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A THESIS REPORT ENTITLED

HUMAN FACTOR CONTRIBUTIONS TO HEAVY MINING EQUIPMENT DAMAGES AND ITS IMPACT ON PRODUCTION: A CASE STUDY OF A GHANAIAN MINING CONTRACTOR

BY

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SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF MASTER OF SCIENCE IN

OCCUPATIONAL HEALTH AND SAFETY

THESIS SUPERVISOR

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TARKWA, GHANA.

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# DECLARATION

I declare that this thesis is my own work. It is being submitted for the degree of Master of Science in occupational health and safety in the University of Mines and Technology (UMaT), Tarkwa. It has not been submitted for any degree or examination in any other University.

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(Signature of Candidate)

………………day of……………………………………………….2025.

# ABSTRACT

The reliability of heavy mining equipment is critical to production continuity and safety in Ghana’s surface mining sector. However, recurring equipment failures particularly those influenced by human factors continue to cause substantial downtime, financial loss, and operational inefficiencies. This study investigates the extent and nature of human factor contributions to equipment damage and their associated impact on production at a Ghanaian mining contractor site. Using a retrospective analysis of incident data from 2016 to 2024, a mixed-method approach was applied. Incidents were classified using the Swiss Cheese Model into active failures (slips, lapses, mistakes, and contraventions) and latent conditions (organizational and environmental weaknesses). Quantitative analyses included Kruskal-Wallis tests and Spearman rank correlation to evaluate the distribution of failure types and inter-variable relationships. Results showed that contraventions were the most frequent active failures (41.7%), while mechanical hose bursts dominated the latent failures under technological conditions. The Kruskal-Wallis tests revealed no statistically significant difference in the distribution of active failures (p = 0.3423) and latent conditions (p = 0.2794), suggesting that various human error types occur at similar rates. Spearman correlation analysis indicated strong positive relationships between damage cost and revenue loss (ρ = 0.86), damage cost and downtime (ρ = 0.71), and downtime and revenue loss (ρ = 0.67) demonstrating the compounding effect of human error on operational and financial performance. Mid-career operators (40 to 49 years) and those with 6 to 10 years of experience were most frequently involved in incidents, while night shift incidents, though fewer, were more severe in impact. The study concludes that human factors play a pivotal role in equipment damage severity and production loss. It recommends the implementation of behavior-based safety (BBS) programs, fatigue risk management systems (FRMS), predictive maintenance, and leadership-driven task assessments. These interventions are essential for minimizing human error, enhancing equipment reliability, and improving overall production efficiency in mining operations.

# ACKNOWLEDGEMENTS

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# CHAPTER ONE INTRODUCTION

## 1.1 Statement of Problem

The use of heavy mining equipment within the mining industry has been increasing, contributing to the possible occurrence of accidents (Stemn *et al*., 2022). The trends of mechanization in the gold mining plays a vital role towards achieving the overall gold production target in Ghana. Owing to the associated risks of mining machinery, researchers have taken large strides in literature on assessment of the reliability in operations and maintenance of mining machines.

Of late human factors are found to be a large contributor to majority of the failures in the operations and maintenance of machines. However, most of the factors are often neglected despite their significant contributions (Dhillon, 2014). These contributory factors ascertain catastrophic impacts on mining equipment, thereby the need to addressing the root cause. The management of most mining companies are interested in high production performance and levels coupled with minimal downtime. Hence, any activity that leads to unplanned downtimes has a lot of implications on achieving production targets (Reason, 2000).

Human error, a component of human factor has been a major cause of industrial and occupational accidents since the very first day of industrialization (Reason, 1990), significantly impacting mining operations by contributing to equipment failure, leading to decreased productivity and increased costs. Despite this, human factor consideration is often overlooked in mining safety frameworks.

The lack of consideration of human factor methods in mining could stem from a widely-held belief that whilst human behaviour can be influenced by design, the major contributor to accidents and equipment defect is the erratic and unpredictable behaviour of unreliable people. This is what Dekker describes as the ‘Bad Apple Theory’ (Dekker, 2006). This justifies the need for research on human factors engineering, which is aimed to reducing human error, increase productivity, safety enhancement and operators’ comfort with a specific focus in the mining sector (Simpson and Horberry, 2018).

While research has addressed human factor and human error in general industrial settings, there is a lack of focus on how specific human factors in equipment operation and maintenance impact on production in the Ghanaian mining industry. This study addresses this gap by investigating equipment damages caused by human factor and how it impacts production (tonnes) at a Ghanaian mining contractor site.

## 1.2 Thesis Objectives

The objectives of this thesis are to:

1. To Identify Human Factor contributions to equipment damages.
2. To Investigate the Relationship between Equipment Damages and Production (Revenue $).

## 1.3 Methods Used

The methods used include:

1. Thematic and quantitative analysis on secondary data from the Ghanaian mining contractor using Microsoft excel.
2. Classification Scheme from Swiss Cheese Accident Causation Model to identify Active Failures and Latent conditions.
3. Non-parametric tests (Kruskal-Wallis Test) and Spearman Rank Correlation test was used to test the hypothesis formed using R-studio programming software.

## 1.4 Facilities Used

The facilities used include:

1. Incident Data on Equipment Damages, Equipment Downtimes and Production Figures from the Ghanaian Mining Contractor
2. Library and internet facilities from the University of Mines and Technology (UMaT)
3. A personal laptop with Microsoft Office Suite (Word, Excel and Power Point)
4. R-Studio programming Software

## 1.5 Organisation of Project Report

This project has five chapters. The problem statement, objectives, methodology, and facilities are all covered in the first chapter. The second chapter examines the relevant literature. The third chapter details the method used for the project as well as how the entire project work analysis was done. The fourth chapter contains the findings and discussion. The project's conclusion and recommendations are discussed in the last chapter.

# CHAPTER TWO LITERATURE REVIEW

## 2.1 Introduction

It is crucial to take a closer look at related studies on the human factors and errors in equipment installation and operations, how they contribute to equipment damages and the impact of these damages on production in order to compare, confirm, and emphasize variations in the data from the research as well as to draw any useful and applicable conclusions.

## 2.2 Mining Operations in Ghana

Mining plays a pivotal role in Ghana's economy, significantly contributing to national revenue, job creation, and economic growth. The country is particularly renowned for its abundant mineral resources, especially gold, making it the leading gold producer in Africa and a major global exporter (Anon, 2021a). Alongside gold, Ghana is also rich in other minerals, such as bauxite, manganese, diamonds, and, more recently, lithium, which has further strengthened its position in the global mining landscape. The origins of mining in Ghana date back to pre-colonial times when traditional methods were used to extract gold and other valuable minerals. The colonial era introduced mechanized mining and large-scale operations, notably following the discovery of significant gold deposits in Obuasi in the late 19th century (Tsikata, 1997). Over time, the sector has evolved through policy changes and the participation of international mining companies (Tsikata, 1997).

Ghana's mining industry is organized into two primary categories: large-scale mining and small-scale or artisanal mining. Large-scale mining is predominantly operated by multinational companies like AngloGold Ashanti, Goldfields, and Newmont Goldcorp, characterized by advanced technologies and substantial capital investment. Small-scale mining, which also contributes significantly to gold production, provides livelihoods for many local communities but is often informal and less regulated (Hilson, 2001). The sector is a key driver of the economy, accounting for about 37 % of total exports and approximately 5 % of GDP in recent years (Anon, 2021a). Additionally, mining generates direct employment for thousands of Ghanaians and supports numerous indirect jobs in sectors like logistics, equipment maintenance, and local commerce.

However, despite its economic importance, the mining sector in Ghana faces several challenges. These include environmental degradation, displacement of communities, and illegal mining activities. Human errors, especially in large-scale mining operations, contribute significantly to equipment damage and reduced efficiency. These issues not only hinder production but also increase operational costs and pose safety risks (Obiri-Yeboah *et al*., 2020).

## 2.3 Production and its Measurement in the Mine

Mining production encompasses the extraction of valuable minerals or resources from the earth, their preparation for processing, and delivery for utilization or sale. This complex process involves several stages, including exploration, drilling, blasting, hauling, and processing, all of which are carefully managed to maximize resource recovery, minimize waste, and ensure economic efficiency (Ding *et al*., 2018). The success and profitability of mining operations depend on precise measurement and monitoring throughout the production process (Hartman and Mutmansky, 2002). Mining production can be categorized into two main components: ore production and waste management (Ding *et al*., 2018). Ore production focuses on extracting and processing materials containing valuable minerals, while waste management involves the removal and disposal of overburden, barren rock, and other non-valuable materials to access the ore body. Both components are vital to the efficiency and sustainability of mining activities.

Several factors significantly influence mining production. Geological conditions, including the size, shape, depth, and grade of the ore body, play a crucial role in determining production rates and selecting suitable mining methods (Hartman and Mutmansky, 2002). Effective mine design and planning are equally essential, ensuring the efficient extraction, transportation, and management of waste materials while keeping operational costs low (Hartman and Mutmansky, 2002). The performance of mining equipment, such as excavators, haul trucks, and crushers, has a direct impact on production. Regular maintenance and the adoption of advanced technologies are critical to maintaining equipment efficiency (Jones and Smith, 2017). Additionally, skilled operators and a well-trained workforce contribute significantly to optimizing equipment use and minimizing delays. Compliance with environmental and safety regulations also supports sustainable and uninterrupted production (Jones and Smith, 2017).

Accurate measurement of production is essential for assessing operational efficiency, fulfilling contractual obligations, and maintaining profitability. Various methods are employed to ensure precise monitoring. Tonnage measurement involves determining the total weight of extracted ore (Run-of-Mine tonnage) and the quantity processed to recover valuable minerals (Jones and Smith, 2017). Tools like weighbridges, belt scales, and truck load scanners enhance accuracy in these measurements. Advanced technologies, such as laser scanners, drones, and GPS-enabled machinery, are used for volume measurement, enabling the calculation of ore and waste material movement (Jones and Smith, 2017). Periodic surveys help track stockpile volumes and material displacement. Recovery and yield metrics, such as recovery rates and yield percentages, measure the effectiveness of mineral extraction. Additionally, key performance indicators (KPIs) like strip ratios, cycle time analyses, and downtime metrics are utilized to monitor equipment performance and address production delays. These strategies and technologies enable mining operations to optimize resource utilization, improve profitability, and adopt sustainable practices.

## 2.4 Equipment and Equipment Damages

In the mining industries, equipment damage is a significant concern due to its impact on productivity, operational costs, and safety. Proper classification of equipment damage helps organizations understand the nature and causes of failures, enabling them to implement preventive and corrective measures effectively.

### 2.4.1 Some Equipment Used by the Ghanaian Mining Contractor in their Operations

The company is a leading provider of mining and construction services in Ghana, utilizes an extensive array of specialized machinery to effectively execute large-scale projects and fulfil client requirements. Their fleet comprises equipment tailored for excavation, hauling, drilling, and other essential mining and construction tasks. These machines are built to withstand the demanding conditions of mining environments, ensuring optimal performance and reduced downtime. Among the critical equipment employed are:

*Excavators*

Excavators are essential for large-scale excavation tasks, including removing overburden and mining ore. They uses heavy-duty excavators from globally recognized brands such as Caterpillar, Komatsu, and Hitachi. These machines come with advanced features like GPS control systems and high-efficiency hydraulic systems for precise and energy-efficient operations.

*Dump Trucks*

Dump trucks transport large volumes of ore and waste materials from the mining face to stockpiles or processing plants. Their fleet includes articulated and rigid dump trucks with varying capacities, such as Caterpillar 777 and 785 models, capable of handling heavy loads under tough conditions. These trucks are equipped with real-time monitoring systems to track fuel consumption, speed, and load metrics, enhancing operational efficiency.

*Drilling Rigs*

Drilling rigs are used for creating blast holes to fragment rock for extraction. The company employs modern drilling rigs capable of operating in deep, hard rock environments. These rigs are equipped with advanced drill bit technology and automated systems to ensure accuracy and reduce drilling time.

*Loaders*

Loaders are used for loading ore and waste material into haul trucks and crusher tray. They uses wheel loaders and tracked loaders with high-capacity buckets for rapid material handling. Machines like the Caterpillar 992 and 988 models are common in their fleet due to their reliability and power.

*Dozers*

Bulldozers are vital for land clearing, levelling, and stockpile management. Their fleet includes robust models like the Caterpillar D11 and Komatsu D475. These dozers are equipped with advanced blade control systems to improve accuracy and reduce operator fatigue.

*Graders*

Graders are used for maintaining haul roads to ensure safe and efficient transportation of materials. Well-maintained haul roads reduce vehicle wear and improve cycle times, enhancing overall production efficiency. Caterpillar motor graders, such as the 14M and 16M models, are frequently utilized.

*Maintenance and Support Equipment*

A reliable fleet requires regular maintenance to minimize downtime. E&P uses mobile service trucks equipped with tools, spare parts, and diagnostic equipment for on-site repairs.

They also employ forklifts and cranes for material handling and machine assembly.

### 2.4.2 Equipment Damage Classification

In mining and construction operations, ensuring the reliability of equipment is vital for sustaining productivity, safeguarding workers, and controlling operational expenses. However, heavy machinery frequently operates under challenging conditions, experiencing significant wear and exposure to unpredictable environmental factors, which can result in damage. Categorizing equipment damage is critical for analyzing its causes, understanding its effects, and determining appropriate corrective actions. This systematic approach helps identify weaknesses, prioritize maintenance tasks, and establish preventive strategies, ultimately improving efficiency and promoting sustainable operations (Hartman and Mutmansky, 2002).

*Classification by Affected Component*

* Structural Damage: structural damage refers to issues affecting the physical integrity of equipment, including its frame, chassis, or external body, which can compromise stability and safety. This type of damage often results from collisions, overloading, or operational accidents. Additionally, prolonged exposure to vibrations or repetitive mechanical stress may cause structural fatigue (Hartman and Mutmansky, 2002). Structural damage can diminish the equipment's load-bearing capacity, cause misalignment of components, and accelerate wear on other parts. To mitigate such damage, regular inspections, proper load management, and the utilization of reinforced materials are essential (Kumar *et al*., 2020).
* Mechanical Damage: mechanical damage refers to failures in moving components such as engines, gearboxes, and hydraulic systems. It often occurs due to extended use, insufficient lubrication, improper upkeep, or the use of low-quality parts (Singhal and Naik, 2018). Such damage typically results in reduced operational efficiency, higher fuel consumption, and potential equipment downtime. In more severe cases, it can lead to catastrophic breakdowns. Adopting predictive maintenance practices, utilizing premium-quality lubricants, and following manufacturer-recommended maintenance schedules are effective strategies to address mechanical damage (Singhal and Naik, 2018).
* Electrical Damage:electrical damage impacts the wiring, sensors, and control systems of machinery, often caused by power surges, moisture penetration, short circuits, or improper installation of electrical components (Singhal and Naik, 2018). This type of damage can lead to operational disruptions, equipment malfunctions, and serious safety risks, including electrical fires or system failures (Kumar *et al*., 2020). Preventative measures such as ensuring proper insulation, installing surge protectors, and conducting regular inspections of electrical systems can help mitigate the occurrence of such damage (Singhal and Naik, 2018).
* Hydraulic Damage: hydraulic systems are crucial for the functioning of heavy machinery, and any damage to these systems can severely impact performance. Issues such as leaks, blockages, or pressure loss in hydraulic lines, often caused by hose failures, contamination of hydraulic fluid, or wear of components, can lead to operational inefficiencies (Jardine *et al*., 2006). Hydraulic damage results in decreased power output and poses potential safety risks due to sudden pressure drops. To prevent such damage, regular replacement of hydraulic fluids, the use of filters to avoid contamination, and routine inspection of hoses and seals are essential. (Jardine *et al*., 2006).
* Operational System Damage: operational system damage refers to failures in GPS, monitoring systems, or automated controls that are vital to the operation of modern mining equipment. Such damage can stem from issues like software bugs, hardware malfunctions, exposure to harsh environmental conditions, or improper updates to system software (Bhaskar and Kumar, 2021). These malfunctions can result in reduced accuracy, inefficiencies in navigation, and disruptions in automated processes, all of which can negatively impact production rates and safety. To prevent this, regular software updates, protection of sensitive components from environmental damage, and the maintenance of backup systems are essential strategies (Bhaskar and Kumar, 2021).

*Classification by Severity of Equipment Damage*

* Minor damage: minor damage usually refers to cosmetic issues like scratches, dents, or paint loss that do not affect the equipment's performance or safety. These issues are typically the result of normal wear and tear, slight impacts, or environmental factors. While they may appear insignificant, if left unattended, minor damage can worsen over time and eventually impact the equipment's overall structural integrity. (Walker, 2019).
* Moderate damage: moderate damage refers to partial failures in non-essential components like mirrors, control panels, or auxiliary systems. While these issues may not immediately halt operations, they can cause inefficiencies, decrease operator comfort, and, if neglected, lead to more serious problems (Turner *et al*., 2018). This type of damage is often caused by prolonged use, minor accidents, or moderate stress on the equipment. Addressing these issues during regular maintenance can prevent further deterioration and ensure the equipment operates at its best (Smith and Brown, 2020).
* Severe damage: severe damage involves failures in essential components such as engines, hydraulic systems, or braking mechanisms, which significantly affect the equipment's performance and safety (Turner *et al*., 2018). It is often caused by overloading, neglecting regular maintenance, or operating under harsh environmental conditions. Such damage usually results in operational downtime and higher repair costs, necessitating prompt intervention to reduce disruptions and mitigate safety hazards (Turner *et al*., 2018).
* Catastrophic damage: catastrophic damage represents the most severe level of equipment failure, resulting in total destruction or complete malfunction due to incidents like rollovers, fires, or structural collapses (Smith and Brown, 2020). This type of damage typically occurs from major accidents, significant operational mistakes, or rare yet extreme environmental factors. It leads to substantial financial losses and safety concerns, often requiring equipment replacement and thorough investigations to avoid future occurrences. Implementing robust safety protocols and comprehensive training programs can help reduce the likelihood of catastrophic damage (Johnson, 2021).

### 2.4.3 Causes of Equipment Damages

*Operational Factors*

Equipment damage in mining and industrial operations arises from multiple interconnected factors, with operational practices being a key contributor. Overloading machinery beyond its specified capacity places undue stress on components, leading to accelerated wear and a higher risk of failure (Walker, 2019). Likewise, improper usage, such as using equipment for tasks it was not designed for, causes both structural and functional damage. Extended operation without sufficient breaks often leads to overheating and fatigue of vital components, further intensifying wear and tear (Hartman and Mutmansky, 2002).

*Environmental Conditions*

Environmental factors also greatly influence the longevity of equipment. Dust infiltration leads to abrasion in moving parts, significantly shortening their lifespan, while extreme temperatures can negatively affect hydraulic systems and batteries (Singhal and Naik, 2018). Corrosion, caused by exposure to moisture, chemicals, or saline environments, weakens metal components, and unstable terrain often causes impact damage to tires, tracks, and suspension systems. To address these environmental challenges, it is essential to incorporate strong design features and conduct regular maintenance to minimize their impact.

*Mechanical Issues*

Mechanical issues are also a major contributor to equipment damage. Repeated stress on components can lead to fatigue, causing cracks and fractures that result in eventual failure. Additionally, poor design or manufacturing defects can undermine the reliability of equipment, making it more prone to early breakdowns. Inadequate lubrication worsens these problems by increasing friction and overheating in moving parts, which accelerates wear and tear (Singhal and Naik, 2018).

*Human Factors*

Human factors, such as operator mistakes and negligence, play a crucial role in equipment damage. Operators who are unskilled or inadequately trained may misuse machinery, while disregarding standard operating procedures such as overloading or ignoring warning signals can lead to preventable damage. Additionally, neglecting regular maintenance, employing improper repair methods, or using low-quality replacement parts accelerates wear and tear, diminishing the equipment's efficiency and dependability (Jardine *et al*., 2006).

*Accidents and Collisions*

Accidents and collisions during operations are also common contributors to equipment damage. Overcrowded work areas increase the risk of machinery impacts, while poor visibility due to adverse weather or inadequate lighting contributes to operational errors. Operator fatigue further compounds these risks, as tired operators are more prone to mistakes that can result in significant damage (Smith and Brown, 2020).

*Maintenance-Related Factors*

Maintenance-related factors, such as inconsistent servicing and improper repairs, significantly contribute to equipment damage. Delaying routine maintenance allows small problems to escalate, and irregular inspections may overlook early signs of wear. Additionally, using inappropriate tools or low-quality parts during repairs worsens existing issues, resulting in repeated failures and increased operational costs (Walker, 2019).

### 2.4.4 Relationship between Equipment Damages and Production

The relationship between equipment damage and production is crucial for the efficiency and profitability of mining and construction operations. Equipment is essential for carrying out daily tasks, and any damage or failure can severely disrupt production processes (Barton *et al*., 2017). When equipment is damaged, it loses its ability to function optimally, leading to negative impacts on productivity, operational continuity, and project timelines.

One of the most immediate effects of equipment damage is a reduction in production capacity (Koch *et al*., 2018). Essential components such as engines, hydraulics, and conveyors are key to operational efficiency. Research indicates that unplanned downtime can decrease production capacity by 5 to 20 % in mining operations (Bartos and Martinez, 2019). This can result in significant revenue losses, particularly in capital-intensive industries like mining. Any malfunction in these components can slow down production or halt operations. For instance, if a conveyor system fails, the transport of materials to processing plants is delayed, affecting the speed of raw material processing and, consequently, production output (Brosnan *et al*., 2015). Even minor breakdowns can lead to disruptions, requiring downtime for repairs and impacting overall workflows.

Additionally, damaged equipment increases operational costs. Repairing or replacing machinery diverts funds that could be used for other operational needs. Frequent unscheduled repairs, high maintenance expenses, and extended downtime amplify the financial strain on the company, making operations less cost-efficient (Koch *et al*., 2018). In severe cases, such as an engine failure, the company may incur substantial financial losses due to the need for significant repairs or even replacement of equipment (Koch *et al*., 2018). According to McKinsey and Company (2021), maintenance costs account for 20 to 50 % of total operating costs in mining operations, with a large portion linked directly to unplanned repairs resulting from equipment damage.

Damage to equipment also affects overall equipment effectiveness (OEE), a key performance metric used to assess the efficiency of production equipment. OEE measures three factors: equipment availability (downtime), performance efficiency (ability to meet production targets), and product quality (Barton *et al*., 2017). When equipment is damaged, it reduces availability, slows down operations, and can impact product quality, leading to lower OEE scores. Poor OEE reflects inefficiencies that reduce production output and profitability (Graham *et al*., 2019). A benchmark study by the Mining Industry Institute revealed that operations with poor maintenance practices had OEE scores as low as 50 to 60%, while industry-leading operations maintained OEE scores of 85 to 90 %. Lower OEE scores are linked to reduced production and higher operational costs (Anon, 2018).

The frequency and type of damage also affect the relationship between equipment damage and production. Repeated minor damage to the same equipment may indicate recurring underlying issues, such as inadequate maintenance or unfavourable operating conditions, which could eventually result in major failures. These cumulative effects can significantly impact production over time. On the other hand, infrequent damage caused by accidents, environmental factors, or human error may have unpredictable effects on operations but still disrupt production (Milton and Van der Meer, 2016).

## 2.5 Human Factor and Human Error

Human error and human factors are critical concepts in understanding and improving safety, productivity, and efficiency in various industries. Human error refers to unintended actions or decisions that deviate from expected behaviour, often leading to undesirable outcomes. On the other hand, human factors encompass the physical, psychological, and social elements that affect human performance in the workplace. This multidisciplinary field examines how humans interact with tools, systems, and environments to optimize safety and efficiency while minimizing errors (Dekker, 2018). Together, these concepts provide a framework for identifying and mitigating risks associated with human behaviour in complex systems.

### 2.5.1 Definition of Human Factor and Human Error

Human factors refers to the broader study and application of understanding human behavior, capabilities, and limitations in the context of systems, environments, and technologies. It involves designing systems, tools, and environments to match human abilities and reduce the likelihood of mistakes or inefficiencies. The goal is to optimize performance, improve safety, and increase user satisfaction by considering how humans interact with various systems (Wickens *et al*., 2019) where as Human error is defined as the "failure of planned actions to achieve the desired outcome without the influence of unforeseen events" (Reason, 1990). It is only after the outcome is assessed that the individual can recognize that an error has occurred (Rasmussen, 1982). The relationship between human factors and human error is that human error is a critical area of focus within the field of human factors. Essentially, human factors research seeks to understand the root causes of human error and design systems that minimize or prevent such errors from happening (Wickens *et al*., 2019). The various forms of human error are not as diverse or numerous as one might expect; instead, they follow a common pattern across different types of mental tasks (Reason, 1990). In general, human error can be divided into active failures, which produce immediate consequences, and failures, which remain hidden within a system until specific conditions activate them (Dekker, 2018).

### 2.5.2 Classification of Human Error

Rasmussen (1982) classified human error based on the cognitive level involved in the behaviour. He categorized human behaviour into three types: skill-based, rule-based, and knowledge-based. Skill-based behaviours occur at an unconscious level and are often automated, requiring little cognitive effort. Rule-based behaviours involve the application of learned rules or procedures for decision-making. Errors in this category happen when an individual uses an incorrect rule or misapplies a correct one. Knowledge-based behaviours arise when an individual encounters a new situation requiring previous knowledge and mental effort. These tasks demand high cognitive load, and errors often occur in unfamiliar or emergency situations due to a lack of training or information. Rasmussen's framework for classifying errors and violations laid the groundwork for further understanding human errors in various contexts.

Reason (1990, 1995) introduced the concept of "unsafe acts" to describe the errors and violations that lead to adverse events. He classified errors into two main types. The first, errors of execution, occur when an individual intends to perform a task correctly but inadvertently makes an error, often due to distractions, fatigue, or lapses in attention. These errors are termed slips or lapses. Slips occur when an individual performs the wrong action unintentionally, while lapses happen when they forget or miss steps in a task. These errors are often linked to failures in attention, memory, or recognition. The second type of error occurs when an individual carries out a plan as intended, but the plan itself is inadequate for the situation. These are classified as mistakes and arise from failures in decision-making or intention (Patterson, 2009). Mistakes can be rule-based or knowledge-based. Rule-based mistakes happen when individuals apply previously learned rules to a situation but misapply or fail to apply them correctly. Knowledge-based mistakes occur when individuals face a new situation and attempt to develop a solution based on insufficient or inaccurate knowledge, often influenced by personal biases.

Violations or contravention, as defined by Reason (1995), involve the deliberate disregard of established rules and regulations. These can be classified as routine or exceptional. Routine violations involve habitual rule-bending condoned by management, while exceptional violations are isolated events that deviate from rules but are not tolerated by management. Such violations increase the likelihood of errors and can lead to negative outcomes. Reason emphasized that errors represent breakdowns in an individual’s mental processes, such as attention, memory, or decision-making (Patterson, 2009). Furthermore, distinguishing between intentional and unintentional behaviour is crucial when classifying human error.

Sater and Alexander (2000) proposed another classification of human error, distinguishing errors of omission, commission, and substitution. Errors of omission occur when an individual fails to perform a required task, while errors of commission arise when a person performs an action incorrectly or at the wrong time. Substitution errors involve the completion of incorrect actions altogether.

Despite these various categorizations, O'Hare (2000) highlighted a lack of consistency in the definitions and criteria used to classify human errors across industries and countries. This inconsistency hinders the ability to compare and share data on human error, which may contribute to the persistent high proportion of accidents attributed to human error over the years (Patterson, 2009).

### 2.5.3 General Causes of Human Error

The human factors theory of accident causation identifies human error as a significant contributor to workplace incidents. According to this theory, accidents typically result from a chain of events driven by three main factors: overload, inappropriate responses, and inappropriate activities (Krause *et al*., 1996; Wickens *et al*., 2015). A deeper understanding of these factors offers crucial insights into how errors occur and how they can be mitigated through targeted interventions.

Overload occurs when the demands placed on an individual exceed their physical, cognitive, or emotional capacity to handle them effectively. Contributing factors to overload include internal influences (such as fatigue, lack of experience, or inadequate training), external influences (like harsh environmental conditions, excessive noise, poor lighting, or extreme weather), and task-related pressures (including high workloads, tight deadlines, or excessive multitasking) (Dekker, 2018). Overload can hinder a person’s ability to assess risks, make informed decisions, and respond appropriately, increasing the likelihood of errors. For example, a worker operating heavy machinery under extreme heat while fatigued might misjudge actions or neglect safety protocols, potentially leading to accidents.

Inappropriate Response refers to an individual's failure to react correctly in a given situation. This may involve ignoring safety warnings, making impulsive decisions, or taking unnecessary risks. Inappropriate responses can stem from various causes, such as misinterpreting critical signals or information, emotional stress, pressure to perform, or overconfidence, which can result in disregarding standard operating procedures (Reason, 1997).

Inappropriate Activities encompass actions that diverge from established practices, whether deliberately or unintentionally. These can include performing tasks for which an individual is inadequately trained, skipping necessary safety checks to save time, or engaging in risky behaviours, such as using makeshift tools or bypassing safety mechanisms (Hollnagel, 2014). These behaviours are often influenced by organizational culture, lack of oversight, or insufficient reinforcement of safety protocols.

### 2.5.4 Human Error Taxonomies

Human error models, taxonomies, and classification systems have been developed to understand the causes of human error. These models include various perspectives such as the cognitive perspective (Wickens and Flach, 1988), the ergonomic perspective (Edwards, 1988), the behavioural perspective (Peterson, 1971), the epidemiological perspective (Suchman, 1961), and the psychosocial perspective (Helmreich and Foushee, 1993). More recent models emphasize that accidents result from a combination of interacting causes. These approaches have shifted from focusing on individual elements of accident causation to considering the system as a whole (Patterson, 2009). These models represent a systems or organizational approach to accident investigation.

*SHEL Model*

The SHEL model is a framework for analyzing human error and accident causation in complex systems, developed by (Edwards, 1970). It examines the interactions between system components and their impact on human performance and errors. The model categorizes failures into four areas; software, hardware, environmental conditions, and liveware as shown in Figure 2.1. Software encompasses documents, policies, regulations, and standards that guide the system. Hardware refers to the physical tools, such as machines, used within the system. Environmental conditions pertain to the physical surroundings where the system operates. Finally, liveware focuses on the individuals involved in the system (Edwards, 1970). Failures arise when any of these components or their connections fail. The model emphasizes the man-machine interface from a systems perspective.

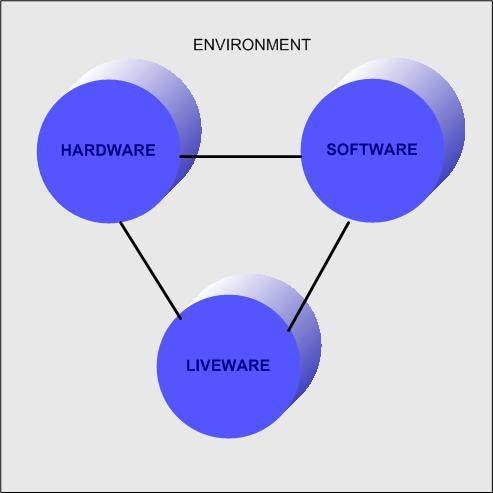


Figure 2.1 SHEL model adapted from Edwards (1972)

*Incident Cause Analysis Method (ICAM)*

The Incident Cause Analysis Method (ICAM) was created by BHP Billiton and introduced in April 2000 (Gibbs *et al*., 2001). Developed with contributions from James Reason, the Australian Transport Safety Bureau, and Dédale Asia Pacific, the ICAM process, as depicted in Figure 2.2, aligns closely with the principles established by James Reason. ICAM is founded on three core beliefs:

1. The root causes of all accidents can be linked to organizational deficiencies,
2. Human error is inevitable and must be accepted, and

#### If an organization is serious about accident reduction then new approaches must be used, and one must learn from past mistakes.

ICAM is an investigative tool designed to first identify organizational deficiencies and failed defences, and then create recommendations to improve these areas within the system and organizational processes. Along with the SCM and these core beliefs, the ICAM process has been utilized to examine accidents in various industries. The goals of an ICAM investigation include: establishing facts, identifying contributing factors and latent conditions, assessing the effectiveness of existing controls and procedures, reporting findings, suggesting corrective actions, detecting organizational issues that may cause recurring problems, and identifying key lessons to be shared across the company (De Landre and Bartlem, 2005). The ICAM system is structured with the belief that accident investigations should focus on identifying failures, not assigning blame or liability. Through the ICAM process, deficiencies within an organization can be pinpointed, and corrective recommendations made to address these issues (Patterson, 2009).

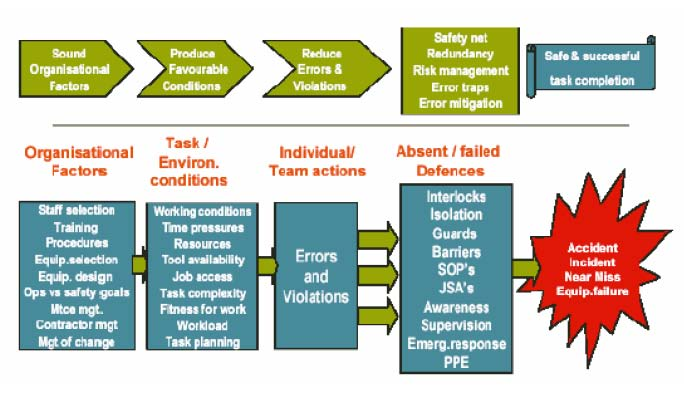


Figure 2.2 The ICAM model of incident causation (De Landre and Bartlem 2005)

*Wheel of Misfortune*

In an effort to examine the role of human factors in accidents involving aviation or other complex systems, O’Hare (2000) introduced a taxonomy known as the “Wheel of Misfortune.” This framework is influenced by the works of Helmreich (1990) and Reason (1990). The Wheel of Misfortune is structured with three concentric spheres that represent the actions of front-line operators, local conditions, and organizational conditions, as shown in Figure 2.3. The innermost sphere, “local actions,” focuses on what occurred, while the second and third spheres aim to explore the underlying causes. The model highlights the interconnectedness of various contributing factors, indicating that accidents are typically the result of a combination of elements rather than a single cause (Smith, 2018).



Figure 2.3 The Wheel of Misfortune (O’Hare 2000)

*Swiss-Cheese Model (SCM)*

The SCM was created by Professor James Reason (1990; 1997), who proposed that accidents occur due to breakdowns within the system. These breakdowns result from a combination of active failures (human errors) and latent conditions. Active failures, typically associated with incidents or accidents, refer to unsafe acts by individuals directly interacting with the system. These failures can be categorized as errors or violations, and they can be either intended or unintended. Unintended errors include slips and lapses, often linked to automatic actions and resulting from lapses in memory or attention. Intended errors are classified as mistakes, which occur when an individual either fails to perform the intended action or carries out the correct action but inappropriately for the situation. Violations are deliberate actions taken with disregard for established rules and regulations. Latent conditions, on the other hand, are often not noticed until an adverse event occurs, and they either create error-provoking situations or weaken system defences (Reason, 2000).

Reason's SCM of human error illustrates the relationship between active failures and latent conditions, operating on the assumption that fundamental components within an organization must function together to maintain a safe and efficient system (Reason, 1990). In the model’s initial form, Reason depicted a normal system as consisting of five “planes” arranged in a sequence: top-level decision-makers, line management, preconditions, productive activities, and defences (Patterson, 2009). The "Swiss cheese" analogy is used to illustrate how “holes” in different planes of the system representing latent and active failures can allow for accidents. System defences are dynamic and vary with the system's characteristics. Adverse events occur when interactions between components fail, or when latent and active failures align, breaching the system’s defences. In 1997, Reason updated the model by removing the labels for the planes, instead representing them as barriers, controls, defences, and safeguards. This version also included an explanation of how the holes emerge and added arrows to indicate the direction of accidents and investigations, as seen in figure 2.4. In all versions of the model, accidents are the result of latent and active failures within the organization, environment, and individuals, which breach system defences and cause losses (Patterson, 2009).

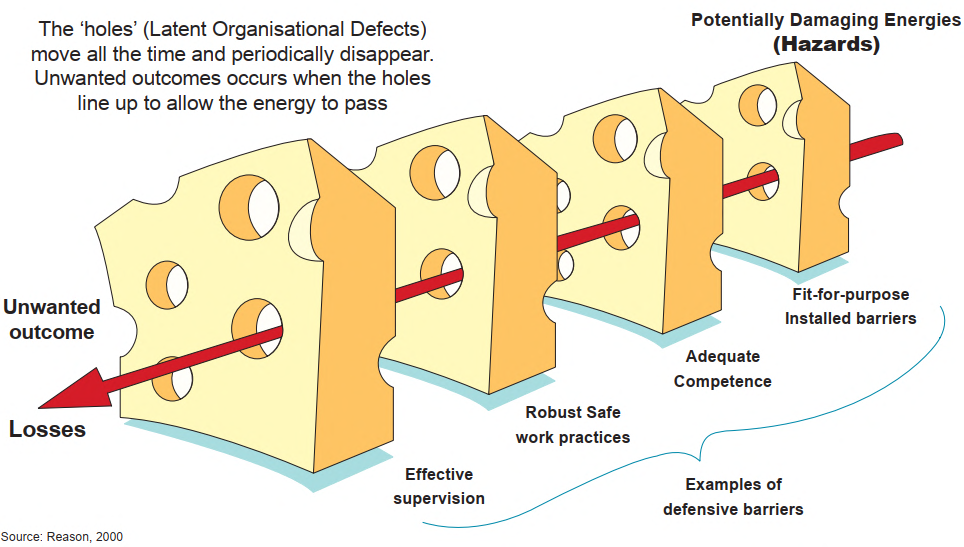


Figure 2.4 Reason’s SCM for accident Causation (adapted from Stemn, 2021)

### 2.5.5 Equipment Life-cycle and Human Error

The equipment life-cycle covers multiple stages, from design to disposal, with each phase vulnerable to human error. These errors can adversely affect equipment performance, safety, and durability, ultimately influencing operational efficiency and profitability. Human error at any point in the life-cycle can result in early failure, expensive repairs, safety hazards, and operational interruptions. Managing human error across the entire equipment life-cycle is essential for maximizing performance, minimizing costs, and improving safety.

Human error during the design phase can have enduring consequences on equipment performance and user interaction. Errors in design, such as overlooking ergonomic considerations, may result in equipment that is challenging or uncomfortable to use, leading to operator strain and a higher chance of misuse or accidents. Furthermore, failing to account for operational conditions like environmental factors (e.g., temperature extremes or dust) can result in equipment that is ill-suited for its intended use (Salvendy, 2012). To reduce these risks, incorporating human factors engineering (HFE) principles into the design process is crucial. This involves engaging end-users during the design phase and utilizing prototyping and simulation methods to test the equipment before finalization (Gould *et al*., 2018).

In the procurement phase, human error often stems from poor planning or communication. Errors in equipment selection, such as purchasing machinery that fails to meet operational requirements or lacks essential features, can lead to inefficiencies. Focusing too heavily on cost savings instead of quality or long-term functionality may result in acquiring equipment that is prone to frequent breakdowns, causing disruptions to operations (Lee *et al*., 2017). To prevent procurement errors, organizations should establish clear criteria for equipment selection, prioritize quality and suitability for specific tasks, and involve cross-functional teams, including technical experts, in the procurement process (Zeng *et al*., 2015).

The installation phase is crucial, as improper setup can impact equipment performance and durability. Errors like incorrect assembly, neglecting installation procedures, or skipping necessary safety checks can lead to immediate operational problems or long-term damage. Human error during this phase is often a result of insufficient training, unclear instructions, or pressure to meet deadlines (Reason, 1990). To reduce these errors, organizations should offer thorough training for installation teams, use detailed, standardized checklists for each installation, and ensure installation supervisors conduct regular quality assurance checks (Snyder, 2019).

The operational phase is particularly susceptible to human error, as operators directly handle machinery on a daily basis. Errors during operation can stem from improper equipment use, failure to follow operational guidelines, and neglecting routine checks. Overloading machinery, bypassing safety features, and ignoring warning signals are common human errors in this phase (Hollnagel, 2014). To minimize these errors, organizations should focus on providing proper training, establishing clear operational procedures, and continuously monitoring equipment performance. Additionally, user-friendly interfaces and automated safety systems can help reduce the likelihood of operator error (Bainbridge, 2016).

Maintenance errors are a major cause of equipment failure and downtime. These errors can include delaying routine servicing, using incorrect parts, or failing to identify early signs of wear and tear. Such errors often result from poor maintenance management, inadequate training, or not following manufacturer-recommended procedures (Dekker, 2018). To reduce the risk of maintenance-related errors and extend equipment lifespan, companies should implement preventive maintenance programs, provide regular training for maintenance personnel, and ensure access to quality parts. Predictive maintenance, which monitors equipment performance to forecast failures before they happen, is another effective method to minimize human error (Hughes *et al*., 2018).

The decommissioning phase involves the safe dismantling and disposal of equipment at the end of its life cycle. Errors during this phase, such as improper disposal of hazardous materials or failure to comply with environmental regulations, can pose serious safety and environmental risks. These errors often stem from inadequate planning and insufficient training in decommissioning procedures (Hudson *et al*., 2015). To mitigate these risks, it is crucial to standardize decommissioning procedures and ensure that personnel are well-trained in safe disposal practices and regulatory compliance.

### 2.5.6 Human Factor, a Solution to Human Errors

Human factors, is a scientific field that studies how people interact with systems, equipment, and environments. It focuses on understanding human abilities, limitations, and behaviours to improve system performance, safety, and well-being (Carayon, 2012). The objective of human factors engineering is to design systems, devices, and processes that meet human needs, boost performance, reduce errors, and enhance safety and efficiency (Mital, 2013). Human factors play a crucial role in high-risk industries like aviation, healthcare, mining, and manufacturing, where poor human-system interaction can lead to accidents, injuries, and fatalities (Mital, 2013). By improving human interaction with complex systems, human factors work to minimize human error, streamline workflows, and enhance user experience.

*Key Classifications of Human Factors*

Human factors is a multidisciplinary field that focuses on understanding human capabilities and limitations to design systems, environments, and tools that enhance performance, safety, and usability. This field is concerned with how humans interact with machines, technology, and each other, and can be classified into several areas: cognitive, physical, environmental, organizational, and social factors, as well as human-system interaction and safety/risk management.

Cognitive human factors explore the mental processes involved in human interactions with systems, including attention, memory, decision-making, perception, and problem-solving. These processes influence how individuals process information and respond to complex tasks. For instance, attention is limited, and excessive distractions can lead to mistakes, particularly in high-pressure situations (Norman, 2013). Memory is another crucial factor; systems are often designed to support human memory by using checklists, alarms, or reminders, which reduce the cognitive load on individuals and help prevent errors (Reason, 1990). Decision-making is influenced by cognitive biases, time pressures, and incomplete information, which can lead to suboptimal choices, especially in emergency contexts (Klein, 2008). In healthcare, decision support systems are used to reduce human error by providing real-time feedback and recommendations to clinicians (Patel *et al*., 2015).

Physical human factors focus on the physical interactions between humans and their environments, including the design of tools, machines, and workspaces. Ergonomics is a key aspect of this classification, as it ensures that systems are designed to fit human capabilities and reduce strain or injury. For example, ergonomic workstations with adjustable chairs and optimized tool designs are commonly used to reduce repetitive strain injuries in office and manufacturing environments (Helander, 2006). Biomechanics, which examines the human body's mechanical movements, plays a significant role in designing tools and equipment that minimize physical stress and improve efficiency (Galletta *et al*., 2019). Proper workplace design is also essential, as it can prevent injuries and improve task performance. Poorly designed workspaces can lead to physical strain and reduce productivity, while well-designed environments enhance efficiency and safety (Konz and Johnson, 2009).

The environmental human factors classification focuses on how the physical environment affects human performance. Factors such as lighting, temperature, noise, and the layout of workspaces play a critical role in influencing how well people perform tasks. Lighting, for example, affects visibility and can reduce performance if inadequate (Boyce, 2014). Temperature and humidity can also impact cognitive function, as extreme conditions lead to fatigue, discomfort, and decreased performance (Sundström *et al*., 1994). Noise is another environmental factor that can be distracting, especially in workplaces that require high levels of concentration, such as control rooms and laboratories (Banbury and Berry, 2005). The layout of a workspace also influences human performance (Wickens *et al*., 2018).

Organizational and social human factors deal with how organizational structures, team dynamics, and social interactions influence performance. Effective teamwork and communication are essential to minimizing errors, particularly in high-risk environments such as aviation or healthcare (Salas *et al*., 2015). Poor communication, unclear roles, and inadequate coordination can lead to catastrophic errors in such settings. Leadership is another critical component; effective leadership ensures that team members understand their responsibilities and prioritize safety (Avolio and Bass, 2004). Continuous training and skill development are necessary for ensuring that individuals possess the competencies required to perform tasks effectively and safely. Organizations that promote a safety culture, where employees feel empowered to report errors or hazards, are better equipped to prevent accidents (Reason, 1990). In aviation, for example, the implementation of standard operating procedures and crew resource management programs has significantly improved safety by fostering better communication and coordination among pilots and crew members (Salas *et al*., 2015).

Human-system interaction (HSI) or human-machine interaction (HMI) focuses on the relationship between humans and systems, particularly the design of user interfaces, control systems, and feedback mechanisms. A well-designed user interface enables users to efficiently interact with complex systems. Poorly designed interfaces can lead to errors due to confusion or unclear instructions (Shneiderman *et al*., 2016). Control systems allow humans to monitor and intervene in automated processes, and clear feedback such as visual, auditory, or haptic signals guides users to correct their actions when necessary (Norman, 2013).

Safety and risk human factors aim to reduce the likelihood of human error and mitigate the consequences of accidents. Error prevention strategies, such as redundancy and fail-safe mechanisms, are key to improving safety. The investigation of accidents provides valuable insights into the causes of human errors, helping to identify systemic issues and implement corrective measures (Reason, 1990). Additionally, risk management involves identifying potential hazards and designing processes to minimize their impact, as seen in industries like aviation and healthcare, where comprehensive safety protocols are in place to prevent accidents (Gordon, 2014).

# CHAPTER THREE METHODOLOGY

## 3.1 Introduction

This chapter outlines the research methodology employed to investigate the contribution of human factor to equipment damage and its impact on production at the Ghanaian mining contractor sites. The methodology covers the research design, data collection techniques, and data analysis procedures used to achieve the study’s objectives. This framework not only ensures the reliability and validity of the findings but also supports the development of actionable recommendations to minimize human factor and improve operational efficiency.

## 3.2 Case Study Method

The Case Study Method is a research approach that enables an in-depth investigation of complex phenomena within their real-life context. In this study, it is used to examine how human factors contribute to equipment damages and affect production at a Ghanaian mining contractor. This method facilitates a comprehensive analysis by integrating both qualitative and quantitative data from multiple sources, including incident reports, maintenance records, production figures, and interviews with key personnel By employing purposive sampling and data triangulation, the case study method provides rich insights into the intricate interplay between human errors, equipment performance, and operational efficiency. This approach is particularly suited for exploring the specific challenges and dynamics of the mining industry, allowing for the development of targeted recommendations to improve safety and productivity (Yin, 2014; Stake, 1995).

## 3.3 Data Collection

In this study, secondary data is sourced from existing records, including incident investigation reports, equipment downtime logs, and production figures provided by the HSE, maintenance, and mine planning departments from 2016 to 2024 (eight years period). This archival data is complemented by observational data collected during site visits, which offers real-time context on operational practices and environmental conditions. This integrated approach not only enhances data accuracy but also provides a fresh, holistic view of how human errors impact equipment performance and production outcomes.

## 3.4 Data Analysis

This chapter presents the data analysis for the study, which examines the impact of human factor contributions on equipment damage and production in a Ghanaian mining contractor. A mixed-methods approach is employed, integrating quantitative analyses such as ANOVA and t-tests to identify statistically significant relationships between human errors, equipment downtime, and production output, along with qualitative analyses of interview and survey data to provide contextual insights. By triangulating these data sources, the analysis aims to validate key hypotheses, reveal underlying trends, and develop actionable recommendations to enhance operational efficiency and safety within the mining industry.

### Non-parametric Tests (Kruskal-Wallis Test)

To assess the statistical significance of differences among various contributing factors under latent conditions and active failures, the Kruskal-Wallis H test was employed using the R studio programming software. This non-parametric test was appropriate given the ordinal nature of the data and the violation of normality assumptions often required for parametric alternatives such as ANOVA (Field, 2013). The Kruskal-Wallis test is a rank-based non-parametric method that determines whether there are statistically significant differences between two or more independent groups of an ordinal or continuous variable without assuming a normal distribution (Gibbons and Chakraborti, 2011). It extends the Mann-Whitney U test to more than two groups and is particularly useful in exploratory studies involving human factors, where data distributions are frequently skewed or ordinally scaled (Pett, 2015).

In the context of this study, the Kruskal-Wallis test was used in two main analyses:

* Latent Conditions: To examine whether the different categories of systemic and organizational failures (e.g., poor supervision, inadequate training, and absence of fatigue systems) contributed differently to equipment damage incidents.
* Active Failures: To test for statistically significant differences in the impact of various unsafe acts (e.g., misjudgement, inattention, fatigue, procedural violations) across incidents.

The test ranks all data points from all groups together, then evaluates whether the mean rank differs significantly between groups. A statistically significant Kruskal-Wallis result indicates that at least one of the groups differs from the others, although it does not specify (Laerd, 2021). The Kruskal-Wallis H test evaluates the null hypothesis (H₀) that the distributions of the dependent variable are the same across all groups. In contrast, the alternative hypothesis (H₁) posits that at least one group differs significantly from the others in terms of median rank.

*Decision (Judgment) Rule:*

If the p-value ≤ α (typically 0.05): Reject the null hypothesis (H₀) suggesting there is a statistically significant difference between at least two of the groups. This suggests that the contributing factors under latent conditions or active failures do not all affect equipment damage incidents equally.

If the p-value > α (typically 0.05) Fail to reject the null hypothesis (H₀). Suggesting there is no statistically significant difference in the effect of the contributing factors across the groups. This implies that the factors under consideration have a comparable influence.

This rule ensures a rigorous, objective basis for interpreting the results of the test and determining whether the contributions of different human factors either latent or active are significantly distinct in their influence on incident outcomes.

### 3.4.2 Classification Scheme from Swiss Cheese Accident Causation Model

To systematically categorize the underlying causes of equipment damage incidents, this study adopted the Swiss Cheese Model of Accident Causation, originally proposed by Reason (1990). This model offers a structured framework for analyzing how both immediate actions and deeper systemic weaknesses contribute to failures. Specifically, the model conceptualizes organizational systems as layered barriers (or "slices of cheese"), where accidents occur when holes in multiple layers align, and allowing hazards to pass through unchecked. Based on this framework, a classification scheme was developed to assign each incident to one of the two major categories of causation as shown in Figure 3.1. Each incident in the dataset was reviewed and coded based on this predefined classification based on the root cause and contributing causes. This approach enabled a dual-level analysis of causation, identifying not only the frontline errors but also the organizational and systemic gaps that allowed those errors to manifest into actual losses. The Swiss Cheese Model classification enhances the depth of accident investigation by shifting the focus from blame to understanding system vulnerabilities (Reason, 2000). Its integration into this study supports a holistic view of incident causation and aligns with best practices in human factors and safety engineering literature (Hollnagel, 2014).

Figure 3.1 Classification Scheme from Swiss Cheese Accident Causation Model

### 3.4.3 Spearman Rank Correlation Analysis

Correlation analysis is a statistical technique used to measure the strength and direction of the relationship between two continuous variables (Cohen et al., 2013). In the context of this study, correlation analysis is employed to evaluate the relationship between human factor induced equipment downtime and operational outcomes, This method helps to identify whether an increase in one variable (equipment downtime) corresponds to a change in another variable (production values) and how closely these variables are related. Khan *et al.* (2020) applied correlation analysis to explore the link between human error frequency and mechanical failures in oil refineries. They found a strong positive correlation (r = 0.62) between operator mistakes and unplanned equipment downtime. The strength of correlation can be interpreted using the following guidelines in Table 3.1 (Al-Mutairi, 2017).

**Table 3.1 Interpreting Correlation Coefficients**

|  |  |
| --- | --- |
| **r Value** | **Interpretation** |
| 0.10 – 0.29 | Weak correlation |
| 0.30 – 0.49 | Moderate correlation |
| 0.50 – 0.69 | Strong correlation |
| 0.70 – 1.00 | Very strong correlation |

### 3.4.3 Quantitative and Thematic Analysis

To explore patterns and underlying factors contributing to equipment damage incidents, this study employed a combined quantitative and thematic analysis approach. This mixed-method strategy facilitated both numerical assessment and the identification of recurring themes across the dataset (Vaismoradi *et al*., 2013). The analysis began with the classification of each incident based on a set of predefined variables that represent common dimensions in occupational health and safety investigations. This thematic categorization was guided by principles of content analysis (Vaismoradi *et al*., 2013), which supports the systematic classification of qualitative data into identifiable patterns. Grouping the data under these recurring themes allowed for meaningful comparisons and trend detection across incident characteristics. The quantitative component of the analysis involved computing frequencies, averages, and distributions for each of the themes identified. This enabled the study to uncover, for example, whether incidents were more common during night shifts, if less-experienced operators were involved more frequently, or if certain types of equipment were disproportionately affected. By integrating thematic coding with descriptive statistics, this approach enabled both structured insight into individual variables and a holistic understanding of their interaction. This is consistent with recommendations in safety science and human error research, where both contextual and quantitative data are essential for meaningful risk assessment (Salmon *et al*., 2012).

# CHAPTER 4 RESULTS AND DISCUSSION

## Thematic and Quantitative Analysis

This chapter presents and discusses the results of the quantitative analysis conducted on equipment damage incidents from 2016 to 2024. The analysis evaluates patterns in the total cost of component damage, mean time to repair, equipment downtime, production revenue lost, and the frequency of incidents. These variables are interpreted in the context of human factors, operational reliability, and their production-related implications.

### 4.1.1 Overall Summary

This study analysed equipment-related incidents that occurred between 2016 and 2024, with particular emphasis on production loss, downtime, and repair durations resulting from human factor-induced failures. A total of 59 incidents were recorded over the nine-year period, with the highest number occurring in 2022 (15 incidents), followed closely by 2021 (14 incidents) and 2020 (12 incidents). The lowest numbers were recorded in 2018, 2019, and 2024, each with only 2 incidents, highlighting an uneven distribution of failure events across the years. This uneven pattern suggests the influence of systemic factors such as workload, organizational controls, or external operational pressures (Reason, 1990).

In terms of equipment downtime, the study recorded a cumulative 3,852.9 hours of downtime from 2019 to 2024, with 2020 contributing the most (1,222.5 hours). The average equipment downtime per incident during this six-year window was 65.3 hours, indicating that most failures had prolonged operational impacts. Notably, 2019 recorded an extreme value of 408 downtime hours per incident, the highest in the entire dataset. This figure dwarfed other years and pointed to unusually severe or complex failures that year possibly caused by human misjudgement, inadequate situational awareness, or delayed responses (Wiegmann and Shappell, 2003).

The total production revenue lost between 2019 and 2024 amounted to $ 3,511,797.35, representing a major economic impact. The year 2019 alone accounted for $ 1,570,552.04, even though it recorded only two incidents. This implies an average revenue loss of $ 785,276.02 per incident, the highest across the entire dataset. This disproportionate loss suggests that although incidents were fewer, they were of greater severity. By contrast, 2022, which had the highest number of incidents (15), recorded a lower average loss of $ 50,976.32 per incident, suggesting that those events were less severe or better managed in terms of response. The average revenue lost per hour of downtime across 2019 to 2024 was calculated at $ 911.47, with 2018 and 2019 showing the highest losses per hour ($ 1,968.43 and $ 1,924.70), respectively. These values underscore the significant financial cost associated with even short interruptions in operations. Years with high hourly losses often correlated with high downtime per incident and lengthy repair durations, indicating that such events were not only costly but also challenging to resolve promptly possibly due to knowledge-based errors, inadequate troubleshooting skills, or poor maintenance planning (Flin *et al*., 2008; Dekker, 2014).

Regarding time to repair, the total mean repair time from 2019 to 2024 was 615.7 hours, with an average of 10.44 hours per incident. However, some years were notably higher, such as 2019 (30 hours per incident) and 2020 (18.43 hours per incident). These figures suggest the presence of complex damage types or insufficient access to technical resources, which may stem from latent conditions like lack of training, absence of fatigue management systems, or poor supervision factors widely recognized in human factors theory (Hollnagel, 2014). The total cost of damaged components for the period 2019 to 2024 amounted to $ 645,976.71, with 2019 ($ 178,000) and 2020 ($ 172,100) again recording the highest values. Interestingly, despite recording only two incidents, 2019’s component damage was the most expensive, reflecting the catastrophic nature of those failures. On the opposite end, 2024 saw the lowest component damage cost of just $ 2,460, aligned with its minimal downtime (30 hours) and revenue loss ($ 3,281.04), possibly due to successful safety interventions or better frontline supervision in that year.

Overall, these findings affirm the critical role of human factors in the severity and frequency of equipment-related incidents. The years with longer repair times, high per-incident downtime, and elevated costs reflect scenarios involving active failures such as operator error, as well as latent conditions like poor organizational safety culture or insufficient training. According to the Swiss Cheese Model (Reason, 1997), such alignment of multiple failure layers significantly increases the risk and impact of incidents. Additionally, the Human Factors Analysis and Classification System (HFACS) developed by Wiegmann and Shappell (2003) supports the idea that both unsafe acts and systemic influences must be addressed to prevent such outcomes. Table 4.1 shows the overall summary for the analysis.

Table 4.1 Overall Summary of Analysis

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **year** | **total cost of damaged component ($)** | **total mean time to repair (Hour)** | **total equipment downtime (Hour)** | **total production revenue lost ($)** | **total incident** | **equipment downtime per incident (Hour/incident)** | **revenue lost per hour of downtime ($/Hour)** | **average revenue lost per incident ($/Incident)** | **mean time to repair per incident (Hour/incident)** |
| 2016 | 14170.00 | 63.00 | 525.00 | 204562.14 | 5.00 | 105.00 | 389.64 | 40912.43 | 12.60 |
| 2017 | 5856.00 | 28.50 | 81.00 | 19097.72 | 3.00 | 27.00 | 235.77 | 6365.91 | 9.50 |
| 2018 | 10780.00 | 25.00 | 120.00 | 236211.84 | 2.00 | 60.00 | 1968.43 | 118105.92 | 12.50 |
| 2019 | 178000.00 | 60.00 | 816.00 | 1570552.04 | 2.00 | 408.00 | 1924.70 | 785276.02 | 30.00 |
| 2020 | 172100.00 | 221.20 | 1222.50 | 258541.94 | 12.00 | 101.88 | 211.49 | 21545.16 | 18.43 |
| 2021 | 133000.00 | 104.00 | 647.40 | 324090.66 | 14.00 | 46.24 | 500.60 | 23149.33 | 7.43 |
| 2022 | 96860.00 | 80.00 | 314.40 | 764644.83 | 15.00 | 20.96 | 2432.08 | 50976.32 | 5.33 |
| 2023 | 32750.71 | 25.00 | 96.60 | 130815.14 | 4.00 | 24.15 | 1354.19 | 32703.79 | 6.25 |
| 2024 | 2460.00 | 9.00 | 30.00 | 3281.04 | 2.00 | 15.00 | 109.37 | 1640.52 | 4.50 |
| 2019 -2024 | 645976.71 | 615.70 | 3852.90 | 3511797.35 | 59.00 | 65.30 | 911.47 | 59521.99 | 10.44 |

### 4.1.1 Categorization of Incidents Based on Shift and Time of the Day

From 2016 to 2024, a total of 59 incidents were analysed, out of which 36 (61 %) occurred during night shifts and 23 (39 %) during day shifts as shown in Figure 4.1. Although the number of incidents was higher on the night shift, the distribution of human error-related cases was almost even, with 12 incidents during the night and 13 during the day. However, the consequences of these incidents differed significantly. Night shift incidents resulted in a total downtime of 2,630.30 hours and total mean time to repair (TMTR) of 355.50 hours, with an associated total revenue loss (TRL) of $ 3,0324,28.95. In contrast, day shift incidents accounted for 1,222.30 downtime hours, 260.20 TMTR hours, and $ 479,368.40 in production loss. This indicates that while night shift incidents caused fewer human errors numerically, they were far more severe in terms of operational disruption and financial impact. The trends of incidents occurring during night shifts is consistent with findings in fatigue and shift-work literature. Fatigue tends to peak during the biological low point of the circadian cycle, typically between 2:00 AM and 5:00 AM, impairing cognitive function, reaction time, and decision-making (Åkerstedt, 1995; Folkard and Tucker, 2003). Reduced supervision, limited access to support services, and monotonous work environments during night shifts further exacerbate the likelihood of active and latent failures (Williamson *et al*., 2011). These conditions make the system more vulnerable to errors with catastrophic outcomes, in line with Reason’s (1990) Swiss Cheese Model, which suggests that holes in multiple layers of defence such as poor supervision and fatigue can align to produce an incident.

Figure 4.1 Categorization of Incidents Based on Shift

The hourly breakdown of incident occurrence shown in Figure 4.2 further reinforces the role of time-based fatigue and workload pressures. The peak incident time was 3:00 AM (7 incidents), followed by 11:00 AM (4 incidents) and 10:00 PM and 5:00 AM (4 incidents each). The 3:00 AM spike reflects the circadian nadir, a period when core body temperature, alertness, and cognitive performance are at their lowest (Rajaratnam and Arendt, 2001). Workers operating machinery during this window are especially vulnerable to attention lapses, micro sleeps, and poor judgment (Di-Milia *et al*., 2011). Meanwhile, a secondary peak in the late morning (11:00 AM) could reflect high task intensity periods during the day, where the pressure to meet production targets or deadlines may increase cognitive workload and trigger procedural violations or decision-based errors (Dawson *et al*., 2012). This highlights that incident occurrence is not solely linked to biological fatigue, but also to workload distribution and task transitions, both of which are key contributors to human error in complex systems (Flin *et al*., 2008). There were no incidents reported at 6:00 AM and 7:00 AM, suggesting a lull in operational activity or effective handovers during shift changes. Such transitions, when managed well, serve as buffers against cumulative error. Overall, these findings provide compelling evidence that time of day and shift type play a significant role in the frequency and severity of incidents, with night operations posing higher risk. Despite nearly equal human-error counts between shifts, the impact of errors during night shifts was significantly greater, both in downtime and revenue loss.

Figure 4.2 Categorization of Incidents Based on Time of the Day

### 4.1.2 Categorization of Incidents Based on Damaged Equipment Type

Among the six equipment types identified; Dump Trucks, Excavators, Articulated Dump Trucks, Loaders, Drill Rigs, Dozers, and Multi-Equipment (more than one equipment involved in the incident) shown in Figure 4.3, the most frequently affected equipment was the Dump Truck, which recorded 30 incidents, representing 50.8 % of the total 59 incidents. Of these, 16 were attributed to human error, the highest for any equipment type. These incidents accounted for a total downtime of 2,577.30 hours and a total mean time to repair (TMTR) of 410.20 hours, resulting in a total revenue loss of $ 487,495.98. The high incident rate for dump trucks could be linked to their constant use in hauling operations, frequent manoeuvring in tight spaces, and vulnerability to operator error during tipping or reversing, especially in areas with poor visibility or uneven terrain. According to Joe-Asare *et al*. (2022), dump truck-related incidents in Ghanaian mines are often the result of fatigue, misjudgement, or failure to follow standard reversing protocols highlighting the need for enhanced situational awareness training and fatigue monitoring systems.

Excavators were the second most frequently involved equipment, accounting for 18 incidents (30.5 %), with 7 linked to human error. Despite fewer incidents than dump trucks, excavators were associated with the highest financial impact, incurring a total revenue loss of $ 2,791,246.15, more than 9.5 times that of dump trucks. The total equipment downtime stood at 1,123.70 hours, with 141.50 hours of mean time to repair. This disproportionate financial burden suggests that excavator-related incidents involve more critical mechanical failures or occur during key operational activities like digging, loading, or trenching. As Stemn *et al*. (2020) observed in a study of mining operations in Tarkwa, Ghana, excavator incidents often result in costly production delays, especially when they occur during peak overburden removal or ore loading operations. The severity of impact also reflects the higher unit value and complexity of excavators, which require specialized maintenance and often longer repair times.

Other equipment types recorded significantly fewer incidents. The Articulated Dump Truck, Loader, Drill Rig, Dozer, and Multi-equipment categories each recorded between 1 and 3 incidents, with varying degrees of severity. For instance, Drill Rigs, despite only three incidents, had 2 attributed to human error, and generated $ 135,879.74 in production revenue loss over 40.4 downtime hours. Drill rigs are typically operated in high-risk, high-precision settings, and as found by Addo *et al*. (2021), drill rig incidents often stem from procedural violations or failure to monitor borehole pressure and alignment. The Dozer, Loader, and Multi-equipment categories had no incidents attributed to human error, suggesting that either these machines are used under more controlled conditions or they are operated by more experienced personnel. Their relatively low revenue losses $ 84,557.60 for dozers, $ 5,298.58 for loaders, and $ 5,864.30 for multi-equipment underscore their lower operational criticality or faster recovery times post-incident. However, these equipment types should not be overlooked in safety planning, as even a single critical failure can pose operational delays, especially in confined or high-gradient environments.

A recurring theme across all equipment categories is the significant role of human error, particularly for frequently operated machinery. Unsafe acts whether due to skill-based errors, misjudgement, or violations remain a consistent cause across all machinery-related incidents. The data validates the assertion that operator behavior, task complexity, and equipment functionality converge to shape incident outcomes.

Figure 4.3 Categorization of Incidents Based Damaged Equipment Type

### 4.1.3 Categorization of Incidents Based on Affected Equipment Sub-system

This study categorized incidents based on the specific subsystems damaged, including mechanical, hydraulic, electrical, structural, undercarriage, cabin, and multiple-damage systems as shown in Figure 4.4, providing a graphical view of how operational risks are distributed across machine components.

The structural subsystem recorded the highest number of incidents, with 19 cases (32.2 %), of which 12 were attributed to human error. These incidents resulted in 456.1 total downtime hours, 104.4 hours of mean time to repair, and a cumulative revenue loss of $ 812,494.81. Structural failures often involve components such as frames, arms, and load-bearing joints, which are susceptible to excessive loading, impact, or poor operational handling. The high human error component here may reflect unsafe operational behaviours, such as improper load placement, or collision with fixed structures errors that have been highlighted in multiple heavy equipment studies as leading causes of structural damage (Amponsah-Tawiah *et al*., 2020). The data reinforces the need for procedural compliance training and real-time feedback systems for operators to prevent repetitive structural damage.

The cabin system followed closely, with 9 incidents, 5 of which were human-error related, contributing to the highest total downtime (1,057.8 hours) and 166 hours of TMTR. The total revenue loss from cabin-related damage was $ 161,464.02. Cabin system failures often result from improper ingress or egress, operator carelessness, or structural compromise from collisions. Given the high downtime despite relatively modest revenue losses, the findings suggest that operator safety-related delays such as investigations, inspections, or medical evaluations may prolong recovery time even when equipment is structurally intact. As noted by Li and Goh (2021), incidents involving the cabin are more likely to result in extended stoppages due to health and safety protocols, thus emphasizing the indirect costs of human error beyond mechanical repair.

The mechanical subsystem, while only recording 12 incidents, caused significant operational disruptions with 317.70 hours of downtime, 72.70 hours of repair, and $ 225,977.02in revenue losses. Interestingly, only one incident was attributed to human error, suggesting that most failures in this subsystem are likely due to wear and tear, delayed maintenance, or inherent design flaws. This aligns with studies by Mensah *et al*. (2022), which found that mechanical failures in dump trucks and excavators were often driven by component fatigue rather than operator fault, highlighting the importance of predictive maintenance.

The hydraulic subsystem, although only involved in 2 incidents, resulted in a massive total revenue loss of $ 1,561,920.56 the highest among all subsystems. This was coupled with 684.6 hours of downtime, but only 30 hours of repair time, which suggests the failures occurred on critical hydraulic systems that disrupted major operational flows. One of the two incidents was human error-related. Given that hydraulic systems are essential for machine articulation, lift, and movement, even a minor valve or pressure line failure can render an entire machine inoperable, especially in excavators or dozers. According to Danquah *et al*. (2021), hydraulic failures in Ghanaian surface mines frequently result from contaminated fluid, misuse of controls, or failure to depressurize before maintenance, all of which are preventable through operator vigilance and standard procedure adherence.

Electrical subsystem failures were responsible for 5 incidents, none of which were human error-related with fire being the predominant incident, yet they accounted for 278.6 hours of downtime, 74 hours of TMTR, and $ 254,614.14in revenue loss. Electrical issues, such as sensor malfunctions, battery failures, or wiring defects, typically stem from design or environmental conditions e.g., moisture, dust, or vibration. This supports the assertion by Asare and Boateng (2020) that electrical reliability in heavy equipment depends more on proactive diagnostics and system hardening than on operator behavior.

In contrast, undercarriage-related failures were relatively rare (3 incidents) and resulted in only 31 hours of downtime, 12.4 hours of repair, and a minimal $ 4,441.61 in revenue loss. However, one incident was human error-induced, suggesting that poor terrain navigation or failure to report undercarriage noise or vibration can result in such failures. Meanwhile, the multiple-damage category (9 incidents, 5 human-error-related) yielded 443.1 hours of downtime, 82.2 hours of repair, and $ 68,842.35 in revenue loss. These cases typically involve cascading failures where a single operator error such as an over-speed collision compromises multiple subsystems simultaneously. These events are especially concerning due to their compounded financial and repair implications. Collectively, these findings underscore the importance of equipment-specific risk profiling. Subsystems such as hydraulics and structural frames, though very different in frequency, pose significant threats due to either catastrophic financial consequences or high repair demands. Human error was most evident in structural and cabin incidents, where operational behavior plays a larger role in incident causation.

Figure 4.4 Categorization of Incidents Based on Affected Equipment Sub-system

### 4.1.4 Categorization of Incidents Based on Operator Experience and Age

The analysis of incident distribution by age group revealed that the majority of incidents occurred among operators aged 40 to 49 years (Adults), who accounted for 34 out of 59 total incidents (57.6%). This was followed by the 30 to 39 (Young Adults) age group, with 23 incidents (39 %), while no incidents were recorded among operators aged 18 to 29 years (Youth) as shown in Figure 4.5. Two incidents involved individuals whose ages were not recorded. The absence of incidents in the youngest age group may reflect the nature of workforce deployment, where younger or entry-level personnel are often given less complex or lower-risk tasks under supervision. On the other hand, the significantly high number of incidents among those aged 40 to 49 years suggests that age-related factors, such as declining physical agility, slower reaction times, or even over-familiarity with tasks, could contribute to lapses in operational performance. According to Yang *et al.* (2020), mid-aged workers, despite being highly experienced, may exhibit cognitive slowing and reduced adaptability, especially when faced with unexpected situations. Furthermore, complacency and reduced attention to safety procedures can increase with time spent in routine work, as noted by Schmalz *et al*. (2021), which may help explain the higher incident counts in this group.

Figure 4.5 Categorization of Incidents Based on Operator Age

When examining the role of operator experience, the findings show a non-linear trend. Operators with 6 to 10 years of experience were involved in the highest number of incidents (27 incidents; 45.8 %), followed by those with 3 to 5 years (21 incidents; 35.6 %). Operators with only 0 to 2 years of experience accounted for 6 incidents, and those with 11 to 15 years recorded 5 incidents. Notably, there were no incidents reported among operators with over 15 years of experience (Old Adults) as shown I Figure in Figure 4.6, which may suggest that individuals in this category had either transitioned into supervisory or non-operational roles, or had accumulated enough wisdom and procedural discipline to avoid incidents altogether. Despite the expectation that more experience reduces risk, the data indicates that mid-experience operators (3 to 10 years) are more prone to incidents. These individuals also recorded a higher number of human error-related incidents (7 for the 3 to 5 year group and 12 for the 6 to 10 year group). This could attributed to the fact that workers in this range of experience have moved beyond the high-alert phase associated with new employment but may not yet have developed the deep intuitive expertise that comes with long-term practice. Li *et al*. (2019) described this as the “danger zone” of experience, where confidence may exceed competence, and risk perception may decline. Operators in this range may also be more frequently assigned to complex tasks without the compensating benefits of oversight given to less experienced staff.

Operators with 11 to 15 years of experience, despite being involved in fewer incidents (5), were associated with disproportionately high severity outcomes including 819.6 total downtime hours, 77 total mean time to repair hours, and a staggering $ 1,807,243.52 in total revenue loss. This suggests that while experienced operators are less frequently involved in incidents, the equipment they handle and the tasks they perform tend to be more critical. Therefore, when incidents do occur, the consequences are far more severe. This phenomenon aligns with findings by Wang *et al*. (2022), who observed that highly experienced personnel are often entrusted with high-value, high-risk operations, and any failure in this context results in substantial financial and operational impacts. Operators with 0 to 2 years of experience were involved in fewer and less severe incidents accounting for just 3 human-error-related cases, with comparatively minimal downtime (41.9 hours) and revenue loss ($ 88,957.08). This may be attributed to stricter supervision, adherence to safety protocols, and cautious behavior among novice operators. Fang *et al*. (2015) noted that early-career workers are typically more compliant with safety rules due to uncertainty and a desire to conform, which can act as a protective factor. These findings highlight the need for customized safety strategies across experience levels.

Figure 4.6 Categorization of Incidents Based on Operator Experience

### 4.1.4 Categorization of Incidents Based on Severity of Incident

The classification of incidents based on severity provides a critical lens for understanding the varying operational, financial, and human factor implications of equipment-related events in mining environments. Severity was categorized into Insignificant (RL < $ 1000), Minor ($ 1000 < RL < $ 10000), Moderate ($ 10000 < RL < $ 100000), Major ($ 1000000 < $ 1000000), and Catastrophic (RL > 1000000) events. Where RL is the total revenue lost due to incident).

The Minor severity category recorded the highest number of incidents (26 cases, 44.1 %), of which 7 (26.9 %) were due to human error. These incidents accounted for 565 hours of total downtime (TDT), 182.70 hours of mean time to repair (TMTR), and an estimated $ 99,830.29 in total revenue loss (TRL). While individually less severe, the high frequency of minor incidents contributes significantly to cumulative productivity losses. Similar observations were made by Asare and Boateng (2022), who highlighted that frequent minor equipment issues in Ghanaian mines often result from overlooked safety practices and inadequate preventive maintenance.

Following closely is the Moderate category, with 17 incidents (28.8 %), the highest proportion of human error cases (11 or 64.7 %). These incidents led to 1,802.9 hours of downtime, 283 hours of repair, and a substantial $ 643,720.53 in revenue loss. The high human error contribution in this category suggests that moderate severity events are typically triggered by unsafe acts such as improper machine handling, miscommunication, or non-adherence to safety protocols which escalate consequences without necessarily destroying equipment. According to Mensah *et al*. (2023), mid-level severity events in Ghanaian mining operations often result from what they describe as “preventable escalations” where operator decisions under pressure result in significant yet avoidable impacts.

Only 5 incidents (8.5 %) were classified as Major, with 2 caused by human error. However, these accounted for $ 1,198,319.3 in revenue loss, a figure that exceeds the cumulative losses from all minor and insignificant incidents combined, despite their lower frequency. These incidents also resulted in 784 hours of downtime and 115 hours of repair. This pattern highlights the disproportionate economic consequences of less frequent but more damaging events, often involving core systems such as hydraulics or structural integrity failures. As Stemn *et al*. (2021) assert, such events in Ghanaian gold mines often lead to full equipment immobilization and production stoppage, especially when critical path operations are affected.

The Insignificant category included 10 incidents, with 4 due to human error, resulting in only 27 hours of downtime, 11 hours of repair, and a minimal $ 7,009.28 in financial losses. Although seemingly negligible, even these small-scale events demand attention due to their potential to accumulate or serve as precursors to more serious failures.

The Catastrophic severity level involved only one incident, but it had the most extreme impact, 673.2 hours of downtime, 24 hours of repair, and $ 1,562,917.95 in production revenue loss. This incident was attributed to human error, underscoring how a single lapse can result in massive operational and financial consequences. In high-stakes environments such as open-pit mining, catastrophic events often entail multi-system failures, extended investigations, and replacement of entire machinery units. Figure 4.7 is a graphical representation of the classification by severity of the incident.

The data indicates a non-linear relationship between frequency and severity. While minor and moderate incidents dominate in number, major and catastrophic events carry significantly higher economic consequences. Moreover, human error is most prevalent in moderate and catastrophic cases, affirming the need for targeted safety interventions, especially for tasks involving system-critical operations. These results highlight the importance of integrating risk-based training, behavioural safety audits, and real-time monitoring to pre-empt high-severity incidents.

Figure 4.7 Classification of incidents based on severity

## 4.2 Active Failure (Human Error) and Latent Conditions Contribution to Incident

### 4.2.1 Active Failures (Human Error)

This section presents an analysis of active failures that directly contributed to equipment damage incidents, based on the Swiss Cheese Model of accident causation. These active failures were categorized into slips, lapses, mistakes, and contraventions, representing the unsafe acts committed by operators at the operational level. A total of 25 active failures were recorded, distributed across the categories as follows: slips (7 cases), lapses (3), mistakes (7), and contraventions (8).

Slips were the second most frequent category, representing 28 % of the total active failures. These occurred due to attention-related failures during routine actions and included improper loading, improper reverse manoeuvre and response error during blast evacuation, and notably, three cases of lack of situational awareness. These types of errors are often linked to distractions, multitasking, or fatigue, which can degrade situational control, especially in dynamic work environments like mines. Recent research by Karimi and Hashemi (2022) emphasized that slips are highly prevalent among equipment operators in surface mining due to repetitive motion, poor visibility, and cognitive fatigue, particularly during extended shifts. Figure 4.8 is a graphical breakdown of the contribution of slips.

Figure 4.8 Active failures caused by slips

Lapses, which are memory-related errors where operators forget to perform a required action, accounted for three incidents (12 %). These included misjudged distance and failures to inspect and monitor equipment prior to use. Such lapses may stem from over-familiarity with tasks, complacency, or lack of procedural reinforcement. A 2023 study by Kumah *et al*. found that in Ghanaian mining operations, equipment pre-inspection lapses were a leading cause of early-stage component failure, especially when operators deviated from standard start-up routines due to time pressure or workload. Figure 4.9 is a breakdown of active failure caused by lapses.

Figure 4.9 Active failures caused by lapses

Mistakes are decision-based errors and were responsible for 28 % incidents, including three due to operating while fatigued. These cases illustrate how knowledge-based and rule-based mistakes can result in significant consequences. Fatigue-induced mistakes are particularly critical as they impair decision-making capacity and reaction time. According to Ansong and Arhin (2021), fatigue remains one of the most underreported yet impactful factors in mining incidents in Ghana, particularly when operators are required to work back-to-back shifts or during night operations without sufficient rest cycles. Figure 4.10 is a graphical breakdown of active failures caused by mistake

Figure 4.10 Active failures caused by mistakes

Contraventions, defined as violations of rules and procedures, were the most common form of active failure with 10 incidents (32 %). These included procedural non-compliance (4 cases), wrong gear selection (2 cases), mobile phone usage, destructive driving, inadequate task planning, failure to perform risk assessments, and operating under the influence of drugs. These are especially concerning as they represent intentional deviations from known safety protocols. A study by Nyame *et al*. (2020) in the Tarkwa mining area revealed that contraventions are often encouraged by workplace cultures that prioritize productivity over compliance, especially where supervision is weak or reactive. These findings suggest the urgent need for behavior-based safety (BBS) systems that integrate positive reinforcement, peer accountability, and real-time feedback to reduce unsafe acts. Figure 4.11 is a graphical representation of active failures under contravention

Figure 4.11 Active failure caused by contravention

In totality, the dominance of contraventions and slips underscores the urgent need for both behavioural interventions and system redesigns. While slips and lapses may be addressed through human-machine interface improvements and procedural aids (like checklists and prompts), contraventions demand deeper cultural transformation and strict supervisory enforcement. Recent work by Boafo *et al*. (2024) underscores that effective incident prevention in mining must combine technical controls with organizational discipline and safety leadership that does not tolerate rule-breaking under any circumstances.

These active failures, though individual in nature, expose systemic vulnerabilities. According to the Swiss Cheese Model (Reason, 2000), such active failures are often the last link in a chain of latent conditions and organizational weaknesses. The interplay between individual behavior and systemic controls must therefore be continuously evaluated to close the gaps that allow these failures to occur.

### 4.2.2 Latent Conditions

Latent conditions refer to hidden systemic weaknesses or organizational deficiencies that set the stage for active failures and eventual accidents. In line with the Swiss Cheese Model of accident causation (Reason, 2000), this study categorized latent conditions under three key domains: Leadership Flaws, Physical Environment, and Technological Environment. These underlying factors, though not directly causing incidents, create vulnerabilities that allow unsafe acts to manifest. A total of 34 latent conditions were identified across the three domains, reinforcing the notion that human error is often rooted in broader organizational and environmental contexts rather than individual negligence alone.

Under the domain of Leadership Flaws, 9 latent issues were identified. These included inadequate risk assessment (1 case), inadequate instruction and training (2 cases), ineffective planned inspection (1 case), inadequate planned maintenance (3 cases), inadequate task assessment (1 case), and improper buffer zone establishment (1 case) as shown in Figure 4.12. These shortcomings reflect fundamental failures in safety leadership and management oversight. Poor planning and instruction increase the likelihood that frontline workers will either act on assumptions or overlook critical hazards. Studies by Zhang and Xie (2021) and Boafo *et al*. (2023) emphasize that effective leadership especially in high-risk sectors like mining must be proactive in hazard identification, resource allocation, and competence development. When supervisors fail to conduct adequate risk assessments or provide task-specific training, frontline operators are left ill-equipped to make safe decisions, often resulting in procedural deviations or situational misjudgements.

Figure 4.12 Latent conditions under leadership flaws

In the Physical Environment category, 11 latent conditions were observed. These included impact from projected rock (2 cases), vibrational impacts (5 cases), and poor pit floor conditions (4 cases) as shown in Figure 4.13. These environmental hazards not only contribute to physical strain and equipment instability but also compromise operator visibility and judgment. Prolonged exposure to whole-body vibration, for instance, has been linked to reduced concentration and increased reaction times, heightening the risk of errors (Kittusamy and Buchholz, 2022). Moreover, irregular pit floor surfaces can lead to tipping, loss of control, and premature wear on equipment factors commonly noted in studies on mining operational hazards (Oppong *et al*., 2021). These conditions highlight the importance of continuous geotechnical assessments and real-time hazard reporting systems to maintain safe and navigable workspaces.

Figure 4.13 Latent conditions under physical environment

The Technological Environment accounted for 15 latent failures, making it the most significant contributor in this analysis. Specifically, electrical short circuits (2 cases) and mechanical hose bursts (13 cases) were the most prominent as shown in Figure 4.14. These failures are symptomatic of poor preventive maintenance, aging equipment, and inadequate engineering controls. Mechanical hose bursts, in particular, pose both operational and safety risks, as they can lead to hydraulic fluid release, loss of equipment control, and fire hazards. According to Adjekum and Parker (2020), such failures are frequently traced back to deferred maintenance or poor inspection routines, often resulting from budgetary constraints or lack of skilled maintenance personnel. These findings echo global research that emphasizes the need for predictive maintenance systems and integration of smart monitoring technologies to reduce unexpected mechanical breakdowns (Jasiulewicz-Kaczmarek and Stachowiak, 2021).

Figure 4.14 Latent conditions under technological environment

The interaction of these latent factors with human performance creates an unsafe ecosystem where even small errors can escalate into serious incidents. This aligns with the work of Reason (2000), who argued that latent conditions often "lie dormant" within systems until aligned with active failures to create a pathway for accidents. Therefore, mitigating latent conditions is just as important if not more so than targeting individual operator behavior. Proactive strategies such as leadership training, environmental audits, and condition-based maintenance must be integrated into operational safety management systems.

## 4.3 Statistical Hypothesis Testing of Human Factor Contributions

To statistically evaluate whether the different categories of human factors classified as active failures and latent conditions under the Swiss Cheese Model occurred in significantly different proportions, the Kruskal-Wallis H test was conducted.

### 4.3.1 Active Failures

The hypotheses for active failures were formulated as follows:

Ho (Null Hypothesis): There is no difference in the distribution of Active Failures; all types (Slips, Lapses, Mistakes, and Contraventions) occur in equal proportions.

H1 (Alternative Hypothesis): There is a difference in the distribution of Active Failures; at least one type occurs at a different proportion than the others.

Using the Kruskal-Wallis test, a p-value of 0.3423 was obtained at a 95 % confidence level. Given that the p-value is greater than the significance level (α = 0.05), we fail to reject the null hypothesis. This result suggests that there is no statistically significant difference in how the various types of active failures are distributed across the dataset. The variations in observed frequencies are therefore not substantial enough to conclude that one type of active failure is more dominant than the others, and may instead be attributed to random variation within the sample. This result underscores the complexity of human behavior in operational contexts where multiple types of unsafe acts may occur with similar regularity depending on situational, task, and systemic influences (Basu and Barua, 2020).

### 4.3.2 Latent Conditions

The hypotheses for latent conditions were similarly established:

Ho (Null Hypothesis): There is no difference in the distribution of latent conditions; all types (leadership flaws, physical environment, and technological environment) occur in equal proportions.

H1 (Alternative Hypothesis): There is a difference in the distribution of latent conditions; at least one type occurs at a different proportion than the others.

The Kruskal-Wallis test for this analysis yielded a p-value of 0.2794, again at a 95 % confidence level. Since this value is greater than 0.05, we again fail to reject the null hypothesis. Thus, no statistically significant difference exists between the types of latent conditions identified in this study. This implies that the frequencies observed among leadership-related, environmental, and technological failures could be due to chance rather than a systematic variation in occurrence. The findings align with prior research that emphasizes how latent factors often exist simultaneously and interact in complex ways, making their individual prevalence difficult to distinguish statistically without larger or more segmented datasets (Le Coze, 2019; Reiman and Rollenhagen, 2018).

## 4.4 Spearman Correlation Analysis

The Spearman rank correlation heatmap illustrates the monotonic relationships among four key variables relevant to equipment-related incidents (damage cost, downtime, revenue loss, and repair time) as shown in Figure 4.15. Spearman’s correlation is particularly suitable for this analysis due to its non-parametric nature, which does not require the assumption of normal distribution or linearityan important consideration given the variability and skew often found in operational incident data (Mukaka, 2012).

The strongest positive correlation observed is between damage cost and revenue loss (ρ = 0.86), indicating that higher component damage costs are closely associated with higher production revenue losses. This is followed by a similarly strong correlation between damage cost and downtime (ρ = 0.71), and between downtime and revenue loss (ρ = 0.67). These results suggest that equipment damage severity significantly affects both the duration of equipment unavailability and the associated financial losses, affirming the critical importance of proactive maintenance systems and timely fault detection. Notably, the correlation between damage cost and repair time is moderate (ρ = 0.41), suggesting that while costlier damage tends to require longer repair periods, other factors such as part availability or maintenance crew efficiency may also influence repair duration. The relationship between repair time and revenue loss is relatively weak (ρ = 0.25), implying that repair duration alone is not a major determinant of revenue impact. This points to the likelihood that delays in initiating repairs, extended diagnostic periods, or scheduling inefficiencies may be more significant contributors to lost production time than the repair activity itself. Additionally, the correlation between repair time and downtime (ρ = 0.64) indicates a moderate-to-strong relationship, suggesting that quicker repairs are generally associated with reduced total downtime, though not always linearly.

The analysis demonstrates that damage cost serves as a central node, strongly associated with both downtime and revenue loss, and moderately with repair time. This highlights the multifaceted impact of equipment failures and supports the implementation of condition-based monitoring, predictive maintenance, and improved operational discipline to mitigate both technical and financial risks. Similar findings were reported by Boahen *et al*. (2022), who highlighted that in Ghanaian surface mining operations, downtime driven by severe equipment failures had a pronounced effect on both productivity and profit margins. Likewise, Bassan and Ayers (2020) emphasized the strategic role of predictive maintenance in minimizing costly breakdowns and revenue disruptions in industrial settings.

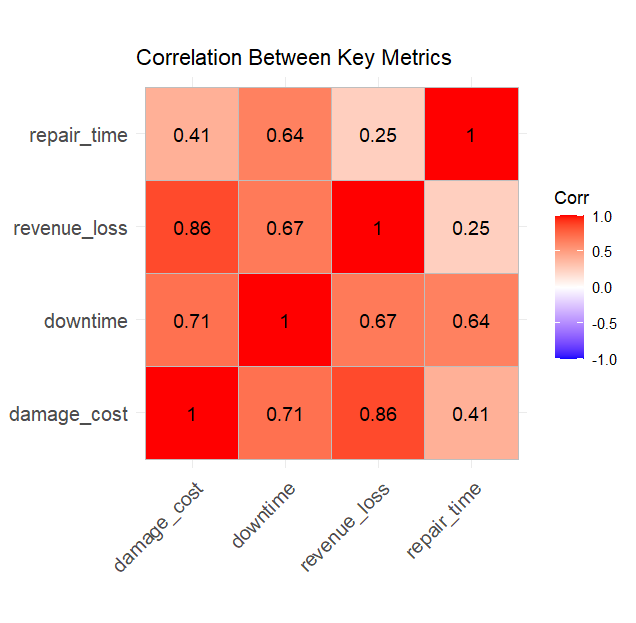


Figure 4.15 Spearman correlation analysis

# CHAPTER FIVE CONCLUSIONS AND RECOMMENDATIONS

## 5.1 Conclusions

This study set out to examine the role of human factors in heavy mining equipment damage and their subsequent impact on production efficiency and financial performance within a Ghanaian mining contractor setting. By applying the Swiss Cheese Model of accident causation, supported by statistical analysis, the research identified key active and latent failures contributing to operational losses. The findings provide a comprehensive understanding of how individual behaviours, systemic weaknesses, and environmental factors intersect to influence equipment reliability. The conclusions drawn from this research summarize the major insights gained and highlight the critical implications for industry practice and future safety management strategies.

1. Human factors are central to equipment-related incidents, with both active failures (e.g., contraventions, slips, mistakes) and latent conditions (e.g., inadequate training, supervision, and maintenance) contributing significantly to equipment damage and production disruptions.
2. Night shifts and mid-career operators (ages 40 to 49, with 6 to 10 years of experience) were associated with higher incident severity, including longer downtime and greater financial losses highlighting the impact of fatigue, complacency, and risk exposure.
3. Statistical analyses revealed strong correlations between damage cost, downtime, and revenue loss, while Kruskal-Wallis test results indicated that all types of active and latent failures occurred with relatively equal distribution, emphasizing the need for comprehensive safety interventions across all categories.

## 5.2 Recommendations

In light of the key findings and conclusions, several actionable recommendations are proposed to reduce the occurrence and impact of human factor-induced equipment incidents. Implementing these recommendations will be vital for mining companies seeking to minimize downtime, optimize maintenance efficiency, and foster a culture of proactive risk management across all levels of operation.

1. Enhance human performance through training and behavior-based safety programs, focusing on reducing contraventions, improving situational awareness, and addressing fatigue especially among experienced operators and night shift workers.
2. Strengthen systems and supervision by enforcing fatigue risk management, improving pre-task risk assessments, increasing leadership accountability, and applying predictive maintenance strategies to address both human and technical vulnerabilities.
3. Adopt technology-driven and data-informed safety management practices, including real-time operator monitoring systems, root cause analyses of incidents, and integration of human factor indicators into organizational KPIs to foster a proactive and sustainable safety culture.

# REFERENCES