (INJ)

Latent Variable	Loading factor to Injury Tendency (INJ)
Emotional Condition (EC)	0.14
Driving Confidence (DC)	-0.13
Level of Supervision (LOSS)	-0.31
Work Risk (WR)	0.34

4. Discussion

The best fit model has the value of RMSEA of 0.09, and it is confirmed to reveal that the model is fit due to less than 0.10[20]. RMSEA shows the measurement of approximate fit in the population[25]. NFI values range from 0 to 1; the higher indicates the better the fit[26]. The NFI, in this case, is 0.95, which represents the fit model also. Similar to NFI, NNFI has a value range from 0 to 1, and the higher NNFI shows a better fit of the model. In this study, the value of NNFI is 0.83; thus, it is not fit enough. According to Jöreskog and Sörbom[27], GFI implies how much the model fits is better compared with "no model at all" (null model). GFI ranges between 0 and 1, and the higher indicates the better the fit. The value of GFI here is 0.98, which shows that the model is fit enough. AGFI was developed by Jöreskog and Sörbom[28] to adjust for the bias from the complexity of the model. The value of AGFI in this study is 0.89. In several works, such as by Schermelleh-Engel *et al.*[23] (2003) and Akinci[21], an AGFI value greater than 0.85 is considered an acceptable fit. The other parameter is IFI, which should be higher than 0.90 and in this study is 0.97, that confirming the model is fit[20].

The structural model developed from the best-fit path diagram demonstrates several significant relationships among EC, driving confidence, supervision, work risk, fatigue, and injury occurrence in surface mining operations. The results indicate that EC has a significant positive direct effect on injury occurrence (γ=0.20, $p<0.05$). This finding suggests that operators experiencing emotional stress, family-related problems, or psychological disturbances are more likely to be involved in workplace injuries. Emotional instability may reduce concentration, situational awareness, and decision-making ability during heavy equipment operation, thereby increasing the likelihood of unsafe actions and incidents in mining environments.

Similarly, Driving Confidence (DC) was found to have a significant positive effect on injury occurrence (γ=0.12, $p<0.05$). Although training and experience generally improve operator competence, excessive confidence may lead operators to underestimate workplace hazards and engage in riskier behaviours. Experienced operators may develop overconfidence due to familiarity with equipment and operational tasks, potentially resulting in reduced compliance with safety procedures and operational standards. This finding highlights the importance of balancing technical competence with continuous safety awareness and behavioural monitoring.

The analysis further revealed that Level of Supervision (LOSS) has a significant negative effect on injury occurrence (β=-0.15, $p<0.05$). This indicates that effective supervision contributes to reducing workplace injuries among heavy equipment operators. Proper supervision ensures compliance with safety procedures, promotes safe work practices, and enables early identification of unsafe behaviours and hazardous conditions. Adequate supervision also strengthens

communication between workers and management, which is essential in high-risk industrial environments such as surface mines.

In addition, Work Risk (WR) demonstrated a negative relationship with injury occurrence (β= 0.05, $p<0.05$). Although the effect size is relatively small, the result suggests that improved management and awareness of workplace risks may contribute to lowering injury rates. Workers who are more aware of operational risks and hazards may adopt safer behaviours and exercise greater caution while performing tasks. This finding emphasises the importance of risk identification, hazard communication, and safety training programs in mining operations.

Among all the endogenous variables, Level of Fatigue (FAT) showed the strongest positive effect on injury occurrence (β=0.40, $p<0.05$). This indicates that fatigue is the most influential factor contributing to workplace injuries in the studied mining environment. Fatigue, represented by sleep duration and sleep disorder indicators, directly affects workers' physical and cognitive performance, including alertness, reaction time, concentration, and judgment. Operators experiencing inadequate sleep or sleep disturbances are more susceptible to human error, delayed responses, and operational mistakes, which can significantly increase the probability of accidents involving heavy equipment.

Based on the result, the following approach, as shown in Figure 5, can be recommended to reduce injuries to operators in surface mines. The figure illustrates a simplified fatigue monitoring and operational decision process for heavy equipment operators in mining operations. The process begins with a sleep detection procedure used to evaluate the physical and mental condition of the operator before work. Based on the assessment results, operators who meet the required fitness criteria are allowed to operate heavy equipment. However, if signs of insufficient sleep are detected, the operator undergoes further examination to determine their suitability for work. This process is intended to reduce fatigue-related risks, improve operator alertness, and enhance overall workplace safety in mining operations.

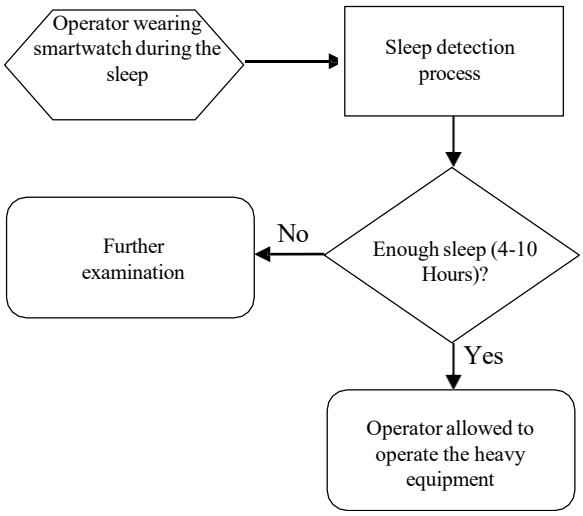


Figure 5. Proposed flowchart model of heavy equipment sleep detection process.

The model also identified an indirect relationship between EC and injury occurrence through the mediating effect of fatigue. EC significantly influenced fatigue levels (γ=0.32, $p<0.05$), which subsequently increased injury involvement. This finding suggests that emotional stress not only directly contributes to workplace incidents but also indirectly affects safety performance by increasing worker fatigue. Employees facing emotional or family-related stress may experience poor sleep quality, mental exhaustion, and reduced recovery, which further elevate the risk of operational errors and injuries.

Based on the causal analysis results, fatigue was identified as the most critical factor contributing to injury occurrence among heavy equipment operators. The findings emphasise the importance of implementing an effective fatigue management system within mining operations. Supervisors play a vital role in continuously monitoring operator fatigue levels, sleep adequacy, mental alertness, and overall physical condition before and during work activities. Since fatigue can significantly impair concentration, reaction time, decision-making ability, and situational awareness, operators experiencing insufficient sleep or mental exhaustion are at a substantially higher risk of workplace incidents and operational errors.

The results also indicate that psychosocial factors, including emotional stress and workplace pressure, may indirectly increase injury risk by contributing to higher fatigue levels. Therefore, supervisors should ensure that the work environment does not create excessive stress, workload imbalance, or psychological pressure that could negatively affect workers' recovery and sleep quality. Appropriate supervisory practices, supportive leadership, and regular communication between supervisors and operators are essential to identify early signs of fatigue and stress-related problems.

To minimise fatigue-related incidents, mining companies should strengthen fatigue management strategies through adequate rest schedules, shift management, sleep monitoring systems, periodic fatigue assessments, and health screening programs. In addition, operators should receive continuous education and safety training regarding the effects of fatigue on operational performance and accident risk. Providing mental health support, sufficient recovery time, and appropriate work-rest cycles can further improve worker alertness and reduce the probability of injuries. Overall, the findings highlight that controlling fatigue is a fundamental requirement for improving occupational safety and operational reliability in surface mining environments.

4.1 Implementation and Validation of the Proposed Fatigue Management System

The findings of this study have practical implications for the implementation of fatigue management systems in surface mining operations. Since fatigue was identified as the strongest predictor of injury occurrence (β=0.40), the proposed framework shown in Figure 5 can be integrated into pre-start fitness-for-work assessments. Operators may wear smartwatches to monitor sleep duration and sleep disturbances prior to commencing work, allowing supervisors to identify individuals at elevated fatigue risk and conduct further assessment when necessary. The practicality of this approach is supported by the SEM results, which demonstrated acceptable model fit (RMSEA=0.09, GFI=0.98, NFI=0.95, IFI=0.97) and confirmed the significant relationship between fatigue and injury occurrence. These findings suggest that smartwatch-assisted fatigue monitoring has the potential to support injury prevention and improve operational safety in mining environments.

4.2 Study Limitations

Several limitations should be considered when interpreting the findings of this study. First, the study was conducted at a single surface coal mine in Indonesia, which may limit the generalizability of the results to other mining operations and workforce populations. Second, fatigue measurements were obtained using a commercially available smartwatch, and although previous studies have reported acceptable reliability, measurement errors related to sensor accuracy and user compliance may still exist. Third, while the model achieved an overall acceptable fit, the NNFI value (0.83) was below the commonly recommended threshold of 0.90, indicating opportunities for further model refinement. Future studies should include larger and more diverse samples, additional fatigue-related variables, and external validation across multiple mining sites to strengthen the robustness and applicability of the proposed framework.

5. Conclusions

This study investigated the relationships among EC, driving confidence, supervision, work risk, fatigue, and injury occurrence among heavy equipment operators in surface mining operations using a Structural Equation Modeling (SEM) approach. The goodness-of-fit indices demonstrated that the proposed structural model achieved an acceptable level of fit, indicating that the developed framework adequately explains the causal relationships among the studied variables.

The findings revealed that fatigue is the most significant factor influencing workplace injuries among heavy equipment operators. Fatigue, represented by sleep duration and sleep disorder indicators, showed the strongest positive effect on injury occurrence, emphasizing the critical role of adequate sleep and physical recovery in maintaining operational safety. Operators experiencing fatigue are more likely to exhibit reduced concentration, slower reaction times, impaired judgment, and decreased situational awareness, all

of which increase the probability of accidents and operational errors in mining environments. EC and driving confidence were also found to positively influence injury occurrence. Emotional stress and psychosocial pressures may directly impair worker performance and indirectly contribute to injuries by increasing fatigue levels. Similarly, excessive confidence among experienced operators may result in lower risk perception and reduced adherence to safety procedures.

In contrast, effective supervision and improved management of workplace risks contributed to reducing injury occurrence. These findings highlight the importance of supportive supervision, hazard awareness, and continuous monitoring of operator conditions in high-risk industrial settings. Based on the results, the study recommends the implementation of a comprehensive fatigue management system incorporating sleep detection procedures, periodic fatigue assessment, adequate rest schedules, shift management, health screening, and continuous safety training. Overall, the study demonstrates that fatigue management is a fundamental component of occupational safety and operational reliability in surface mining operations and should be integrated into organizational safety policies and supervisory practices.

The proposed fatigue management framework provides a practical pathway for implementing the study findings into operational safety improvements. By integrating smartwatch-based sleep monitoring with supervisory assessment processes, mining organizations may be able to identify fatigue-related risks before work commences and implement timely interventions. Nevertheless, further validation across multiple mining operations and workforce populations is recommended to confirm the generalizability, reliability, and long-term effectiveness of the proposed approach.

6. Acknowledgements

The authors gratefully acknowledge the support and cooperation of mine management (Pamapersada Nusantara ABKL District, Indonesia) for providing access to operational data and facilitating field studies. We also extend our appreciation to the heavy equipment operators who participated in this study and contributed valuable insights.

In addition, the first author would like to acknowledge the financial support from Indonesian Endowment Fund for Education (LPDP) for the scholarship and for making the study at Curtin University possible. He expresses sincere gratitude to his supervisors and colleagues at the Western Australian School of Mines, Curtin University, for their guidance and encouragement throughout the course of this research.

7. References

1. World Health Organization. Global status report on road safety 2018 [Internet]. 2018 [cited 2026 Jul 11]. Available from: https://www.who.int/publications/i/item/9789241565684
2. Department of Mines Industry Regulation and Safety. Monthly safety and health snapshot for the Western Australian mineral's sector [Internet]. 2017 [cited 2026 Jul 11]. Available from: https://www.dmp.wa.gov.au/Documents/Safety/MSH-MSS_Sep17.pdf
3. Department of Mines Industry Regulation and Safety. Safety performance in the Western Australian mineral industry: accident and injury statistics 2019-20 [Internet]. Government of Western Australia; 2020 [cited 2026 Jul 11]. Available from: https://nla.gov.au/nla.obj-2906061551/view
4. Department of Mines Industry Regulation and Safety. Traffic management fundamentals audit – guide; 2018.
5. Jones R, Cattani M, Cross M, Boylan J, Holmes A, Boothroyd CA, *et al.* Serious injuries in the mining industry: Preparing the emergency response. Australas J Paramedicine. 2019.
6. Bener A, Yildirim E, Özkan T, Lajunen T. Driver sleepiness, fatigue, careless behavior and risk of motor vehicle crash and injury: Population based case and control study. J Traffic Transp Eng (Engl Ed). 2017; 4. https://doi.org/10.1016/j.jtte.2017.07.005
7. Lavidor M, Weller A, Babkoff H. How sleep is related to fatigue. Br J Health Psychol. 2003; 8:95-105. https://doi.org/10.1348/135910703762879237 PMid:12643819

8. Luca A, Barsocchi P, Cimino MGCA, La Rosa D, Palumbo F, Vaglini G. Sleep behavior assessment via smartwatch and stigmergic receptive fields. Pers Ubiquitous Comput. 2018; 22. https://doi.org/10.1007/s00779-017-1038-9
9. Ricchio K, Lyter P, Palao J. Reliability of fitness trackers at different prices for measuring steps and heart rate: A pilot study. Cent Eur J Sport Sci Med. 2018; 24:57-64. https://doi.org/10.18276/cej.2018.4-06
10. Commission for Occupational Safety and Health, Government of Western Australia. Code of practice: working hours [Internet]. 2006 [cited 2026 Jul 11]. Available from: https://www.commerce.wa.gov.au/sites/default/files/atoms/files/copworkinghours.pdf
11. Pamapersada Nusantara ABKL District. Operator personal assistance report, Mine Report. Pamapersada Nusantara; 2021.
12. Pamapersada Nusantara. Our operation area [Internet]. 2021 [cited 2026 Jul 11]. Available from: https://pamapersada.com/en/Map
13. Memon M, Ting H, Hwa C, Ramayah T, Chuah F, Cham TH. Sample size for survey research: Review and recommendations. 2020; 4:i-xx. https://doi.org/10.47263/JASEM.4(2)01
14. Tibbitts GM. Sleep disorders: Causes, effects, and solutions. Prim Care. 2008; 35(4):817-837. https://doi.org/10.1016/j.pop.2008.07.006 PMid:18928832
15. Suhr, D. The Basics of structural equation modeling. University of Northern Colorado; 2006.
16. Li S, Sari YA, Kumral M. New approaches to cognitive work analysis through latent variable modeling in mining operations. Int J Min Sci Technol. 2019; 29. https://doi.org/10.1016/j.ijmst.2019.06.014
17. Hoyle R. Confirmatory factor analysis. In: Handbook of applied multivariate statistics and mathematical modelling; 2012. https://doi.org/10.1016/B978-012691360-6/50017-3
18. Ghosh A, Bhattacherjee A. Predictors of occupational injuries among coal miners: Causal analysis. Min Technol. 2007; 116:16-24. https://doi.org/10.1179/174328607X161879
19. Rigdon E. CFI versus RMSEA: A comparison of two fit indexes for structural equation modeling. Struct Equ Modeling. 1996; 3:369-379. https://doi.org/10.1080/10705519609540052 PMCid: PMC11078367
20. Medsker GJ, Williams LJ, Holahan PJ. A review of current practices for evaluating causal models in organizational behavior and human resources management research. J Manage. 1994; 20:439-464. https://doi.org/10.1177/014920639402000207
21. Akinci DE. Information criteria in structural equation models [doctoral thesis]. Istanbul: Mimar Sinan University of Fine Arts, Institute of Science; 2007.
22. Wasserstein RL, Lazar NA. The ASA statement on p-values: Context, process, and purpose. Am Stat. 2016; 70(2):129-133. https://doi.org/10.1080/00031305.2016.1154108
23. Joreskog KG, Sorbom D. LISREL 8.53 user's reference guide. Scientific Software International; 2002.
24. Gorsuch RL. Factor analysis. 2nd ed. Hillsdale (NJ): Erlbaum; 1983.
25. Steiger JH. Structural model evaluation and modification: An interval estimation approach. Multivariate Behav Res. 1990; 25(2):173-180. https://doi.org/10.1207/s15327906mbr2502_4 PMid:26794479
26. Schermelleh-Engel K, Moosbrugger H, Müller H. Evaluating the fit of structural equation models: Tests of significance and descriptive goodness-of-fit measures. Methods Psychol Res Online. 2003; 8:23-74.
27. Jöreskog KG, Sörbom D. LISREL 8: Structural equation modeling with the SIMPLIS command language; 1993.
28. Jöreskog KG, Sörbom D. LISREL 7: A guide to the program and applications. Chicago (IL): SPSS; 1989.

Author Contribution

Aditya Martha Wijaya contributed to the study's conceptualization, methodology, investigation, formal analysis, and writing the originaldraft. Dr. Apurna Ghosh and Professor Ashis Bhattacherjee participatedin the supervision, guidance of the research methodology, and revisionof the paper. Dr. Nearkasen chau, Dr. Ping Chang, Dr. Boris Albijanic and Prof. Jianwei Cheng and others have helped in reviewing and editing.