BINDURA UNIVERSITY OF SCIENCE EDUCATION

DEPARTMENT OF ENVIRONMENTAL SCIENCE

The Impact of Artificial Intelligence (AI) on Enhancing the Health and Safety Status of Mine Workers at Freda Rebecca Gold Mine.

A Research Project submitted in partial fulfilment of the requirements of the Masters of Science Degree in Safety, Health and Environmental Management.

By

Fanuel Chinyemba (B241180A)

JUNE 2025

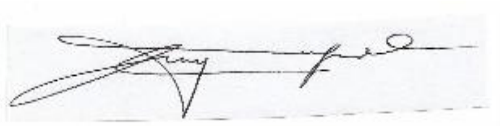
Declaration

The undersigned confirms that they have read and recommended this research project entitled, "The Impact of Artificial Intelligence (AI) on Enhancing the Health and Safety Status of Mine Workers at Freda Rebecca Gold Mine" in partial fulfilment of Master of Science Degree in Safety, Health and Environmental Management.

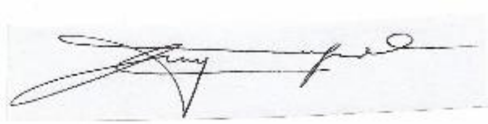
Student Fanuel Chinyemba

Signature: FChinyemba

Supervisor



I certify that I have supervised Fanuel Chinyemba (B241180A) for this research titled, "The Impact of Artificial Intelligence (AI) on Enhancing the Health and Safety Status of Mine Workers at Freda Rebecca Gold Mine" in partial fulfilment of Master of Science Degree in Safety, Health and Environmental Management, and recommends that it proceeds for examination.

Mr D T Dzvene Signature…pp 

……………………….

(Supervisor) Date10/10/25………………………………

ABSTRACT

The mining sector remains one of the most hazardous industries globally, characterized by high rates of occupational injuries, chronic illnesses, and safety-related fatalities. At Freda Rebecca Gold Mine in Zimbabwe, persistent health and safety challenges, such as respiratory ailments, fatigue, exposure to heat and dust, and delayed incident responses have continued to affect worker welfare and productivity. This study investigates the potential of artificial intelligence (AI) technologies to enhance occupational health and safety (OHS) within the mine. Drawing on a mixed-methods approach, the research combines quantitative data collected through structured questionnaires with qualitative insights from semi-structured interviews conducted with key informants, including mine managers and OHS officers. The study is guided by the pragmatic paradigm and informed by Systems Theory, the Technology Acceptance Model (TAM), and Risk Management Theory. A sample of 120 respondents was selected from a target population of approximately 1,200 employees using stratified random sampling to ensure representation across departments and roles. Additionally, purposive sampling was used to select ten key informants for the qualitative component. Quantitative data were analysed using descriptive statistics and Probit regression modelling, while thematic analysis was applied to qualitative responses. The findings reveal that AI acceptance among workers significantly correlates with the perceived improvement of OHS outcomes. However, AI awareness alone is insufficient without concurrent acceptance and practical application. The research also uncovers systemic deficiencies in current safety protocols, which are predominantly reactive and lack real-time responsiveness. Barriers to AI adoption, such as limited infrastructure, financial constraints, and worker resistance were also identified. Based on these findings, the study concludes that AI technologies have the potential to transform safety practices by enabling predictive risk assessment, continuous monitoring, and timely interventions. It recommends a phased and inclusive implementation strategy supported by worker training, infrastructural upgrades, and policy support.

Keywords: Artificial Intelligence, Occupational Health and Safety, Mining Sector, Predictive Analytics, Probit Regression

ACKNOWLEDGEMENT

This study would not have been possible without the invaluable support and contributions of several individuals and institutions to whom I extend my deepest appreciation.

First and foremost, I am sincerely grateful to my supervisor, Mr. Gushungo Dzvene, for his unwavering guidance, insightful feedback, and constructive critique throughout the course of this research. His keen eye for detail and consistent encouragement were instrumental in refining the quality and coherence of this work.

I would also like to extend my heartfelt thanks to Mr. Nzou, whose mentorship and words of encouragement served as a continual source of inspiration during this academic journey.

My appreciation is also directed to the management of Freda Rebecca Gold Mine for granting me the permission and support necessary to carry out this study on their premises. Their cooperation was essential in facilitating access to relevant data and participants.

I am equally thankful to all the participants who generously offered their time and insights, making a significant contribution to the success of this research.

Finally, I wish to acknowledge the support and critical input of my colleagues, Moja and Jena, whose thoughtful suggestions and encouragement helped shape the direction and depth of this study.

To all who contributed, directly or indirectly, I extend my sincere gratitude.

DISCLAIMER

This research is an original work conducted by the researcher. The views, opinions and findings expressed herein are those of the author and do not necessarily reflect the views or policies of any organization, institution or individual acknowledged in the study. All sources used are properly cited in the reference section. The researcher takes full responsibility for the accuracy, completeness, and originality of the research presented in this dissertation.

DEDICATION

To those suffering from occupational related illnesses and injuries

TABLE OF CONTENTS

LIST OF TABLES

LISTS OF FIGURES

CHAPTER 1: INTRODUCTION

1.1 Introduction

The integration of artificial intelligence (AI) technologies across various industries has proven transformative, particularly in enhancing operational efficiency, safety, and decision-making processes (Saxena, 2024). Within the mining sector, a traditionally high-risk industry, AI offers innovative solutions to long-standing challenges, including the health and safety of mine workers. This chapter provides an overview of the research topic, establishes the background of the study, identifies the research gap, and presents the rationale for exploring AI's impact on improving the health and safety of mine workers in Zimbabwe. The chapter concludes with a statement of the research problem, objectives, hypothesis, and significance of the study, study area, limitations and finally delimitations of the study followed by chapter summary.

1.2 Background to the Study

The mining industry plays a crucial role in global economic development, providing essential raw materials for industries such as construction, energy, and manufacturing. Despite its economic significance, mining remains one of the most hazardous occupations, exposing workers to a range of occupational safety and health (OSH) risks. These include respiratory diseases from prolonged dust exposure, noise-induced hearing loss, musculoskeletal injuries, and fatalities due to mine accidents (Khanzadeh et al., 2022; Mumba et al., 2025). The International Labour Organization (ILO, 2021) estimates that mining accounts for approximately 8% of all workplace fatalities globally, despite employing less than 1% of the global workforce. This statistic highlights the urgent need for enhanced OSH measures to mitigate risks and improve worker well-being.

Technological advancements, particularly in artificial intelligence (AI), have revolutionized safety measures in high-risk industries, including mining. AI-driven solutions, such as predictive analytics, automation, and real-time hazard detection, offer transformative potential for minimizing workplace accidents and improving health outcomes (Pishgar et al., 2021). However, the integration of AI in mining is uneven across different regions, with some parts of the world advancing rapidly while others struggle with adoption due to infrastructural and financial constraints.

South America has witnessed significant progress in AI-driven mining safety. In Chile, automation and AI-powered monitoring systems have enhanced workplace safety by minimizing human exposure to hazardous environments (Codoceo-Contreras et al., 2024). Similarly, in Brazil, mining companies are leveraging AI-integrated automation to reduce accidents and improve operational efficiency (de Holanda Araujo, 2024). Despite these advancements, research indicates that AI applications in the region predominantly focus on productivity rather than directly improving occupational health outcomes.

North America has pioneered AI-based predictive maintenance frameworks and wearable sensors to detect real-time hazards in mining operations (Campero-Jurado et al., 2020; Dayo-Olupona et al., 2023). In the United States and Canada, AI-powered analytics are used to predict equipment failures and prevent catastrophic incidents, ensuring safer working environments. However, while these technologies have contributed to accident reduction, their direct impact on long-term health issues such as respiratory diseases remains underexplored (Nguyen et al., 2022).

Europe has also made strides in AI adoption for mining safety. Lööw (2022) analysed the role of technology in shaping work environments, emphasizing the potential benefits of AI in reducing occupational hazards. Yet, gaps persist in the implementation of AI-driven health monitoring systems tailored to the mining sector. In Germany and Sweden, automated ventilation systems have been deployed to control airborne contaminants in underground mines, but the direct health impacts on workers require further empirical validation (Lund et al., 2024).

Asia, particularly China and India, has invested heavily in AI-driven mining safety solutions. China has implemented intelligent monitoring systems and predictive analytics to detect hazardous conditions in underground mines (Miao et al., 2023). Additionally, AI-enhanced sensors for coal mine safety have been developed, yet their integration with holistic health management strategies remains limited (Liang et al., 2024). In India, emerging technologies such as smart helmets equipped with AI and IoT capabilities are being tested to enhance worker safety in deep mining operations (Bhattacharyya & Shah, 2022).

In contrast, Africa, home to some of the world's richest mineral reserves, faces significant challenges in implementing AI-driven OSH measures in mining. Despite the sector's economic importance, AI adoption remains uneven across the continent, hindered by factors such as high implementation costs, limited technological infrastructure, and regulatory gaps.

In North Africa, research on AI-based safety solutions is emerging. Imam et al. (2023) examined AI-driven anti-collision systems in underground mines in Morocco, focusing on accident prevention. However, research on AI applications addressing long-term health risks, such as respiratory diseases, remains limited.

West Africa has seen minimal AI-driven innovations in mining safety, with most studies focusing on artisanal and small-scale mining, which presents unique OSH challenges. Research on AI applications for worker health in countries such as Ghana and Nigeria is scarce, although some initiatives aim to integrate AI-powered dust monitoring and ventilation control systems in gold mines (Tapo et al., 2024).

Central Africa, particularly the Democratic Republic of the Congo (DRC), faces some of the most severe mining safety challenges due to high levels of informal and artisanal mining. While AI adoption in large-scale mining operations is limited, there is growing interest in leveraging digital technologies to improve safety standards. However, the lack of infrastructure and regulatory frameworks continues to impede large-scale implementation (Onifade et al., 2023).

In Southern Africa, South Africa leads in AI-driven mining safety innovations. Gaokgorwe (2023) analysed the role of robotics in deep-level mining, highlighting improvements in safety but noting a lack of health-focused AI applications. Zimbabwe, a major mining economy, faces acute OSH challenges, including outdated safety protocols, poor dust control, and high injury rates (Mpofu et al., 2018; Mumba et al., 2025). Despite its significance, Zimbabwe's mining sector has lagged in adopting AI-driven health interventions. The Freda Rebecca Gold Mine, a key case study for this research, exemplifies these systemic issues, with workers experiencing high rates of respiratory ailments and musculoskeletal disorders (Zvarivadza et al., 2024).

Existing literature predominantly explores AI's role in operational efficiency and accident prevention, with limited focus on its direct impact on workers' health. Studies such as Mahmood and Shareef (2024) highlight AI applications for conveyor belt monitoring, while Rybak and Hassall (2025) examine AI-driven workplace safety frameworks. However, few studies explicitly link AI to improved health outcomes in mining. Santosh and Gaur (2022) explored AI's role in public health, but their scope excludes mining contexts.

This study fills a critical gap by investigating AI's direct impact on occupational health outcomes in Zimbabwe's Freda Rebecca Gold Mine. It explores how AI technologies such as smart sensors (Wang et al., 2024), predictive analytics (Saxena, 2024), and AI-driven risk assessment models, can be adapted to Zimbabwe's mining sector. By bridging global AI advancements with localized health challenges, this research offers novel insights for sustainable OSH practices in under-researched regions of Africa.

1.2. Problem Statement

The mining sector remains one of the most hazardous industries, with workers exposed to a wide range of occupational health and safety risks. At Freda Rebecca Gold Mine, statistics from the SHEQ (Safety, Health, Environment, and Quality) system reveal persistent and severe health and safety challenges despite existing interventions. Between 2022 and 2024, three fatalities were recorded due to workplace incidents, while lost time injuries (LTIs) average over one thousand cases per year, resulting in significant operational disruptions. Additionally, the mine spends over one hundred thousand United States dollars annually on injury-related medical expenses, further emphasizing the economic impact of occupational health issues.

A major concern at Freda Rebecca is work-related chronic illnesses, with 80% of off-sick days are attributed to work-related chronic conditions, including heat stress and respiratory ailments, underscoring systemic gaps in proactive health monitoring (Freda Rebecca Medical Reports, 2024). Many workers suffer prolonged exposure to dust and hazardous materials, leading to irreversible respiratory diseases, while physically demanding tasks contribute to early retirements via medical discharge. Some affected workers face challenges in receiving compensation, with a few cases taken to court, while others are discharged without benefits.

The mine also faces increased safety risks due to rock falls, particularly in specific operational zones that require remote-controlled interventions, a solution that AI-driven automation could potentially provide. Furthermore, employee burnout due to excessive work hours is a growing concern, with many workers resorting to performance-enhancing substances such as marijuana and morphine. According to the 2024 Drug and Substance Abuse Testing Surveillance Program, 15% of machine operators tested positive for controlled substances, raising safety concerns in high-risk areas where AI-powered sensor monitoring systems are critically needed.

Despite these alarming statistics and implementation of basic safety protocols, the mine relies on traditional, reactive health and safety monitoring systems, such as biannual medical checkups, which fail to detect early signs of fatigue, heat stress, or ergonomic strain. For instance, long shifts with minimal rest have led to widespread burnout, prompting some workers to use stimulants to maintain productivity a practice worsening safety outcomes. Existing systems lack real-time, continuous monitoring capabilities to address these dynamic risks.

Artificial Intelligence (AI) presents a transformative opportunity to enhance health and safety management in mining. AI-driven wearable technologies, predictive analytics, and real-time environmental monitoring can help identify hazards before they escalate, detect signs of fatigue and exposure to hazardous conditions, and implement timely interventions. While developed nations have successfully integrated AI into mining operations, its application in Zimbabwe remains largely unexplored.

This study seeks to bridge this gap by investigating the effectiveness of AI-driven health and safety monitoring systems at Freda Rebecca Gold Mine. By integrating wearable sensors, machine learning algorithms, and automated risk detection systems, the study will evaluate AI's potential in reducing accidents, improving workplace safety, and enhancing the overall well-being of mine workers. Ultimately, the research aims to provide data-driven recommendations for the adoption of AI technologies to create a safer and more sustainable mining environment in Zimbabwe.

1.3 General Objective

To investigate the impact of artificial intelligence (AI) on enhancing the health and safety status of mine workers at Freda Rebecca Gold Mine in Bindura.

1.4 Specific Objectives:

- To assess the current occupational health and safety practices at the Freda Rebecca Gold Mine and identify the major health risks faced by mining workers.
- To explore the potential applications of AI technologies in monitoring and improving the health status of mining workers at the Freda Rebecca Gold Mine.
- To develop and propose a comprehensive AI-driven framework for improving the health status of mining workers at the Freda Rebecca Gold Mine.

1.5 Hypotheses

H_0: The integration of artificial intelligence (AI) technologies has no significant impact on enhancing the health and safety status of mine workers at Freda Rebecca Gold Mine.

H_1: The integration of artificial intelligence (AI) technologies significantly enhances the health and safety status of mine workers at Freda Rebecca Gold Mine.

1.6. Significance of the Study

This study is significant as it contributes to academia, the mining industry, policymakers, and national development by exploring the integration of artificial intelligence (AI) in enhancing occupational health and safety in the mining sector. For the mining industry, the study provides data-driven insights that can guide the adoption of AI-driven safety innovations, such as predictive analytics, wearable monitoring devices, and automated hazard detection. These innovations aim to minimize workplace hazards, improve risk management, and reduce medical expenses and compensation claims.

Policymakers and regulatory bodies will benefit from evidence-based recommendations that can inform the revision of occupational health and safety policies, ensuring compliance with international labour standards while promoting ethical AI deployment. Academically, the study fills a critical research gap by contributing empirical findings on AI applications in an African mining context. This offers valuable insights for scholars in engineering, occupational health, and industrial automation.

The research also aligns with Zimbabwe's Education 5.0 framework and National Development Strategy 1 (NDS1), which emphasize technological innovation, problem-solving, and industrialization as key drivers of economic growth. By supporting the integration of AI into workplace safety, the study enhances national aspirations for sustainable mining, workforce protection, and industrial efficiency. It also contributes to the Sustainable Development Goals (SDGs), particularly SDG 8 (Decent Work and Economic Growth) and SDG 9 (Industry, Innovation, and Infrastructure).

For the researcher, the study offers an opportunity to develop expertise in AI applications for health and safety, fostering professional growth and positioning them as a key contributor to technological advancements in Zimbabwe's mining sector. Additionally, the findings may inspire future research collaborations, innovation-driven solutions, and AI-driven entrepreneurial opportunities in workplace safety management.

The broader socio-economic impact of this research is substantial, as improved health conditions for mine workers will lead to increased productivity, reduced absenteeism, and enhanced economic stability for mining communities. Ultimately, this study is pivotal in advancing industrial safety, technological progress, and national development, laying the foundation for a safer, more efficient, and AI-driven mining sector in Zimbabwe.

1.7. Study Area Description

The Freda Rebecca Gold Mine, situated near Bindura in Zimbabwe's Mashonaland Central Province, serves as the focal area for this research due to its economic prominence and operational complexity within the mining sector. This section delineates the map, the geographical, environmental, and socio-economic characteristics of the mine and its surrounding region, providing context for its selection as a case study.

1.7.1 Freda Rebecca Gold mine Map

Figure 1: Freda Rebecca Gold mine Map

Source: FRGM Technical Services(2025)

Geographical and Environmental Profile

Located at coordinates 17°18'10"S, 31°19'30"E, the mine lies within Zimbabwe's mineral-rich Great Dyke geological formation. It occupies an elevation of 1,100 meters above sea level on the Highveld plateau, characterized by a subtropical highland climate. The region experiences an average annual rainfall of 850 mm, predominantly between November and March, with periodic droughts influenced by El Niño oscillations. Mean annual temperatures range from 10°C in winter (June–July) to 28°C in summer (December–February), creating thermally stressful conditions for underground operations.

Vegetation in the area is dominated by miombo woodland, comprising Brachystegia and Julbernardia tree species, interspersed with savanna grasslands. The predominant soil type is ferrosol, a red clay soil typical of Zimbabwe’s greenstone belts, known for moderate fertility and susceptibility to erosion. These environmental factors influence both mining operations and local agricultural practices.

Socio-Economic Context of Bindura

Bindura, the administrative capital of Mashonaland Central, has a population of approximately 50,000 residents, with mining and agriculture forming the backbone of the local economy. The town derives 30% of its employment from mining activities, supplemented by small-scale farming of maize and tobacco. Freda Rebecca Gold Mine alone contributes 15% of Bindura’s GDP, producing approximately 2,000 kilograms of gold annually, underscoring its economic significance.

Despite its economic contributions, the region faces challenges in infrastructure development. Access to healthcare and education remains limited, with one public hospital and twelve clinics serving the district. Unemployment rates, particularly among youth, exceed national averages, driving migratory trends toward urban centres.

Operational Overview of the Mine

Freda Rebecca employs a hybrid mining model, combining open-pit and underground operations, with shafts extending beyond 500 meters in depth. The mine’s infrastructure includes processing plants, waste dumps, and ventilation systems critical for deep-level extraction. Key operational zones, such as the North and South underground faces, are prone to geotechnical hazards, including rock falls, which account for 40% of reported accidents (SHEQ Report, 2024).

The workforce comprises approximately 1,200 employees, the majority engaged in labour-intensive roles such as drilling, blasting, and ore transportation. Occupational health risks, including silica dust exposure and heat stress, remain persistent challenges, necessitating advanced mitigation strategies.

Rationale for Selection

Freda Rebecca Gold Mine exemplifies the intersection of economic necessity and occupational hazard management in Zimbabwe's mining sector. Its operational scale, environmental constraints, and socio-economic impact render it an ideal case study for evaluating technological innovations in health and safety. The mine's reliance on conventional safety protocols, juxtaposed with emerging risks such as climate-induced thermal stress, highlights the urgency of adopting AI-driven solutions.

A map of the mine, to be included in subsequent sections, will illustrate spatial features such as high-risk zones, infrastructure layout, and environmental vulnerabilities. This geographic context will further align the study's analytical framework with on-the-ground realities, ensuring relevance and applicability of findings.

1.8 Limitations of the Study

1. **Accessibility and Data Collection:**
    - Gaining access to detailed and specific data from the mine could be challenging due to confidentiality and operational security policies.
    - Limited access to certain areas within the mine due to safety restrictions might impede comprehensive data collection.
2. **Technological Constraints:**
    - The implementation of AI technologies in the study may be restricted by the availability and compatibility of existing infrastructure at the mine.
    - Lack of prior implementation of AI in similar contexts could limit comparative analysis and benchmarking.
3. **Financial and Time Constraints:**
    - Conducting extensive research within a mining environment is resource-intensive. Limited funding may restrict the scope and scale of the study.
    - The time frame for conducting the research may be insufficient to capture long-term impacts of AI interventions on health and safety.
4. **Human Factors:**

- Resistance to change from mine workers and management could affect the adoption and effectiveness of AI-driven solutions.
- Variability in the skill levels and technological proficiency of mine workers may influence the implementation and success of AI technologies.

5. **Environmental and External Factors:**
    - External factors such as economic fluctuations, regulatory changes, and environmental conditions can impact the mining operations and thereby affect the study outcomes.
    - Natural disasters or unexpected events such as pandemics could disrupt data collection and the overall research process.
6. **Generalizability:**
    - The findings from the Freda Rebecca Gold Mine may not be easily generalizable to other mining sites due to differences in operational practices, environmental conditions, and regulatory frameworks.
    - Specific local factors influencing the health and safety status at Freda Rebecca may not be present in other mining contexts, limiting the broader applicability of the study's recommendations.

1.9 Chapter Summary

This chapter introduced the study by outlining the significance of AI in enhancing health and safety in the mining sector. It explored global, regional, and local perspectives, highlighting how developed regions have integrated AI technologies while Zimbabwe lags in adoption. The discussion identified a research gap, emphasizing the limited application of AI in Zimbabwe’s mining industry, particularly at the Freda Rebecca Gold Mine. The chapter established the study’s uniqueness in addressing this gap and its potential contribution to occupational health and safety improvements. The next chapter will review relevant literature on AI applications in mining safety.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This chapter reviews existing literature related to occupational health and safety (OHS) in the mining sector and the role of artificial intelligence (AI) in enhancing worker safety and well-being. It begins by discussing relevant theoretical perspectives that underpin OHS and technological advancements in workplace safety. A conceptual framework is then presented to illustrate the relationship between current OHS practices, AI applications, and health outcomes. The chapter further examines empirical studies that demonstrate the application of AI technologies in monitoring, hazard detection, and improving worker health in mining environments. Additionally, the challenges and benefits associated with AI adoption in mining safety are explored. The chapter also reviews best practices from global mining operations to inform AI-driven safety improvements at Freda Rebecca Gold Mine. It concludes with a summary highlighting key findings that will guide the development of an AI-based framework for improving OHS at the mine.

2.2 Theoretical Review

The application of artificial intelligence (AI) in occupational health and safety (OHS) practices within the mining industry can be better understood through a range of theoretical perspectives. These theories provide a foundation for explaining how AI technologies can be integrated into mining operations to enhance worker safety and health outcomes. Theoretical approaches such as Systems Theory, the Technology Acceptance Model (TAM), and Risk Management Theory are particularly relevant to this study. They offer insight into the complexity of mining systems, the factors influencing the adoption of new technologies, and the role of AI in enhancing risk identification and mitigation processes. The following section provides a detailed discussion of these theoretical frameworks and their relevance to the integration of AI technologies in mining.

2.2.1 Systems Theory

Systems Theory, conceptualized by Ludwig von Bertalanffy in 1949, provides a comprehensive lens through which the interconnectedness of elements within a system can be analysed. The theory challenges reductionist views by asserting that the performance and outcomes of a system result from the complex interactions between its components rather than from isolated variables (Von Bertalanffy, 1968). Within the context of occupational health and safety (OHS) in the mining industry, this systems-oriented perspective shifts the focus from individual errors to the dynamic interplay between human behaviour, machinery, environmental conditions, and organizational processes. Safety outcomes, therefore, emerge from the collective functioning of these components rather than the failure of any single element.

The mining industry, characterized by high-risk environments, exemplifies a socio-technical system in which various subsystems workers, technology, physical infrastructure, and safety protocols operate interdependently. When these elements are not synchronized, accidents and health issues often arise, underscoring the necessity for integrated safety management. The adoption of artificial intelligence (AI) technologies in mining safety management exemplifies the systems approach, as AI enhances the capacity to monitor, analyse, and predict risks across multiple system components. Pishgar et al. (2021) demonstrate how AI-powered platforms aggregate data from diverse sources, including wearable sensors, environmental monitoring devices, and operational machinery, enabling real-time hazard detection and pre-emptive interventions. This capacity to synthesize inputs from various subsystems aligns seamlessly with the core principles of Systems Theory, which emphasize the necessity of understanding the entire system rather than focusing on individual parts.

Furthermore, Lööw (2022) illustrates that mining operations increasingly rely on digital technologies to enhance their systemic resilience. AI applications assist in identifying latent system-wide vulnerabilities that may otherwise remain undetected through conventional safety assessments. By providing an overarching perspective on mining operations, AI tools facilitate the timely identification of emergent risks before they escalate into accidents, thus enhancing operational stability. These findings suggest that Systems Theory offers a robust explanatory framework for understanding how AI-driven safety solutions function within the mining industry, reinforcing the relevance of the theory to this study.

However, the holistic nature of Systems Theory can also complicate practical applications. The emphasis on interdependencies requires extensive data collection and cross-functional coordination, which can be resource-intensive and technically demanding. Onifade et al. (2023) note that the successful integration of digital technologies into mining operations necessitates significant infrastructural investments and organizational adaptation, a reality that can strain mining companies, particularly in developing regions. In some instances, the complexity of system interactions may obscure the root causes of safety failures, potentially delaying corrective action. This challenge is highlighted in Nguyen et al. (2022) analysis of health risk management in extractive industries, where digital systems occasionally produced overwhelming volumes of data, complicating the identification of actionable safety insights.

Despite these limitations, Systems Theory remains valuable for understanding the transformative potential of AI technologies in enhancing mining safety. It provides a theoretical basis for viewing AI not merely as an isolated innovation but as an integrative tool capable of improving the coordination and functionality of the broader mining safety system. This perspective is supported by Liang et al. (2024), whose study on intelligent monitoring systems in coal mines demonstrates how AI enhances both individual worker protection and overall system efficiency. These empirical applications reinforce the theory's relevance by showcasing AI's capacity to synchronize human, technological, and environmental inputs into a cohesive safety mechanism.

Nevertheless, gaps persist in the existing literature. While studies such as those by Pishgar et al. (2021) and Liang et al. (2024) demonstrate the effectiveness of AI within certain mining contexts, there is limited research on the adaptive capacity of AI systems in environments where data infrastructure is underdeveloped, or where human-technology interaction is constrained by low digital literacy among workers. Additionally, the sociotechnical balance emphasized by Systems Theory remains underexplored in the context of AI adoption, as current research often prioritizes technological performance over human adaptation. This study, therefore, seeks to contribute to the literature by examining how AI technologies can be holistically integrated into mining OHS systems, particularly in contexts where technical, human, and organizational capacities vary widely.

2.2.2 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), developed by Davis (1989), is a widely recognized theoretical framework that explains how individuals come to accept and use new technologies. Central to TAM is the assertion that technology adoption is primarily influenced by two perceptions: perceived usefulness, which reflects the extent to which individuals believe a technology will enhance their performance, and perceived ease of use, referring to the degree to which they consider the technology to be free from effort. In the context of occupational health and safety (OHS) in the mining industry, this model provides a useful foundation for understanding how artificial intelligence (AI)-driven safety technologies are received by workers and management.

Mining remains a predominantly labour-intensive industry with deeply entrenched operational practices. The introduction of AI technologies, such as real-time monitoring systems, predictive safety analytics, and automated hazard detection, represents a significant departure from conventional safety procedures. However, the success of these technological interventions is not solely determined by their technical efficiency; rather, the attitudes and perceptions of the workforce play a decisive role. As noted by Bhattacharyya and Shah (2022), technological innovations in mining often encounter resistance, particularly from workers who view these systems as disruptive or perceive them as threatening their job security. Such resistance can be exacerbated when AI systems are perceived as difficult to operate or if their practical benefits are not made evident to end-users.

On the other hand, when AI systems are designed with user-friendliness in mind and accompanied by adequate training, acceptance tends to increase. Codoceo-Contreras et al. (2024) highlight that mining firms that actively foster technological literacy and demonstrate the safety-enhancing potential of AI tools tend to experience smoother technology transitions. Their review of automation in mining emphasizes that perceived competence and familiarity with AI solutions are crucial for reducing apprehensions and improving adoption rates. Similarly, Liang et al. (2024) examined the use of wearable AI devices in underground mining operations and found that acceptance was significantly higher when workers could easily interpret the health data provided and when the devices were non-intrusive. This underscores the importance of aligning AI technologies with the physical and cognitive capabilities of end-users.

TAM's relevance to this study lies in its human-centered focus on acceptance as a critical determinant of AI integration in mining safety. While AI promises to revolutionize OHS practices by enabling predictive maintenance, hazard detection, and real-time worker health monitoring, these benefits can only be fully realized if the workforce perceives the technology as both valuable and easy to operate. Nguyen et al. (2022) reinforce this point in their examination of health risk management in extractive industries, emphasizing that technological solutions often fail to achieve their intended outcomes when workers lack confidence in their usability or harbour concerns about data privacy and surveillance.

Nonetheless, TAM's individualistic orientation has been critiqued for underestimating the structural and contextual constraints present in industrial settings such as mining. Onifade et al. (2023) argue that, particularly in developing regions, the adoption of AI-based safety systems is frequently impeded by inadequate infrastructure, unreliable connectivity, and a lack of institutional support factors that lie beyond individual perceptions. These contextual barriers suggest that while TAM effectively captures the psychological determinants of technology acceptance, it must be complemented by broader socio-technical perspectives when applied to complex environments like mining.

Although TAM has been extensively applied across various industrial sectors, including manufacturing, healthcare, and mining (Bhattacharyya & Shah, 2022; Codoceo-Contreras et al., 2024), a notable gap in the mining literature concerns the longitudinal evolution of acceptance. Most studies, such as those by Liang et al. (2024), focus on initial adoption phases. However, less is known about how worker perceptions of AI technologies develop over time, particularly in response to ongoing training, changes in work routines, or operational challenges. This study, therefore, seeks to extend the existing research by examining not only the initial reception of AI-based OHS technologies but also the factors that sustain long-term acceptance and integration within mining environments.

2.2.3 Risk Management Theory

Rooted in the early work of Knight (1921), has been extensively developed within modern safety management literature to emphasize the systematic identification, assessment, and mitigation of risks in organizational systems. The theory holds that workplace hazards are not random but arise from identifiable patterns and operational vulnerabilities. It suggests that safety outcomes improve when organizations adopt proactive measures, such as continuous monitoring, hazard detection, and early intervention, rather than relying solely on reactive responses to accidents. This theoretical perspective has been particularly influential in high-risk sectors such as mining, where even minor oversights can escalate into catastrophic incidents.

In the contemporary mining context, the integration of artificial intelligence (AI) technologies has reinforced the principles of Risk Management Theory by transforming risk assessment processes from reactive to predictive models. Liang et al. (2024) demonstrate this alignment through the development of intelligent monitoring systems in coal mines, where wearable sensors and environmental tracking devices are integrated with AI algorithms to monitor workers' vital signs and detect hazardous conditions such as excessive heat, toxic gases, and abnormal heart rates. These systems enable the early identification of health risks, allowing interventions before conditions deteriorate into medical emergencies.

Similarly, Imam et al. (2023) examine the application of computer vision-based anti-collision systems in underground mining operations, showing how AI technologies enhance situational awareness by autonomously detecting and mitigating collision risks involving heavy machinery and personnel. These AI-powered systems scan work zones in real-time, triggering alerts or equipment shutdowns when unsafe proximities are detected. By intervening before accidents occur, such systems exemplify the transition from reactive safety management to predictive hazard prevention, reflecting the core tenets of Risk Management Theory.

The growing body of research supports the notion that AI applications in mining strengthen risk identification and mitigation capabilities in line with this theory. Miao et al. (2023) investigate data-mining techniques for hidden hazard analysis in coal mines, revealing that AI-powered clustering algorithms effectively classify high-risk areas based on historical incident data and real-time operational inputs. This predictive capacity enhances safety planning by enabling managers to prioritize risk hotspots, preventing potential accidents rather than merely responding to them. Similarly, Wang et al. (2024) highlight the use of hybrid sensor technologies coupled with AI in underground mines to optimize safety monitoring systems. Their study emphasizes that the fusion of AI with multi-sensor networks can enhance the accuracy and timeliness of hazard detection, further advancing the proactive risk management approach championed by this theory.

While Risk Management Theory provides a robust framework for understanding the value of predictive safety systems, the successful operationalization of AI technologies often reveals practical challenges. Onifade et al. (2023) caution that the predictive strength of AI in mining is contingent on the availability of accurate data and reliable digital infrastructure elements that are not consistently present across all mining regions. Deficiencies in sensor coverage, data transmission failures, or poor maintenance can undermine AI systems, causing either false alarms or missed hazards, thereby compromising the risk detection process. In such cases, the reliance on AI can inadvertently introduce new vulnerabilities, raising concerns about overconfidence in automated solutions at the expense of human oversight. This tension highlights an ongoing complexity within Risk Management Theory’s application in mining, where the balance between technological reliance and human judgment remains delicate.

Moreover, the theory’s emphasis on proactive interventions aligns well with AI’s potential but underplays the sociocultural dimensions that shape risk perception and safety compliance in mining. Nguyen et al. (2022) note that digital risk management systems in extractive industries can face resistance from workers who view automated monitoring as intrusive or fear disciplinary actions based on data surveillance. Such concerns can erode trust in AI tools, limiting their effectiveness even when technological capabilities are robust. This suggests that while Risk Management Theory provides a conceptual foundation for predictive safety technologies, its practical application requires a nuanced understanding of worker behaviour, organizational culture, and the broader socio-technical environment.

Empirical studies consistently affirm that AI-driven systems can enhance OHS outcomes when integrated within the proactive framework of Risk Management Theory. However, gaps persist in understanding the long-term performance of these systems under conditions of technological degradation, worker complacency, or operational complexity. Current research, such as that of Liang et al. (2024) and Miao et al. (2023), predominantly focuses on the initial deployment and effectiveness of AI-based hazard detection systems. Less attention has been directed toward evaluating their sustained performance over time or assessing how mining firms adapt to system limitations and evolving risk profiles. This study, therefore, seeks to contribute to the literature by examining not only the capacity of AI technologies to enhance risk detection but also the organizational practices necessary to maintain their reliability and worker acceptance within the mining industry.

2.3 Conceptual Framework

The conceptual framework guiding this study is predicated on the assumption that AI technologies can significantly enhance OHS practices in mining. The framework illustrates the relationship between the current OHS practices, AI applications, and safety outcomes.

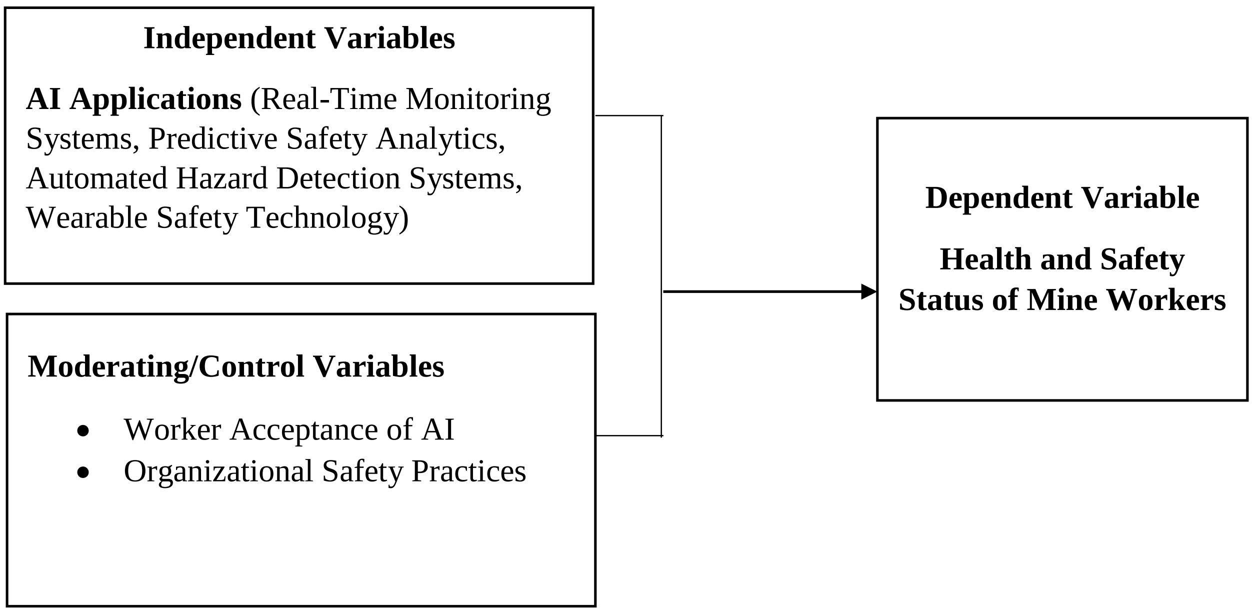
At the foundation are the existing health and safety practices at the mine, which rely heavily on human supervision and traditional risk management approaches. The introduction of AI technologies such as predictive maintenance systems, wearable health monitoring devices, and real-time hazard detection systems, serves as an intermediary that strengthens these practices.

Predictive maintenance minimizes machinery failures, wearable sensors provide continuous health surveillance, and hazard detection systems enable early identification of environmental threats. Collectively, these interventions are expected to enhance the overall health and safety status of mine workers.

The relationships within this conceptual framework can be depicted as follows:

Conceptual Framework Diagram

The conceptual framework below figure 2.1, visually depict a unidirectional effect from the independent variable to the dependent variable:



Source: Liang et al. (2024), with modifications by the researcher

Figure 2: Conceptual framework

The conceptual framework for this study figure 2.1, is structured around a set of interrelated variables that capture the relationship between artificial intelligence (AI) applications and the health and safety status of mine workers. These variables will guide both the theoretical orientation and the methodological approach of the study. They are categorized into three main types: the dependent variable, the independent variables, and the moderating/control variables.

The health and safety status of mine workers represents the dependent variable in this study. It refers to the overall well-being of employees within the mining environment, assessed in terms of the reduction in workplace accidents, improved health conditions, and the minimization of occupational hazards. The mining industry is inherently dangerous, with workers often exposed to physical injuries, toxic gases, dust inhalation, noise pollution, and equipment-related accidents. As such, any intervention aimed at improving workplace safety and health must ultimately be evaluated based on its effectiveness in reducing these risks and enhancing the physical and psychological welfare of mine workers.

The independent variables in this study focus on various applications of artificial intelligence (AI) that are increasingly being integrated into occupational health and safety (OHS) systems within the mining industry. Real-time monitoring systems represent one of the key AI interventions, involving wearable devices and sensor-based technologies that track workers' vital signs and environmental conditions continuously. These systems can detect deviations in health parameters such as abnormal heart rates, body temperature, or exposure to toxic gases, triggering immediate alerts for intervention (Liang et al., 2024). Predictive safety analytics constitutes another AI application, which leverages data-driven models to forecast safety risks before they materialize. By analysing operational patterns and historical incident data, predictive systems can identify emerging hazards and support pre-emptive safety measures, reducing the likelihood of accidents (Miao et al., 2023). Automated hazard detection systems, powered by AI-driven computer vision and environmental sensors, further enhance workplace safety by identifying dangerous conditions such as equipment malfunctions, structural instabilities, or unsafe worker behaviour in real time. These systems facilitate immediate corrective actions, minimizing the potential for injuries (Imam et al., 2023).

Additionally, wearable safety technology has gained prominence in the mining industry, with devices such as smart helmets and intelligent protective gear embedded with sensors to enhance situational awareness and enable the detection of physical impacts or hazardous environmental changes (Campero-Jurado et al., 2020; Lee et al., 2022). These AI applications collectively serve as the independent variables, as their adoption is expected to influence the health and safety status of mine workers.

The health and safety status of mine workers serves as the dependent variable in this study. It encompasses the overall well-being of employees, with specific attention to reductions in workplace injuries, improved health outcomes, and minimization of occupational hazards. This variable captures the extent to which AI interventions contribute to creating a safer mining environment, reducing exposure to risks such as machinery accidents, airborne pollutants, and heat stress (Nguyen et al., 2022; Mumba et al., 2025).

Worker acceptance of AI technologies is considered a moderating variable, as perceptions regarding the usefulness and ease of use of AI systems can influence the extent to which such innovations are successfully integrated into daily safety practices. Studies have shown that resistance to digital solutions is often driven by concerns about technological complexity or potential job displacement, which can hinder adoption despite the effectiveness of AI systems (Bhattacharyya & Shah, 2022; Codoceo-Contreras et al., 2024). Organizational safety practices also function as a moderating variable, as the strength of existing OHS policies, training programs, and management's commitment to safety can either support or impede the performance of AI-driven safety technologies. Mining companies with robust safety cultures and clear protocols tend to facilitate the integration of new technologies more effectively than those with weak regulatory enforcement (Onifade et al., 2023; Lööw, 2022).

2.4 Empirical Review

Research on the intersection of artificial intelligence (AI) and occupational health and safety (OHS) in mining has gained significant traction in recent years, driven by the need to enhance workplace safety in high-risk environments.

In developed economies, Liang et al. (2024) conducted a study in China focusing on the development and application of intelligent monitoring and protection equipment designed to track the vital signs of underground coal mine workers. The research adopted an experimental approach, employing AI-powered wearable sensors integrated with real-time data analytics to monitor heart rates, temperature fluctuations, and the presence of toxic gases. The findings demonstrated that such AI systems could detect early signs of health deterioration, enabling prompt interventions to prevent accidents. However, the study acknowledged that the effectiveness of these systems depends on robust data transmission infrastructure, which may not be universally available in developing regions.

In Canada, de Holanda Araujo (2024) investigated the impact of automation and AI on workforce skillsets in the mining industry. Using a qualitative methodology, including interviews with mining operators and industry experts, the study found that while AI technologies significantly reduced workplace hazards by automating dangerous tasks, they also created a skill gap among workers. The demand for digitally skilled employees increased, leaving traditionally trained miners vulnerable to displacement. This study underscores the need to balance technological advancement with human capacity development.

Moving to Australia, Codoceo-Contreras et al. (2024) conducted a systematic review utilizing natural language processing techniques to assess the impact of automation in mining. The review synthesized data from over 200 peer-reviewed publications, identifying AI-driven systems as instrumental in reducing workplace accidents through predictive safety analytics and real-time hazard detection. The study concluded that while automation has revolutionized OHS in developed mining economies, its adoption is often hindered by resistance from workers due to fears of job loss and mistrust of technology.

In the United States, Imam et al. (2023) conducted a study exploring the use of computer vision-based anti-collision systems in underground mines to enhance worker safety. The study employed an experimental research design, testing AI-powered anti-collision systems integrated with visual sensors on mining vehicles. These systems analysed real-time spatial data to detect unsafe proximity between machinery and workers, automatically triggering collision avoidance measures. The findings demonstrated that the AI systems significantly reduced vehicle-related accidents. However, the research also noted that false positives occasionally disrupted operations, suggesting a need for more refined detection algorithms. This study is particularly relevant as it highlights the role of AI in reducing accidents related to mobile equipment, a common hazard in underground mining.

In Sweden, Lööw (2022) investigated the impact of advanced technologies, including AI and automation, on the mining work environment. The research adopted a qualitative approach, conducting interviews with engineers, safety managers, and mine workers across multiple mining companies. The study found that AI-driven automation systems not only improved safety by minimizing human involvement in hazardous tasks but also altered traditional work patterns, creating new psychosocial risks such as worker isolation and reduced social interaction. While the study acknowledged the safety gains associated with AI, it raised concerns about the long-term implications of technology-driven work environments on employee well-being. This dual perspective underscores the complexity of AI adoption in mining, revealing that safety improvements may sometimes come at the cost of worker satisfaction and mental health.

In Ghana, Onifade et al. (2023) examined the challenges and applications of digital technologies, including AI, in the mining industry. The study adopted a mixed-methods approach, combining survey data from mine workers and interviews with safety managers across large-scale mining companies. The research highlighted that AI-powered predictive maintenance systems had the potential to enhance safety by preventing equipment failures that often lead to accidents. However, the study found that technological adoption faced resistance from workers due to fears of redundancy and limited digital literacy. The study concluded that capacity building and stakeholder engagement were crucial for successful AI implementation.

In Nigeria, Dayo-Olupona et al. (2023) explored predictive maintenance approaches in the mining industry and their implications for safety. The study employed a literature review methodology, synthesizing evidence from mining operations across West Africa. The research found that AI-powered predictive systems were increasingly being tested to monitor the performance of mining machinery, aiming to prevent mechanical failures and reduce accident risks. The findings suggested that while predictive maintenance had demonstrated promising results in pilot projects, full-scale adoption was hindered by poor infrastructure, limited funding, and a lack of skilled personnel capable of operating AI-driven systems. The study underscored the importance of aligning AI innovations with workforce development and infrastructure improvements to ensure their sustainability in resource-constrained settings.

In Kenya, Mwakio and Mbuvi (2021) investigated the occupational health and safety practices in small-scale mining operations in Taita Taveta County. The study adopted a descriptive survey research design, collecting quantitative and qualitative data from small-scale miners and local mining authorities. The research highlighted that health and safety practices were largely informal and inadequate, with miners being exposed to hazardous working conditions, including dust inhalation, unstable mine shafts, and the use of rudimentary tools.

The study found that there were minimal technological interventions in OHS management, with hazard detection and incident response being reactive rather than proactive. The miners relied on traditional safety practices such as visual inspections and manual labour-based safety checks. The study recommended the adoption of modern safety technologies, including real-time monitoring and hazard detection systems, but acknowledged that the miners' limited access to financial resources and technical expertise posed significant barriers to technological uptake.

Although the study did not focus on AI applications, it identified the potential for technology to transform mining safety practices. This represents a contextual gap, as no research in Kenya has empirically assessed the use of AI-driven OHS systems such as real-time worker monitoring, predictive analytics, or automated hazard detection. The present study, focusing on AI technologies in mining safety, seeks to bridge this gap by investigating how AI could enhance the health and safety status of mine workers, particularly in the Southern African context, where mining remains a cornerstone of economic activity.

Within South Africa, Gaokgorwe (2023) explored the application of robotics and AI in deep-level mining and its influence on health and safety. The study was based on a case study methodology, involving data collection from mining companies operating at depths exceeding 3,000 meters. The research revealed that robotic systems, combined with AI-powered monitoring devices, reduced human exposure to hazardous conditions such as rock falls and heat stress. However, the findings also indicated that the high cost of AI implementation and the need for specialized technical expertise limited its widespread adoption.

Further in South Africa, Miao et al. (2023) analysed coal mine accident patterns and developed a risk early warning system using data mining techniques. The research applied a quantitative design, utilizing K-means clustering algorithms to identify high-risk zones within underground mines. The study concluded that AI-based risk analysis could significantly improve OHS outcomes by proactively addressing accident-prone areas. Nonetheless, the authors emphasized that effective implementation requires continuous system maintenance and worker cooperation.

In Tanzania, Mumba et al. (2025) assessed the health implications of dust exposure in artisanal and small-scale mining operations. A cross-sectional survey involving 150 miners revealed high incidences of respiratory diseases due to poor ventilation and inadequate protective equipment. Although the study did not explicitly focus on AI, it highlighted the potential for AI-powered ventilation monitoring systems to mitigate dust exposure risks, pointing to a gap in research on AI applications in small-scale mining settings.

Turning to Zimbabwe, no study was found to have specifically investigated AI applications in mining safety. However, research by Zvarivadza et al. (2024) assessed the broader impact of the Industrial Internet of Things (IIoT) in the mining sector. The study employed a qualitative approach, gathering insights from mining executives and engineers. The findings suggested that while digital technologies, including sensor-based monitoring, hold promise for improving safety, their adoption in Zimbabwe remains in the infancy stage due to limited investment and low levels of technological literacy among workers.

In a separate study, Masiya et al. (2022) focused on occupational health and safety practices in Zimbabwe's mining sector, specifically within small and medium-scale mining enterprises. The study employed a cross-sectional survey methodology, collecting data from miners and safety officers across several mining communities. The findings revealed that health and safety practices were largely reactive, with minimal use of technological solutions for hazard detection and risk management. The study concluded that mining operations heavily relied on traditional methods of risk control, such as personal protective equipment (PPE) and safety inspections, rather than leveraging modern technologies. Masiya et al. emphasized that the absence of real-time hazard detection systems exposed workers to preventable accidents and health complications. This study highlights the technological deficit in OHS systems within Zimbabwean mining operations, indicating a significant gap in the adoption and evaluation of AI applications.

The empirical review reveals that developed countries have made notable progress in integrating AI into OHS systems, leading to enhanced safety and reduced accident rates. However, in developing countries, including those within Southern Africa, the adoption of AI technologies is often constrained by infrastructural limitations, skills gaps, and financial constraints. The review also exposes a significant research gap in Zimbabwe, where studies on AI-driven OHS interventions in the mining sector remain virtually non-existent. This study, therefore, seeks to bridge this gap by investigating the impact of AI technologies on enhancing the health and safety status of mine workers in Zimbabwe, contributing to both local and regional knowledge on AI integration within mining OHS frameworks.

2.5 Chapter Summary

This chapter reviewed the theoretical and empirical literature underpinning the application of AI in enhancing OHS practices in the mining sector. Systems Theory, Technology Acceptance Model, and Risk Management Theory collectively frame the potential for AI to improve health and safety outcomes. Empirical studies provide compelling evidence of AI's effectiveness in predictive maintenance, health monitoring, and hazard detection. However, financial, technical, and cultural barriers may hinder AI adoption in mining. The next chapter will outline the research methodology employed to investigate the impact of AI on the health and safety status of mine workers.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Introduction

This chapter presents the methodology employed in investigating the impact of artificial intelligence (AI) on enhancing the health and safety status of mine workers at Freda Rebecca Gold Mine in Bindura. The methodology is structured to align with the study's general objective and specific research objectives. It details the research paradigm, approach, and design while outlining the procedures followed in data collection, sampling, and data analysis. Furthermore, the chapter discusses issues of validity, reliability, credibility, trustworthiness, and ethical considerations to ensure the rigor and integrity of the research process.

3.2 Research Paradigm

This study is grounded in the pragmatic research paradigm, which emphasizes the application of multiple methods to address research problems by focusing on the practical implications of findings. Pragmatism is appropriate because the study seeks both to understand the current health and safety practices and explore the technological potential of AI to improve those practices at the mine (Creswell, 2014). By integrating both qualitative and quantitative elements, the paradigm enables the researcher to gain comprehensive insights into the intersection of occupational health, safety, and AI technologies. The complexity of health and safety concerns in mining requires a flexible approach, consistent with pragmatism, which values problem-solving over adherence to a single epistemological stance (Saunders et al., 2019).

3.3 Research Approach

The study adopts a mixed-methods approach, combining both quantitative and qualitative research techniques. This approach is justified as it allows for the triangulation of data, ensuring a more comprehensive understanding of the research problem (Creswell, 2014). The quantitative component involves collecting numerical data on the frequency of accidents, health issues, and OHS compliance, while the qualitative aspect captures the perceptions of workers and management regarding AI applications in health and safety management. Similar mixed-methods approaches have been employed in mining safety research (Bhattacharyya &

Shah, 2022; Onifade et al., 2023), indicating their suitability for exploring both statistical trends and contextual experiences.

3.4 Research Design

A descriptive survey design is employed, complemented by case study elements. The descriptive survey is appropriate for gathering data on the current health and safety practices at Freda Rebecca Gold Mine, as well as workers' perceptions of AI applications. Descriptive designs are commonly used in Occupational Health and Safety research to profile workplace risks and safety performance (Nguyen et al., 2022). The case study element allows an in-depth examination of AI's potential within the mine's specific context, offering insights into site-specific challenges and opportunities (Yin, 2018). This combination enhances the study's ability to meet the objectives by capturing both broad trends and contextual details.

3.5 Population

The target population comprises employees, management at Freda Rebecca Gold Mine and external contractors. This includes underground mine workers, health and safety officers, supervisors, and senior managers involved in operational and safety decision-making. The estimated population is approximately 1200 employees, reflecting the workforce size reported in internal company reports and industry sources.

3.6 Sample and Sampling Techniques

A sample of 120 respondents is selected, representing 10% of the target population. This proportion aligns with Saunders et al.'s (2019) recommendation for determining sample size in descriptive surveys, ensuring a balance between statistical representativeness and feasibility. A 10% sample is justified as it provides sufficient data for meaningful analysis while remaining manageable in terms of time and resources. Additionally, it mitigates potential non-response bias by maintaining a representative subset of the population.

The study employs a stratified random sampling technique to ensure proportional representation of different categories of employees, including mine workers, supervisors, and safety officers. Stratification is essential because perspectives on occupational health and safety (OHS) and AI adoption may vary across these occupational groups. The qualitative component involves purposive sampling of 10 key informants, such as senior management and OHS experts, who possess specialized knowledge of workplace safety practices and AI implementation.

3.7 Data Collection Instruments and Procedures

3.7.1 Structured Questionnaires

A structured questionnaire is administered to gather quantitative data on health and safety practices, frequency of incidents, and attitudes toward AI technologies. The questionnaire is adapted from validated OHS instruments used in previous mining studies (Liang et al., 2024; Miao et al., 2023) and tailored to the Zimbabwean mining context. It is pre-tested with 10 respondents to ensure clarity and appropriateness.

3.7.2 Semi-Structured Interviews

Semi-structured interviews were conducted with key informants to explore managerial insights and expert opinions on the feasibility and effectiveness of AI solutions in enhancing worker safety. This method is suitable for eliciting detailed, context-specific information and has been employed in similar mining sector studies (Gaokgorwe, 2023; Zvarivadza et al., 2024).

3.7.3 Document Review

Internal OHS reports, incident records, and AI trial documentation (if any) at Freda Rebecca Gold Mine are reviewed to complement primary data and validate worker and managerial responses.

3.8 Data Analysis

3.8.1 Quantitative data Analysis

Quantitative data will be analysed using Stata 14 and Microsoft Excel packages to ensure statistical precision and facilitate data visualization. Descriptive statistics will be employed to summarize occupational health and safety (OHS) practices, accident rates, and worker perceptions. These will include frequencies, percentages, measures of central tendency (mean, median, and mode), as well as standard deviation, which will provide insights into the dispersion of the data. Additionally, kurtosis and skewness will be calculated to assess the shape and distribution characteristics of the data, ensuring that data symmetry and peakedness are considered in the descriptive evaluation.

Inferential statistical analysis will be performed to examine the relationship between AI applications and OHS outcomes. The study will adopt a Probit Regression Model, which is appropriate given the nature of the dependent variable, representing whether health and safety status improves (or not) with AI integration. This model is suitable when the outcome variable is binary, enabling the estimation of the probability that certain predictor variables (such as AI technologies) influence health and safety enhancements. The Probit model has been widely used in occupational health and technology adoption research to estimate outcome probabilities based on predictor variables.

3.8.1.1 Probit Regression Model Specification

Given that the primary objective of the study is to investigate the impact of artificial intelligence (AI) on enhancing the health and safety status of mine workers, a Probit Regression Model will be used, as the dependent variable is binary in nature. The dependent variable will represent health and safety status (improved or not improved), while the independent variables will capture different dimensions of AI applications in OHS practices.

Let the dependent variable be defined as:

$$Y_i = \begin{cases} 1, & \text{if health and safety status is improved} \\ 0, & \text{otherwise} \end{cases}$$

The Probit model is based on an underlying latent variable model defined as:

$Y_i{*}{=}\beta_0{+}\beta_1X_{1i}{+}\beta_2X_{2i}{+}\beta_3X_{3i}{+}\beta_4X_{4i}{+}\ \beta_5D_{1i}{+}\beta_6D_{2i}{+}\beta_7D_{3i}{+}\ \varepsilon i$

Where:

- Y_i* is the latent (unobserved) variable representing the likelihood of improved health and safety.
- Y_i is the observed binary outcome (1 = improved health and safety; 0 = not improved).
- X_{1i} = AI Awareness Score (number of AI technologies the respondent is aware of, 0–4)
- X_{2i} = AI Acceptance (support level for use of AI at the mine)

- X_{3i} = Safety Practice Rating (rating of current safety measures at the mine)
- X_{4i} = Interaction Term (AI Awareness × AI Acceptance)
- D_{1i} = Gender -Binary variable (0 = Male, 1 = Female)
- D_{2i} = Age Group-Ordinal variable representing age categories (1 = 18–25, ..., 5 = 60+)
- D_{3i} = Experience - Ordinal variable indicating years of experience (1 = <1 year, 4 = >10 years)
- β_0 is the intercept.
- $\beta_1, \beta_2, \ldots, \beta_7$ are coefficients measuring the influence of each independent variable.
- ε_i is the error term.

The observed binary outcome is expressed as:

$$Y_i = \begin{cases} 1 & \text{if } Y_i^* > 0 \\ 0 & \text{otherwise} \end{cases}$$

The Probit model assumes that the error term ε_i follows a standard normal distribution. The probability that health and safety is improved can be expressed as:

$P(Y_i=1/X,D)=P(Yi*>0)=P(\varepsilon_i>-(\beta_0+\beta_1 X_{1i}+\cdots+\beta_7 D_{3i}))$

This can be re-expressed as:

$P(Y_i=1/X,D)=\Phi(\beta_0+\beta_1 X_{1i}+\cdots+\beta_7 D_{3i})$

Where **Φ** is the cumulative distribution function (CDF) of the standard normal distribution.

The Probit model will estimate the coefficients $\beta_0,\ldots,\beta_4$, which reflect the marginal effects of the independent variables on the probability that health and safety status improves with the application of AI technologies in mining OHS practices.

This functional form allows for the examination of the impact of AI applications and moderating variables on health and safety outcomes, aligning with the study's specific objectives.

3.8.1.2 Post Diagnostic Tests

To ensure the robustness and validity of the Probit model, post-estimation diagnostic tests will be conducted. These will include the link test for model specification to check for functional form misspecification, the heteroscedasticity test to detect whether the variance of the error terms is constant, and multicollinearity assessment using correlation coefficients to evaluate the strength of linear relationships between independent variables, ensuring that no high correlation distorts the regression estimates.

3.8.2 Qualitative data Analysis

Qualitative data from interviews will be analysed through thematic analysis, which involves the systematic identification, coding, and interpretation of patterns or recurring themes from participants' responses. This approach is suitable for capturing subjective experiences and managerial insights on the role of AI in OHS improvement. R statistical package will be used for the qualitative data analysis. Thematic analysis is particularly useful in workplace research as it uncovers the underlying perspectives of respondents and contextualizes their views within organizational realities. The suitability of this approach is reinforced by studies such as Codoceo-Contreras et al. (2024) and de Holanda Araujo (2024**)**, which demonstrate the effectiveness of thematic analysis in exploring safety innovations and workforce adaptation in mining operations.

Combining descriptive statistics, Probit regression analysis, and thematic analysis will allow the study to capture both quantitative patterns and qualitative insights, enabling a holistic understanding of the relationship between AI applications and OHS status in mining. This integrated approach is well-suited to the complexity of mining environments, where technological adoption intersects with human behaviour, workplace culture, and organizational safety policies.

3.9 Validity and Reliability

To ensure validity and reliability in the quantitative component, the questionnaire is pilot-tested and refined before full deployment. Content validity is assured by consulting OHS professionals and AI specialists during the instrument development phase. Reliability is tested using Cronbach’s alpha, with a threshold value of 0.7 deemed acceptable, consistent with the standards set in occupational safety research (Saunders et al., 2019).

3.10 Credibility and Trustworthiness

For the qualitative component, credibility is ensured through member checking, where interviewees review the transcriptions and interpretations of their responses. Triangulation is achieved by comparing interview findings with quantitative survey data and document analysis, enhancing the robustness of the conclusions. Transferability is supported by providing detailed contextual descriptions of the mining environment, enabling readers to assess the applicability of the findings to other settings.

3.11 Ethical Considerations

The study adheres to ethical research principles, including informed consent, confidentiality, and voluntary participation. Ethical clearance is sought from the relevant academic and industry authorities before data collection. Respondents are informed of their right to withdraw from the study at any stage without consequence. Data is anonymized to protect participants' identities, and all collected information is securely stored in compliance with data protection regulations (Saunders et al., 2019).

3.12 Chapter Summary

This chapter outlined the research methodology adopted to investigate the impact of AI on enhancing the health and safety status of mine workers at Freda Rebecca Gold Mine. A pragmatic research paradigm and mixed-methods approach were justified as appropriate for addressing the study's objectives. The descriptive survey design, supplemented by case study elements, was chosen to enable both quantitative and qualitative data collection. The population comprised mine workers and management, with stratified random sampling and purposive sampling techniques ensuring representative and expert inputs. Questionnaires, semi-structured interviews, and document reviews were identified as primary data collection tools, with statistical and thematic analysis methods planned for data interpretation. The chapter further addressed validity, reliability, credibility, and ethical considerations, ensuring the rigor and integrity of the research process. The subsequent chapter will present the results and analysis of the collected data.

CHAPTER 4: DATA PRESENTATION, ANALYSIS AND DISCUSSION

4.1 Introduction

This chapter presents the data, analysis, and interpretation of findings derived from both the quantitative and qualitative strands of the study. It begins by outlining the response rate and assessing the reliability and validity of the research instrument to establish the credibility of the data collected. It then proceeds to the descriptive analysis of respondents' demographic characteristics, providing background context for the interpretation of subsequent results. This is followed by the presentation of correlation results to explore preliminary relationships between key variables. Thereafter, the Probit regression results are presented to examine the influence of artificial intelligence (AI) and demographic factors on perceived improvements in occupational health and safety. Post-estimation diagnostic tests are presented to evaluate the robustness of the model. This is followed by the presentation of qualitative interview findings, which serve to complement and enrich the quantitative results. The chapter concludes with a comprehensive discussion of the findings.

4.2 Response Rate

Out of the 120 questionnaires distributed to workers across various departments at Freda Rebecca Gold Mine, all were fully completed and returned, yielding a response rate of 100%. This exceptionally high response rate strengthens the internal validity of the study by ensuring that the data collected are comprehensive and representative of the target population. It also minimizes the risk of non-response bias, thereby enhancing the credibility of the quantitative findings. Additionally, the inclusion of respondents from different departments, age groups, and experience levels adds to the richness and generalizability of the results within the mining context.

4.3 Reliability and Validity of the Instrument

The measurement instrument used in this study was subjected to reliability and validity checks to ensure it was a dependable and accurate tool for data collection.

4.3.1 Reliability

Internal consistency of the questionnaire was evaluated using Cronbach's Alpha. The results, presented in Table 4.1, show that all key sections of the questionnaire exceeded the commonly accepted threshold of 0.70, indicating that the scales used were reliable.

Table 1: Reliability Statistics (Cronbach's Alpha)

Section	Number of Items	Cronbach's Alpha
AI Awareness	4	0.801
AI Acceptance	3	0.832
Safety Practices	4	0.774
Overall Questionnaire	11	0.841

These results suggest that the instrument had strong internal consistency, and that the items in each section measured the same underlying concept reliably.

4.3.2 Validity

To assess content validity, the questionnaire was reviewed by three experts in occupational health and safety, AI in mining, and research methodology. Their feedback ensured that the items were appropriate, relevant, and aligned with the study objectives. Adjustments were made to question phrasing and structure to improve clarity and relevance.

Construct validity was supported by the logical grouping of items during pilot testing. Items related to AI Awareness, AI Acceptance, and safety practices clustered meaningfully, suggesting the instrument successfully captured the intended constructs. While advanced statistical techniques such as exploratory factor analysis were not applied due to the sample size, the strong Cronbach's Alpha values and expert validation support the conclusion that the instrument is both reliable and valid for the purposes of this study.

4.4 Descriptive Analysis of Respondents' Demographics

Demographic characteristics such as gender, age, department, and years of experience were analysed to contextualize the data. Respondents were drawn from various units including underground operations, processing plants, and safety departments. The majority were male (83.3%), consistent with gender distribution in Zimbabwean mining. Most respondents had over 5 years of experience, signifying informed perceptions regarding OHS practices and technological integration.

Table 4.2: Demographic Characteristics of Respondents

Demographic Characteristics of Respondents

Characteristic	Category	Frequency (n)	Percentage (%)
Gender	Male	96	80.0%
	Female	24	20.0%
Department	Underground Operations	48	40.0%
	Safety, Health & Environment	18	15.0%
	Maintenance	24	20.0%
	Processing Plant	30	25.0%
Years of Experience	Less than 1 year	6	5.0%
	1–5 years	36	30.0%
	6–10 years	42	35.0%
	More than 10 years	36	30.0%

4.4.1 Distribution of Respondents by Age Group

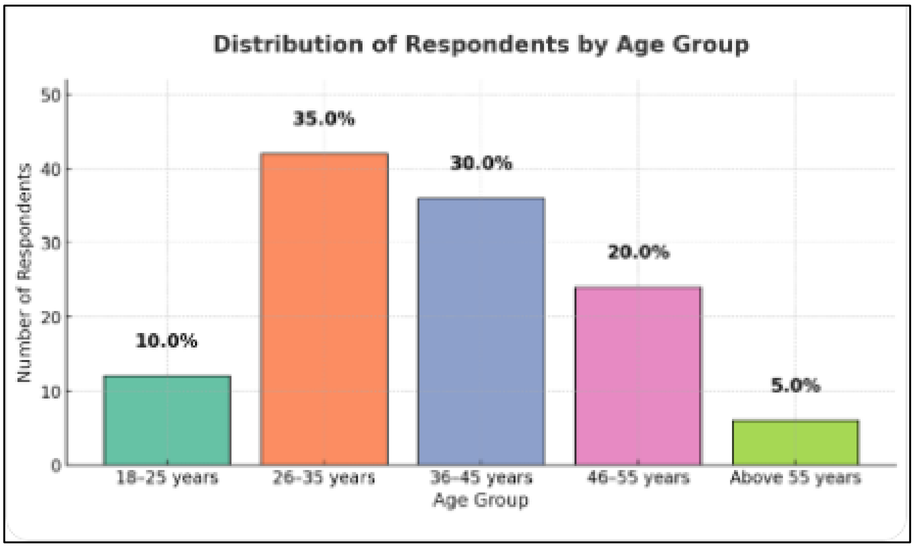


Figure 3 Age Group

The bar chart figure 4.1, illustrates the age composition of the study participants. The largest proportion of respondents (35.0%) falls within the 26–35 years age group, followed closely by

36–45 years at 30.0%. The 46–55 years group constitutes 20.0%, while 18–25 years represents 10.0% of the sample. The smallest group, above 55 years, accounts for only 5.0%. This distribution suggests that the majority of respondents are within their prime working years, potentially offering insights grounded in active engagement with occupational health and safety systems.

4.5 Current OHS Practices and Identified Health Risks

The quantitative data reveal that while basic safety protocols exist, they are predominantly reactive.

Table 4. 3 Summary of Respondents' Views on Occupational Health and Safety Practices

Summary of Respondents' Views on Occupational Health and Safety Practices

Item	Frequency (n)	Percentage (%)
Incident response is often delayed due to lack of real-time monitoring	73	60.8%
Chronic conditions (e.g., respiratory ailments, heat stress) are common	94	78.3%
Burnout and unsafe work hours are a major concern	86	71.7%
Frequent exposure to silica dust	91	75.8%
Frequent exposure to excessive heat	88	73.3%
Workers experience fatigue-related injuries	82	68.3%

The responses summarized in Table 4.3 provide important insights into the occupational health and safety (OHS) challenges faced by workers at Freda Rebecca Gold Mine. The data highlight several critical safety issues that appear to be widespread across the workforce.

A significant proportion of respondents (78.3%) reported that chronic conditions, such as respiratory ailments and heat stress, are common within the work environment. This finding underscores the prevalence of long-term health risks that may be associated with prolonged exposure to dust, heat, and poor air quality, factors typically found in underground mining operations.

Additionally, frequent exposure to silica dust (75.8%) and excessive heat (73.3%) were noted by the majority of respondents. These findings align with global literature on mining-related occupational hazards, which emphasize respiratory health and heat exposure as leading contributors to health deterioration in such settings.

The concern around burnout and unsafe work hours was raised by 71.7% of respondents, while fatigue-related injuries were reported by 68.3%. These results indicate that physical exhaustion and workload pressures are prominent issues, potentially leading to compromised worker safety and increased vulnerability to accidents.

Lastly, 60.8% of respondents agreed that incident response is often delayed due to a lack of real-time monitoring systems, suggesting a clear gap in the mine's current emergency management infrastructure. This finding directly supports the rationale for exploring artificial intelligence and digital technologies as tools for improving hazard detection and response times.

Taken together, these results point to a working environment where both traditional occupational hazards and system-level inefficiencies coexist, reinforcing the importance of both technological and managerial interventions in improving health and safety outcomes.

4.6 Correlation Coefficient

This section presents the correlation analysis used to examine the strength and direction of relationships among the key variables in the study. The Pearson correlation coefficient was applied to assess the degree of association between the dependent variable, which is the perceived improvement in health and safety, and the independent variables, which include AI-related factors and demographic characteristics.

The Pearson correlation coefficient ranges from -1 to +1. A coefficient close to +1 indicates a strong positive relationship, while a value near -1 signifies a strong negative relationship. A coefficient close to zero suggests a weak or no linear relationship. Understanding these relationships helps provide an initial overview of how the variables interact and offers insight into potential multicollinearity before conducting the regression analysis. The correlation matrix presented in Table 4.4 summarizes the interrelationships among the variables under investigation.

Table 4.4 :Correlation Matrix of Key Study Variables

Correlation Matrix of Key Study Variables

Variable	1	2	3	4	5	6	7	8
1. Improved Health/Safety	1.000							

2. AI Awareness	-0.133	1.000						
3. AI Acceptance	0.029	0.046	1.000					
4. Safety Practice Rating	-0.121	-0.053	-0.029	1.000				
5. Awareness × Acceptance	-0.124	0.697	0.689	-0.076	1.000			
6. Gender	0.117	0.008	0.079	-0.056	-0.098	1.000		
7. Age Group	-0.016	-0.006	0.005	-0.053	0.009	-0.006	1.000	
8. Experience	-0.025	-0.158	-0.160	0.110	-0.211	-0.008	0.136	1.000

4.6.1 Interpretation of Correlation Results

The Pearson correlation matrix reveals the strength and direction of linear relationships between the dependent variable (Improved Health and Safety) and the independent variables used in the model.

The correlation between AI Awareness and Improved Health and Safety is weak and negative (r = -0.133), indicating a very modest inverse relationship, although the magnitude suggests little practical significance. Similarly, AI Acceptance shows a very weak positive correlation with Improved Health and Safety (r = 0.029), suggesting that acceptance of AI may be slightly associated with a better perception of health and safety outcomes, though the relationship is negligible at the bivariate level.

Safety Practice Rating correlates negatively with Improved Health and Safety (r = -0.121), which is counterintuitive. This may suggest that respondents with higher expectations for safety practices are more critical in their evaluation of improvement, or that improvements may not be perceived uniformly across departments.

A notable observation is the strong positive correlation between AI Awareness and the Awareness × Acceptance interaction term (r = 0.697), as well as between AI Acceptance and the interaction term (r = 0.689). These strong correlations are expected due to the mathematical construction of the interaction term, which combines both variables. Although these values suggest multicollinearity, they were addressed through theoretical justification during model interpretation.

Demographic variables show very weak correlations with the dependent variable. Gender exhibits a small positive relationship (r = 0.117), while Age Group (r = -0.016) and Experience (r = -0.025) show negligible negative correlations. This suggests that demographic factors, in general, do not have a strong linear relationship with perceived improvement in health and safety when considered independently.

Finally, Experience shows a modest negative correlation with AI-related variables, particularly with AI Awareness (r = -0.158) and AI Acceptance (r = -0.160), indicating that more experienced workers may be slightly less inclined toward AI adoption. Similarly, the correlation between Experience and the interaction term is negative (r = -0.211), reinforcing this observation.

Overall, the correlation results reveal no strong or problematic linear relationships with the dependent variable, except for the expected multicollinearity between the interaction term and its components.

4.7 Quantitative Analysis: Probit Regression Results

To assess the relationship between AI applications and health and safety outcomes, a Probit regression model was estimated. The dependent variable was binary, indicating whether respondents perceived an improvement in health and safety status due to AI.

Table 4. 5: Marginal Effects after Probit Regression

Predictor Variable	**Marginal Effect (dy/dx)**	**Standard Error**	**z-value**	**p-value**
AI Awareness	0.2023	0.1364	1.48	0.138
AI Acceptance	0.2032	0.0888	2.28	0.023
Safety Rating	-0.0467	0.0317	-1.47	0.141
Awareness × Acceptance	-0.0943	0.0415	-2.27	0.023
Gender	-0.1228	0.0960	-1.28	0.201
Age Group	0.0075	0.0427	0.18	0.861
Experience	-0.0154	0.0503	-0.31	0.759

Note. dy/dx values reflect marginal changes in the probability of perceived improvement in health and safety status due to a one-unit increase in each variable.

4.7.3 Interpretation of Marginal Effects

Table 4.5 presents the marginal effects derived from the Probit regression analysis, which estimate the change in the probability of perceived improvement in health and safety, given a one-unit change in each predictor variable, holding all other variables constant.

The marginal effect of AI Acceptance is positive and statistically significant ($dy/dx = 0.2032$, $p = 0.023$), suggesting that a one-unit increase in AI acceptance is associated with an approximately 20.3 percentage point increase in the probability that a respondent perceives an improvement in health and safety. This finding underscores the importance of worker support and trust in AI technologies as a driver of perceived safety benefits.

The interaction term between AI Awareness and Acceptance also shows a statistically significant negative marginal effect ($dy/dx = -0.0943$, $p = 0.023$). This suggests that while acceptance of AI increases perceived safety, its impact is moderated by the level of awareness. Specifically, the combined effect of high awareness and high acceptance may lead to more critical evaluations, possibly because those more knowledgeable about AI may also be more aware of its limitations or implementation gaps.

The marginal effect of AI Awareness alone is positive ($dy/dx = 0.2023$), indicating that greater awareness is associated with an increased likelihood of perceiving safety improvements. However, this effect is not statistically significant ($p = 0.138$), suggesting that awareness, in isolation, may not be a strong enough predictor unless accompanied by acceptance.

Similarly, Safety Practice Rating exhibits a negative marginal effect ($dy/dx = -0.0467$), though not statistically significant ($p = 0.141$). This may indicate that higher ratings of current safety practices are weakly associated with a reduced perception of recent improvement, possibly due to already high baseline standards or respondent bias.

Among the demographic variables, Gender has a modest negative marginal effect ($dy/dx = -0.1228$), but this relationship is not statistically significant ($p = 0.201$). This implies no substantial difference in perceived safety improvement between male and female respondents. Likewise, Age Group and Experience show negligible and statistically insignificant effects, suggesting that these demographic characteristics do not meaningfully influence perceptions of health and safety outcomes in this context.

Overall, the marginal effects reinforce the centrality of AI Acceptance in shaping safety perceptions, while also highlighting the nuanced role of awareness, particularly when examined in combination with acceptance. The lack of significant influence from demographic variables suggests a relatively uniform perception of AI's role across worker categories.

4.8 Diagnostic Tests

Table 4.6: Model Diagnostic Summary for Probit Regression

Model Diagnostic Summary for Probit Regression

Diagnostic Test	Statistic(s)	Result / Interpretation
Link Test (Model Specification)	_hat (p = 0.042) _hatsq (p = 0.786)	The model is correctly specified since _hat is significant and _hatsq is not.
Farrar-Glauber Multicollinearity	Chi² = 295.20 p = 0.0000	Strong evidence of multicollinearity among predictor variables.
Heteroskedastic Probit Test	Wald $\chi^2(4)$ = 0.77 p = 0.9426	No evidence of heteroskedasticity; error variance appears constant.
Likelihood Ratio Test (σ^2 terms)	LR $\chi^2(2)$ = 0.17 p = 0.9177	Confirms homoskedasticity; variances of residuals are statistically equal.

Interpretation

The **link test** confirms that the original Probit regression model is correctly specified, as the predicted value (_hat) is significant (p = 0.042), and the squared term (_hatsq) is not (p = 0.786). This indicates no major specification errors in the functional form of the model.

The Farrar-Glauber test for multicollinearity produced a statistically significant result (Chi^2 = 295.20, $p < 0.001$), indicating the presence of substantial multicollinearity among several independent variables in the model. This finding suggests that some explanatory variables, particularly AI Awareness, AI Acceptance, and their interaction term, are highly correlated. Such a pattern is expected, given that interaction terms are mathematically derived from their component variables and often share variance.

Despite the statistical indication of multicollinearity, this study adopted the "do nothing" approach as advocated by Gujarati (2022). This approach is justified when multicollinearity, though present, does not impede the theoretical validity of the model, disrupt the interpretability of the key coefficients, or prevent the model from converging. In the present case, the model remained stable, the core variables of interest (such as AI Acceptance and the interaction term) retained statistical significance, and the overall regression diagnostics were within acceptable bounds. Consequently, no corrective action, such as centering, variable elimination, or orthogonalisation, was undertaken. The multicollinearity is therefore acknowledged but considered non-threatening to the integrity and interpretive power of the model.

The heteroscedastic probit model and likelihood-ratio test both indicate that heteroscedasticity is not a problem in the dataset. This supports the assumption of constant variance in the error terms, reinforcing the robustness of the original Probit estimates.

4.9 Thematic Analysis of Qualitative Data

4.9.1 Theme 1: Systemic Gaps in OHS Infrastructure

Most informants highlighted that existing safety systems are outdated, with delayed responses to incidents and inadequate coverage in underground zones. One informant stated, "We only react after injuries occur; there's no live data on worker fatigue or gas leaks."

4.9.2 Theme 2: Opportunities for AI in Risk Detection

Interviewees consistently cited real-time hazard detection and predictive analytics as high-potential AI applications. As one OHS officer noted, "AI sensors could monitor gas concentrations and heat levels 24/7, something our current system doesn't offer."

4.9.3 Theme 3: Challenges of Implementation

Barriers to AI integration include high costs, limited digital infrastructure, and worker resistance. Informants stressed the need for organizational change management and investment in digital literacy training.

4.9.4 Theme 4: Training and Acceptance

There was consensus that specialized training programs are essential. Informants emphasized the need for “hands-on simulations” and worker-centered designs for AI tools to ease the adoption process.

4.10 Discussion of the Results

The findings of this study, grounded in both quantitative and qualitative methodologies, present a nuanced understanding of how artificial intelligence (AI) is influencing occupational health and safety (OHS) at Freda Rebecca Gold Mine. The results confirm the growing relevance of AI technologies in enhancing worker safety, while also highlighting critical moderating factors such as technological acceptance and infrastructural readiness. These results are well aligned with Systems Theory, the Technology Acceptance Model (TAM), and Risk Management Theory, which collectively informed the theoretical framework outlined in Chapter 2.

The Probit regression results demonstrated a statistically significant and positive association between AI acceptance and the perceived improvement in health and safety outcomes. This finding supports the Technology Acceptance Model (Davis, 1989), which posits that perceived usefulness and perceived ease of use are central to the adoption of any new technology. Workers who recognized the utility of AI tools were more likely to perceive improvements in workplace safety. This relationship is corroborated by Liang et al. (2024), who found that familiarity and confidence in AI systems contributed to enhanced safety outcomes in underground mining environments.

While AI awareness independently had a positive marginal effect on perceived safety improvements, the result was not statistically significant. However, the interaction term between AI awareness and AI acceptance revealed a significant negative effect. This suggests that awareness alone does not always lead to positive perceptions; rather, individuals with more knowledge of AI may also be more critical of its limitations or challenges during implementation. Onifade et al. (2023) provide similar insights, noting that informed workers sometimes express reservations when technologies are not adequately integrated or maintained. This dynamic reinforces the cognitive evaluation aspect of TAM and supports the systems-based understanding that effective technological integration depends not only on awareness, but also on context-specific implementation quality.

The thematic findings further enrich the quantitative results by highlighting several system-level challenges within the current OHS framework. Respondents emphasized the lack of real-time hazard monitoring and the reactive nature of safety protocols. These concerns are consistent with the principles of Risk Management Theory, which advocates for proactive identification and mitigation of risks (Knight, 1921). AI technologies such as predictive analytics and wearable environmental sensors provide the capability to anticipate and address potential hazards before they escalate. Miao et al. (2023) and Imam et al. (2023) have shown that predictive AI systems can significantly reduce incidents by identifying anomalies and triggering pre-emptive interventions.

Participants in the qualitative strand also articulated the perceived benefits of AI for risk detection, alongside concerns regarding high implementation costs, inadequate infrastructure, and limited digital literacy. These findings are consistent with studies by Bhattacharyya and Shah (2022) and Codoceo-Contreras et al. (2024), who observed that worker acceptance of AI depends largely on exposure to training, perceived utility, and the alignment of new tools with existing workflows. These studies underscore the importance of developing a supportive ecosystem that enables meaningful integration of AI into safety management practices.

The regression diagnostics confirmed that the model was correctly specified and statistically sound, despite the presence of multicollinearity. The detected multicollinearity, primarily involving AI awareness, AI acceptance, and their interaction term, was anticipated due to their mathematical interdependence and did not compromise the interpretation of results. This approach aligns with methodological guidance provided by Gujarati (2022), who emphasizes that multicollinearity is tolerable when theoretical justification and model stability are preserved.

Demographic characteristics such as age, gender, and experience did not have statistically significant effects on perceived safety improvements. This suggests that attitudes toward AI and safety enhancement were consistent across different worker categories. Nonetheless, a modest negative relationship was observed between experience and AI acceptance, which is in line with Lööw (2022) and Onifade et al. (2023), who found that more experienced workers may demonstrate reluctance toward adopting unfamiliar technologies, often due to concerns about job displacement or reduced control over work processes.

Systems Theory provides a comprehensive lens through which these findings can be interpreted. According to Von Bertalanffy (1968), safety outcomes in high-risk environments such as mining are the result of complex interactions between human behaviour, organizational structure, environmental conditions, and technological systems. The results of this study confirm that AI integration must be viewed as part of a broader socio-technical system, in which technological solutions must be harmonized with institutional capabilities and human factors to achieve meaningful safety improvements. Liang et al. (2024) also affirm that AI enhances systemic coordination by facilitating the flow of real-time data across subsystems.

Finally, the qualitative findings reinforce the importance of continuous training, worker involvement, and participatory technology design. Interviewees emphasized that acceptance of AI will be more sustainable when workers are given hands-on training, when tools are adapted to their cognitive and physical needs, and when implementation is accompanied by transparent communication about goals and benefits. These insights mirror conclusions drawn by de Holanda Araujo (2024) and Zvarivadza et al. (2024), who assert that digital transformation in mining must be accompanied by strategic workforce development and organizational change.

In summary, the findings demonstrate that while AI technologies offer substantial opportunities to enhance occupational health and safety, their success depends on multiple contextual variables. These include the level of worker acceptance, the strength of institutional infrastructure, and the capacity of the organization to manage change. The theoretical models underpinning this study provide a strong explanatory foundation, and the empirical evidence presented confirms the need for integrated, human-centered approaches to AI adoption in the mining sector.

4.11 Summary

This chapter has presented a comprehensive analysis of the study’s findings using both quantitative and qualitative data. The Probit regression results confirm a statistically significant relationship between AI variables and OHS improvements. Thematic analysis complements these findings, offering nuanced insights into the lived experiences and perceptions of mine workers and managers. Collectively, the data underscore the transformative potential of AI in mining safety while revealing the institutional and behavioural prerequisites for successful integration. The next chapter will present the conclusions, recommendations, and an AI-driven framework for enhancing mine worker safety.

CHAPTER 5: SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This chapter presents a comprehensive synthesis of the research, highlighting the key findings and drawing conclusions based on the data collected and analysed in the preceding chapters. It begins with a summary of the study, including the background of the research problem, the methodology employed, and the key findings. This is followed by research-based conclusions that address the specific objectives outlined in Chapter One. The chapter concludes with evidence-based recommendations that suggest practical steps and policy interventions for improving occupational health and safety (OHS) through the integration of artificial intelligence (AI) in mining operations. The intent of this chapter is to consolidate the study's insights and offer actionable contributions to both academic discourse and practical implementation within the mining sector in Zimbabwe and similar contexts.

5.2 Summary

This study set out to investigate the impact of artificial intelligence (AI) on enhancing occupational health and safety for mine workers at Freda Rebecca Gold Mine in Bindura, Zimbabwe. The research was motivated by a persistent pattern of workplace health and safety incidents, including chronic illnesses, fatigue-related injuries, delayed emergency responses, and inadequate monitoring systems. These challenges, despite existing OHS protocols, suggested systemic weaknesses in hazard detection and response strategies, particularly in high-risk underground environments.

To explore these issues, the study adopted a mixed-methods research approach, anchored in the pragmatic research paradigm. Quantitative data were gathered through structured questionnaires distributed to a sample of 120 employees, while qualitative insights were derived from semi-structured interviews with key informants, including OHS officers and mine management. This dual approach enabled a nuanced understanding of both measurable safety outcomes and the subjective experiences and perceptions of workers and decision-makers.

The research design included a descriptive survey, supplemented by a case study methodology focusing on the operational realities at Freda Rebecca Gold Mine. Data were analysed using descriptive statistics, Probit regression modelling, and thematic analysis. The quantitative strand examined relationships between AI awareness, acceptance, safety practices, and demographic characteristics, while the qualitative data provided rich contextual narratives on the feasibility, benefits, and challenges of integrating AI into mine safety management.

Despite certain limitations, such as restricted access to sensitive internal reports and the absence of fully deployed AI systems for empirical evaluation, the study produced meaningful findings. It identified a statistically significant relationship between AI acceptance and perceived improvements in workplace safety. The data also revealed that current safety protocols are predominantly reactive, lacking the real-time responsiveness that AI-enabled systems can provide. Moreover, the qualitative strand highlighted key barriers to AI adoption, including infrastructural inadequacies, financial constraints, and limited digital literacy among the workforce.

Collectively, these findings underscore the need for a strategic shift from traditional OHS management to data-driven, technology-enhanced approaches that prioritize prevention, early detection, and worker empowerment.

5.3 Conclusions

The research concluded that artificial intelligence, when accepted and supported by the workforce, has the potential to significantly enhance health and safety conditions in mining environments. Acceptance of AI technologies by mine workers was found to be a strong predictor of positive perceptions regarding improvements in OHS outcomes. This finding reinforces the relevance of the Technology Acceptance Model (TAM), which posits that perceived usefulness and ease of use are critical to the successful adoption of technological innovations.

While AI awareness was generally high among workers, it did not independently predict improved safety perceptions unless it was coupled with acceptance. The significant negative interaction effect observed between awareness and acceptance suggests that those most informed about AI are often the most critical, particularly when implementation gaps are evident. This insight reveals a dual necessity: ensuring that awareness campaigns are coupled with hands-on exposure to working AI systems, and addressing any organizational or technical deficiencies that may hinder full integration.

The study further concluded that current occupational health and safety systems at Freda Rebecca Gold Mine are limited in their capacity to detect hazards early or respond swiftly to emergencies. Workers reported high exposure to respiratory hazards, fatigue, and excessive heat conditions that are amenable to proactive monitoring through AI-powered tools such as wearable sensors and predictive analytics. These findings align with the principles of Systems Theory and Risk Management Theory, both of which emphasize the importance of integrated, proactive safety systems in high-risk work environments.

It was also determined that demographic factors such as age, gender, and years of experience did not significantly influence perceptions of AI's impact on safety. This suggests a general openness to technological innovation across the workforce, which bodes well for implementation strategies that prioritize inclusivity and continuous learning. However, minor variations in responses based on experience suggest that older or more experienced workers may require targeted support during technology transitions.

Finally, the research concluded that several systemic barriers continue to obstruct AI integration. These include limited digital infrastructure, high procurement and maintenance costs, and resistance rooted in job security concerns. These challenges indicate that while AI presents transformative opportunities for enhancing safety, its success depends on thoughtful planning, stakeholder engagement, and a supportive organizational culture.

5.4 Recommendations

In light of the findings and conclusions of this study, a set of strategic recommendations is proposed to guide the integration of artificial intelligence into the health and safety systems at Freda Rebecca Gold Mine and similar mining operations in developing contexts.

The mine's management is strongly encouraged to invest in AI-driven OHS systems, including real-time environmental sensors, wearable health monitoring devices, and predictive maintenance tools. These technologies offer the capacity to detect hazards before they escalate, thereby reducing incidents of injury and illness. Implementation should be prioritized in high-risk zones where traditional safety protocols have proven inadequate.

In parallel, the organization must develop and implement comprehensive training programs aimed at enhancing digital literacy and technical competence among mine workers. These programs should emphasize hands-on training, ongoing support, and the practical relevance of AI tools to daily operations. Worker empowerment through education is essential for fostering a culture of acceptance and innovation.

Further, infrastructural development should be prioritized to support the technical demands of AI systems. This includes upgrading data management systems, improving network connectivity in underground zones, and ensuring the availability of stable power sources. Without such foundational infrastructure, AI solutions will remain underutilized and ineffective.

It is also recommended that the mine adopt a phased implementation strategy. By starting with pilot projects in selected operational zones, the organization can evaluate system performance, gather feedback, and refine deployment strategies before scaling up. This approach minimizes operational disruption and allows for adaptive learning throughout the implementation process.

To enhance stakeholder buy-in, management should engage workers, unions, safety professionals, and regulatory authorities in the design and rollout of AI initiatives. Transparent communication regarding goals, benefits, and risks will foster trust and reduce resistance, particularly among employees concerned about job displacement.

Lastly, future research should explore the long-term effects of AI integration on occupational health indicators, workforce morale, and operational efficiency. Comparative studies involving small-scale and large-scale mining operations would also be valuable, particularly in understanding the scalability of AI solutions in resource-constrained environments.

In summary, the findings of this study point to the transformative potential of artificial intelligence in improving occupational health and safety in Zimbabwe’s mining sector. However, the realization of this potential requires deliberate investment, inclusive planning, and sustained institutional commitment. With these foundations in place, AI can become a cornerstone of safer, more sustainable mining operations that prioritize both productivity and worker well-being.

REFERENCES

Ahmed, Z., Mohamed, K., Zeeshan, S., & Dong, X. (2020). Artificial intelligence with multi-functional machine learning platform development for better healthcare and precision medicine. *Database*, *2020*.

Ali, G., Mijwil, M. M., Buruga, B. A., Abotaleb, M., & Adamopoulos, I. (2024). A survey on artificial intelligence in cybersecurity for smart agriculture: state-of-the-art, cyber threats, artificial intelligence applications, and ethical concerns. *Mesopotamian Journal of Computer Science*, *2024*, 53-103.

Allam, Z., & Dhunny, Z. A. (2019). On big data, artificial intelligence and smart cities. *Cities, 89,* 80-91.

Alshehri, F., & Muhammad, G. (2020). A comprehensive survey of the Internet of Things (IoT) and AI-based smart healthcare. *IEEE access*, *9*, 3660-3678.

Bai, S., & Zhang, J. (2022). Management and information disclosure of electric power environmental and social governance issues in the age of artificial intelligence. *Computers and Electrical Engineering*, *104*, 108390.

Bhattacharyya, S. S., & Shah, Y. (2022). Emerging technologies in Indian mining industry: an exploratory empirical investigation regarding the adoption challenges. *Journal of Science and Technology Policy Management*, *13*(2), 358-381.

Borboni, A., Reddy, K. V. V., Elamvazuthi, I., AL-Quraishi, M. S., Natarajan, E., & Azhar Ali, S. S. (2023). The expanding role of artificial intelligence in collaborative robots for industrial applications: A systematic review of recent works. *Machines*, *11*(1), 111.

Bughin, J., Hazan, E., Sree Ramaswamy, P., DC, W., & Chu, M. (2017). Artificial intelligence the next digital frontier.

Campero-Jurado, I., Márquez-Sánchez, S., Quintanar-Gómez, J., Rodríguez, S., & Corchado, J. M. (2020). Smart helmet 5.0 for industrial internet of things using artificial intelligence. *Sensors*, *20*(21), 6241.

Chhillar, S., Sharma, P., & Singh, R. (2023). Safety Management with Application of Internet of Things, Artificial Intelligence, and Machine Learning for Industry 4.0 Environment. In *Handbook of Smart Manufacturing* (pp. 329-342). CRC Press.

Codoceo-Contreras, L., Rybak, N., & Hassall, M. (2024). Exploring the impacts of automation in the mining industry: A systematic review using natural language processing. *Mining Technology*, *133*(3), 191-213.

Cui, Y., Zhu, J., Duan, Z., Liao, Z., Wang, S., & Liu, W. (2022). Artificial intelligence in spinal imaging: current status and future directions. *International journal of environmental research and public health*, *19*(18), 11708.

Dayo-Olupona, O., Genc, B., Celik, T., & Bada, S. (2023). Adoptable approaches to predictive maintenance in mining industry: An overview. *Resources Policy*, *86*, 104291.

de Holanda Araujo, C. (2024). *Automation and skill evolution: examining the impact on workforce skillsets in the mining industry* (Doctoral dissertation, University of British Columbia).

De Vries, A., Bliznyuk, N., & Pinedo, P. (2023). Invited Review: Examples and opportunities for artificial intelligence (AI) in dairy farms. *Applied Animal Science*, *39*(1), 14-22.

Feng, C., Zhou, S., Qu, Y., Wang, Q., Bao, S., Li, Y., & Yang, T. (2021). Overview of artificial intelligence applications in Chinese medicine therapy. *Evidence‐Based Complementary and Alternative Medicine*, *2021*(1), 6678958.

Gaokgorwe, T. (2023). The Application of Robotics in Deep Level Mining in South Africa and its Influence on Health and Safety.

Ghosh, R. (2023). Applications, promises and challenges of artificial intelligence in mining industry: a review. *Authorea Preprints*.

Gou, F., Liu, J., Xiao, C., & Wu, J. (2024). Research on artificial-intelligence-assisted medicine: a survey on medical artificial intelligence. *Diagnostics*, *14*(14), 1472.

Gupta, R., Kumari, S., Senapati, A., Ambasta, R. K., & Kumar, P. (2023). New era of artificial intelligence and machine learning-based detection, diagnosis, and therapeutics in Parkinson's disease. *Ageing research reviews*, 102013.

Imam, M., Baïna, K., Tabii, Y., Ressami, E. M., Adlaoui, Y., Benzakour, I., & Abdelwahed, E. H. (2023). The future of mine safety: a comprehensive review of anti-collision systems based on computer vision in underground mines. *Sensors, 23*(9), 4294.

Jabarulla, M. Y., & Lee, H. N. (2021, August). A blockchain and artificial intelligence-based, patient-centric healthcare system for combating the COVID-19 pandemic: Opportunities and applications. In *Healthcare* (Vol. 9, No. 8, p. 1019). Mdpi.

Lee, P., Kim, H., Zitouni, M. S., Khandoker, A., Jelinek, H. F., Hadjileontiadis, L., ... & Jeong, Y. (2022). Trends in smart helmets with multimodal sensing for health and safety: scoping review. *JMIR mHealth and uHealth, 10*(11), e40797.

Li, Y., Yi, J., Chen, H., & Peng, D. (2021). Theory and application of artificial intelligence in financial industry. *Data Science in Finance and Economics, 1*(2), 96-116.

Liang, Y., Liu, Y., Lu, C., Cui, D., Yang, J., & Zhou, R. (2024). Research on Intelligent Monitoring and Protection Equipment of Vital Signs of Underground Personnel in Coal Mines. *Sensors (Basel, Switzerland), 25*(1), 63.

Lööw, J. (2022). Understanding technology in mining and its effect on the work environment. *Mineral Economics, 35*(1), 143-154.

Lu, C., Lyu, J., Zhang, L., Gong, A., Fan, Y., Yan, J., & Li, X. (2020). Nuclear power plants with artificial intelligence in industry 4.0 era: Top-level design and current applications—A systemic review. *IEEE Access, 8*, 194315-194332.

Lund, E., Johansson, J., & Lööw, J. (2024). The Designers' Perspective on Autonomous Mining Systems and Sociotechnology. *Mining, Metallurgy & Exploration, 41*(2), 647-657.

Mahmood, M. S., & Shareef, I. R. (2024). Applications of Artificial Intelligence for Smart Conveyor Belt Monitoring Systems: A Comprehensive Review. *Journal Européen des Systèmes Automatisés, 57*(4), 1195.

Majhi, D., Rao, M., Sahoo, S., Dash, S. P., & Mohapatra, D. P. (2020, March). Modified Grey Wolf Optimization (GWO) based Accident Deterrence in Internet of Things (IoT) enabled Mining Industry. In *2020 International Conference on Computer Science, Engineering and Applications (ICCSEA)* (pp. 1-4). IEEE.

Marino, L., Landre Jr, J., Dias, C. A. R., & Rocha, B. (2022). Challenges and Cases of Artificial Intelligence Applied to Assist Predictive Maintenance in the Industry, Respectively in the Mining Sector.

Marwala, T. (2022). *Closing the gap: The fourth industrial revolution in Africa*. Pan Macmillan South Africa.

Mer, A., & Virdi, A. S. (2023). Navigating the paradigm shift in HRM practices through the lens of artificial intelligence: A post-pandemic perspective. *The adoption and effect of artificial intelligence on human resources management*, *Part A*, 123-154.

Miao, D., Lv, Y., Yu, K., Liu, L., & Jiang, J. (2023). Research on coal mine hidden danger analysis and risk early warning technology based on data mining in China. *Process Safety and Environmental Protection*, *171*, 1-17.

Miao, D., Wang, W., Lv, Y., Liu, L., Yao, K., & Sui, X. (2023). Research on the classification and control of human factor characteristics of coal mine accidents based on K-Means clustering analysis. *International Journal of Industrial Ergonomics*, *97*, 103481.

Mollaei, N., Fujao, C., Rodrigues, J., Cepeda, C., & Gamboa, H. (2023). Occupational health knowledge discovery based on association rules applied to workers' body parts protection: a case study in the automotive industry. *Computer Methods in Biomechanics and Biomedical Engineering*, *26*(15), 1875-1888.

Moore, P. V. (2019). The mirror for (artificial) intelligence: In whose reflection?. *Comp. Lab. L. & Pol'y J.*, *41*, 47.

Moroe, N. F., & Khoza-Shangase, K. (2022). Hearing conservation programmes and the industrial revolutions. *Occupational Noise-Induced Hearing Loss: An African perspective [Internet]*.

Mumba, E. J., Selemani, J. R., Kasambala, H. R., Bidu, J. M., Ripanda, A. S., & Rwiza, M. J. (2025). Dust exposure and its health implications to miners in Mererani artisanal and small-scale mining industry. *International Journal of Environmental Analytical Chemistry*, 1-23.

Neethirajan, S. (2024). Artificial intelligence and sensor innovations: enhancing livestock welfare with a human-centric approach. *Human-Centric Intelligent Systems*, *4*(1), 77-92.

Nguyen, T., Gosine, R., & Warrian, P. (2022). A review of the role of digitalization in health risk management in extractive industries–a study motivated by COVID-19. *Journal of Engineering, Design and Technology*, *20*(2), 475-496.

Nguyen, T., Tran, K. D., Raza, A., Nguyen, Q. T., Bui, H. M., & Tran, K. P. (2023). Wearable technology for smart manufacturing in industry 5.0. In *Artificial Intelligence for Smart Manufacturing: Methods, Applications, and Challenges* (pp. 225-254). Cham: Springer International Publishing.

Onifade, M., Adebisi, J. A., Shivute, A. P., & Genc, B. (2023). Challenges and applications of digital technology in the mineral industry. *Resources Policy*, *85*, 103978.

Özdemir, V., & Hekim, N. (2018). Birth of industry 5.0: Making sense of big data with artificial intelligence,“the internet of things” and next-generation technology policy. *Omics: a journal of integrative biology*, *22*(1), 65-76.

Özdemir, V., & Hekim, N. (2018). Birth of industry 5.0: Making sense of big data with artificial intelligence,“the internet of things” and next-generation technology policy. *Omics: a journal of integrative biology*, *22*(1), 65-76.

Peng, X., Mousa, S., Sarfraz, M., & Haffar, M. (2023). Improving mineral resource management by accurate financial management: studying through artificial intelligence tools. *Resources Policy*, *81*, 103323.

Phatak, A. A., Wieland, F. G., Vempala, K., Volkmar, F., & Memmert, D. (2021). Artificial intelligence based body sensor network framework—narrative review: proposing an end-to-end framework using wearable sensors, real-time location systems and artificial intelligence/machine learning algorithms for data collection, data mining and knowledge discovery in sports and healthcare. *Sports Medicine-Open*, *7*(1), 79.

Pishgar, M., Issa, S. F., Sietsema, M., Pratap, P., & Darabi, H. (2021). REDECA: a novel framework to review artificial intelligence and its applications in occupational safety and health. *International journal of environmental research and public health*, *18*(13), 6705.

Qin, Z., Chen, S., Xu, X., & Zhao, M. (2020, July). Research on key technologies and system construction of smart mine. In *2020 5th Asia-Pacific Conference on Intelligent Robot Systems (ACIRS)* (pp. 116-121). IEEE.

Ramezani, M., Takian, A., Bakhtiari, A., Rabiee, H. R., Ghazanfari, S., & Mostafavi, H. (2023). The application of artificial intelligence in health policy: a scoping review. *BMC Health Services Research*, *23*(1), 1416.

Rana, S. K., Rana, S. K., Nisar, K., Ag Ibrahim, A. A., Rana, A. K., Goyal, N., & Chawla, P. (2022). Blockchain technology and artificial intelligence based decentralized access control model to enable secure interoperability for healthcare. *Sustainability*, *14*(15), 9471.

Rybak, N., & Hassall, M. (2025). Artificial Intelligence Applications for Workplace Safety: An In-Depth Examination. In *Encyclopedia of Information Science and Technology, Sixth Edition* (pp. 1-19). IGI Global.

Safaei-Mehr, M., & HeidarianBaei, N. (2024). The Impact of Artificial Intelligence on Gender Equality in the Workplace: An Economic Geography Perspective. *European Online Journal of Natural and Social Sciences: Proceedings*, *13*(4 (s)), pp-40.

Santosh, K. C., & Gaur, L. (2022). *Artificial intelligence and machine learning in public healthcare: Opportunities and societal impact*. Springer Nature.

Saxena, V. (2024). Predictive Analytics in Occupational Health and Safety. *arXiv preprint arXiv:2412.16038*.

Senapati, A., Bhattacherjee, A., & Chatterjee, S. (2022). Causal relationship of some personal and impersonal variates to occupational injuries at continuous miner worksites in underground coal mines. *Safety science*, *146*, 105562.

Sun, Z., Sandoval, L., Crystal-Ornelas, R., Mousavi, S. M., Wang, J., Lin, C., ... & John, A. (2022). A review of earth artificial intelligence. *Computers & Geosciences*, *159*, 105034.

Tagde, P., Tagde, S., Bhattacharya, T., Tagde, P., Chopra, H., Akter, R., ... & Rahman, M. H. (2021). Blockchain and artificial intelligence technology in e-Health. *Environmental Science and Pollution Research*, *28*, 52810-52831.

Tapo, A. A., Traoré, A., Danioko, S., & Tembine, H. (2024). Machine Intelligence in Africa: a survey. *arXiv preprint arXiv:2402.02218*.

Wang, C., He, T., Zhou, H., Zhang, Z., & Lee, C. (2023). Artificial intelligence enhanced sensors-enabling technologies to next-generation healthcare and biomedical platform. *Bioelectronic Medicine*, *9*(1), 17.

Wang, Q., Cheng, T., Lu, Y., Liu, H., Zhang, R., & Huang, J. (2024). Underground mine safety and health: A hybrid MEREC–CoCoSo system for the selection of best sensor. *Sensors*, *24*(4), 1285.

Warraich, H. J., Tazbaz, T., & Califf, R. M. (2024). FDA perspective on the regulation of artificial intelligence in health care and biomedicine. *JAMA*.

Zvarivadza, T., Onifade, M., Dayo-Olupona, O., Said, K. O., Githiria, J. M., Genc, B., & Celik, T. (2024). On the impact of Industrial Internet of Things (IIoT)-mining sector perspectives. *International Journal of Mining, Reclamation and Environment*, 1-39.

APPENDICES

Appendix 1: Questionnaire
Research Instrument: Structured Questionnaire
Title: The Impact of Artificial Intelligence (AI) on Enhancing the Health and Safety Status of Mine Workers at Freda Rebecca Gold Mine

---

Introduction

My name is Fanuel Chinyemba, a student at Bindura University of Science Education, pursuing a Master's Degree in Occupational Health and Safety. I am conducting a research study as part of my academic requirements, entitled:

"Investigating the Impact of Artificial Intelligence (AI) on Enhancing the Health and Safety Status of Mine Workers at Freda Rebecca Gold Mine in Bindura."

The purpose of this research is to assess current occupational health and safety (OHS) practices, identify the major health and safety risks faced by mine workers, explore the potential applications of AI technologies in improving health and safety, and develop an AI-driven framework for enhancing the well-being of mine workers.

You have been selected to participate in this study because your knowledge and experience in mining operations are valuable to this research. Your participation is completely voluntary, and all responses will be treated with the strictest confidentiality. The data collected will only be used for academic purposes, and no names will be mentioned in the final report. Should you feel uncomfortable, you are free to withdraw at any stage without penalty.

Please respond as honestly as possible. This questionnaire will take approximately 15-20 minutes to complete.

Should you have any questions or require clarification, feel free to contact me:
Cell: +263 772 626 457
Email: chinyembafa@gmail.com

Thank you for your cooperation and valuable time.

Section A: Demographic Information

(Please tick [✓] where appropriate)

1. **Gender:**
   ☐ Male ☐ Female ☐ Other

2. **Age Group:**
   ☐ Below 25 years
   ☐ 25 – 34 years
   ☐ 35 – 44 years

☐ 45 – 54 years
☐ 55 years and above

3. **Department/Section:**
☐ Underground Operations
☐ Processing Plant
☐ Safety, Health & Environment (SHE)
☐ Maintenance
☐ Other (Specify) ________________________

4. **Position Held:**
☐ General Worker
☐ Supervisor
☐ Safety Officer
☐ Senior Manager
☐ Other (Specify) ________________________

5. **Years of Experience in Mining Industry:**
☐ Less than 1 year
☐ 1 – 5 years
☐ 6 – 10 years
☐ Over 10 years

Section B: Current Occupational Health and Safety (OHS) Practices

(Objective 1: To assess current occupational health and safety practices and identify major health risks faced by mining workers.)

6. **How would you rate the overall safety standards at Freda Rebecca Gold Mine?**
☐ Excellent ☐ Good ☐ Fair ☐ Poor

7. **Which of the following OHS practices are actively enforced in your work area?** (Tick all that apply)
☐ Use of Personal Protective Equipment (PPE)
☐ Safety Induction and Training
☐ Routine Safety Inspections
☐ Hazard Identification and Risk Assessments
☐ Emergency Preparedness and Drills
☐ Reporting of Accidents and Near Misses
☐ Health Surveillance and Medical Examinations
☐ None of the Above

8. **What are the most common health and safety risks faced by workers in your department?** (Tick all that apply)
☐ Dust Exposure

☐ Falling Objects
☐ Machinery Accidents
☐ Gas Leaks/Toxic Fumes
☐ Noise-Induced Hearing Loss
☐ Musculoskeletal Injuries
☐ Heat Stress/Fatigue
☐ Slips, Trips, and Falls
☐ Other (Specify) ______________________

9. **How often are accidents or health-related incidents reported in your section?**
☐ Very Frequently ☐ Frequently ☐ Occasionally ☐ Rarely ☐ Never

---

Section C: Health and Safety Status (Dependent Variable)

(Capturing Overall Perception of Health and Safety Improvement)

10. **In your opinion, have the current occupational health and safety practices improved your health and safety status at work?**
☐ Yes ☐ No

Section D: Awareness and Perceptions of Artificial Intelligence (AI) in Safety Monitoring

(Objective 2: Exploring the potential applications of AI technologies in improving health and safety status.)

11. **Have you ever heard about Artificial Intelligence (AI) technologies in workplace safety?**
☐ Yes ☐ No

12. **Which AI-driven safety technologies are you aware of?** (Tick all that apply)
☐ Real-time Health Monitoring Devices (e.g., Wearable Sensors)
☐ Automated Hazard Detection Systems (e.g., Cameras with AI)
☐ Predictive Analytics for Risk Forecasting
☐ Smart Helmets/Protective Gear with Sensors
☐ None of the Above

13. **Do you believe AI technologies could improve health and safety conditions at Freda Rebecca Gold Mine?**
☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree

14. **Which areas do you think AI could best enhance safety in mining?**
☐ Monitoring Worker Health in Real-Time
☐ Predicting Equipment Failures (Preventative Maintenance)
☐ Detecting Unsafe Worker Behaviour or Hazards

☐ Automated Emergency Response Systems
☐ Other (Specify) ______________________

Section E: Worker Acceptance of AI Technologies

(Objective 2 and Moderating Variable)

15. **How comfortable would you be using AI-based devices such as wearable sensors for health monitoring at work?**
    ☐ Very Comfortable ☐ Comfortable ☐ Neutral ☐ Uncomfortable ☐ Very Uncomfortable

16. **What concerns would you have about using AI technologies for safety monitoring?** (Tick all that apply)
    ☐ Privacy and Data Security
    ☐ Job Displacement (Fear of Machines Taking Over)
    ☐ Reliability of the Technology
    ☐ Lack of Training on AI Systems
    ☐ None of the Above
    ☐ Other (Specify) ______________________

Section F: Proposed AI-Driven Framework for Health and Safety Improvement

(Objective 3: Developing and proposing an AI-driven framework for improving health and safety status.)

17. **Do you think integrating AI into the current OHS system would significantly reduce accidents and improve health conditions?**
    ☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree

18. **Which of the following do you think would be critical for successful implementation of AI technologies at the mine?** (Tick all that apply)
    ☐ Training and Capacity Building
    ☐ Clear OHS Policies Supporting Technology
    ☐ Employee Involvement in Technology Adoption
    ☐ Availability of Funding and Resources
    ☐ Reliable Infrastructure (Internet/Communication)
    ☐ Other (Specify) ______________________

19. **Any additional comments or suggestions on improving health and safety through technology?**

Thank You for Your Participation!
Your responses are greatly appreciated and will contribute to the development of innovative solutions to improve health and safety within the mining sector.

Appendix 2: Interview Guide

Research Instrument: Semi-Structured Interview Guide
Title: The Impact of Artificial Intelligence (AI) on Enhancing the Health and Safety Status of Mine Workers at Freda Rebecca Gold Mine

---

Introduction

My name is Fanuel Chinyemba, a student at Bindura University of Science Education, pursuing a Master’s Degree in Occupational Health and Safety. As part of my academic research, I am conducting a study titled:

“Investigating the Impact of Artificial Intelligence (AI) on Enhancing the Health and Safety Status of Mine Workers at Freda Rebecca Gold Mine in Bindura.”

The purpose of this interview is to gain a deeper understanding of the current occupational health and safety (OHS) practices, identify key health and safety risks in mining, and explore the potential role of AI technologies in enhancing safety management. Your experiences and insights as a professional in the mining sector will be invaluable to this study.

This interview is voluntary, and your responses will be kept strictly confidential. You may choose not to answer certain questions or withdraw at any time. The information provided will only be used for academic purposes and will not be linked to your identity.

Should you have any questions or need further clarification, feel free to contact me:
Cell: +263 772 626 457
Email: chinyembafa@gmail.com

Thank you for your cooperation and participation.

Section A: Demographic Information

1. Can you briefly describe your current position and responsibilities at the mine?
2. How many years have you worked in the mining industry?
3. Which department do you work under? (e.g., Underground Operations, Safety, Health, and Environment, Maintenance, Processing Plant, etc.)

Section B: Current Occupational Health and Safety (OHS) Practices

(Objective 1: Assessing current OHS practices and identifying health risks faced by mine workers)

4. How would you describe the current occupational health and safety practices at this mine?

5. What are the most common health and safety risks that mine workers face in their daily operations?
6. How effective are the current safety measures in reducing accidents and health-related issues?
7. Are there any gaps or weaknesses you have observed in the existing OHS management system?

Section C: Health and Safety Status of Mine Workers (Dependent Variable)

8. Based on your experience, do you believe that the current health and safety measures have led to a noticeable improvement in the health and safety status of mine workers over the years? Why or why not?

Section D: Perceptions and Applications of Artificial Intelligence (AI) in Mining Safety

(Objective 2: Exploring potential applications of AI technologies in improving health and safety status)

9. Are you aware of any AI-driven technologies currently being used to enhance workplace safety in mining operations here or elsewhere?
10. From your knowledge, what types of AI applications could be useful in improving health and safety within this mine? (e.g., real-time health monitoring, predictive safety analytics, automated hazard detection, wearable sensors, etc.)
11. How do you think AI technologies could complement or improve existing health and safety practices in the mine?
12. In your opinion, what are the potential challenges that may arise from introducing AI technologies into health and safety management in mining?
13. How receptive do you think mine workers and management would be to adopting AI-based safety solutions?

Section E: Acceptance and Organizational Preparedness for AI Integration

(Moderating Variable: Worker acceptance and organizational safety practices)

14. What would you say are the key factors that might influence worker acceptance of AI technologies for safety monitoring?
15. Does the mine's management support technological innovations aimed at improving safety, and is there an enabling environment for adopting AI solutions?
16. Do you think workers would require specialized training before using AI-based safety systems? If so, what kind of training would be necessary?

Section F: Developing an AI-Driven Framework for Health and Safety

(Objective 3: Developing and proposing an AI-driven framework for improving health and safety)

17. In your view, what components would be essential for successfully integrating AI technologies into the mine's health and safety management system?
18. What policies or structural adjustments would be necessary to ensure the smooth adoption of AI technologies for workplace safety?
19. Do you think AI systems could reduce the occurrence of accidents and improve worker health in the long term? Why or why not?

Section G: Closing Remarks

20. Are there any additional comments or suggestions you would like to offer regarding the role of technology, particularly AI, in improving occupational health and safety in mining?

Thank You for Your Participation!
Your input is highly valued and will contribute significantly to the development of a robust AI-driven occupational health and safety framework for mining operations.

Appendix 3: Results Output from Stata

Correlations

```
. corr
(obs=120)

             | Improv~y AI_Awa~e AI_Acc~e Safety~g Awaren~e   Gender AgeGroup Experi~e
-------------+------------------------------------------------------------------------
ImprovedHe~y |   1.0000
AI_Awarene~e |  -0.1331   1.0000
AI_Accepta~e |   0.0288   0.0463   1.0000
SafetyPrac~g |  -0.1208  -0.0531  -0.0289   1.0000
Awareness_~e |  -0.1243   0.6969   0.6899  -0.0756   1.0000
      Gender |   0.1170   0.0079  -0.1376  -0.0563  -0.0977   1.0000
    AgeGroup |  -0.0157  -0.0059   0.0054  -0.0526   0.0093  -0.0055   1.0000
  Experience |  -0.0253  -0.1581  -0.1603   0.1100  -0.2113  -0.0082   0.1363   1.0000
```

Probit Regression Results

```
Probit regression                               Number of obs     =        120
                                                LR chi2(7)        =      11.51
                                                Prob > chi2       =     0.1179
Log likelihood =  -75.00677                     Pseudo R2         =     0.0713

------------------------------------------------------------------------------------
ImprovedHealthSafety |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------------+--------------------------------------------------------------
  AI_Awareness_Score |   .5276003    .356401     1.48   0.139    -.1709329    1.226133
       AI_Acceptance |   .5277197   .2329094     2.27   0.023     .0712256    .9842138
SafetyPracticeRating |  -.1217826   .0827942    -1.47   0.141    -.2840561     .040491
Awareness_x_Acceptance | -.2459066  .1086914    -2.26   0.024    -.4589378   -.0328754
              Gender |   .3275604   .2638657     1.24   0.214    -.1896069    .8447276
            AgeGroup |  -.0195524    .111294    -0.18   0.861    -.2376846    .1985798
          Experience |  -.0402917   .1312609    -0.31   0.759    -.2975583    .2169748
               _cons |  -.5173461   .9009827    -0.57   0.566     -2.28324    1.248548
------------------------------------------------------------------------------------
```

Average Marginal Effects

```
. margins, dydx(*)

Average marginal effects                        Number of obs     =        120
Model VCE    : OIM

Expression   : Pr(ImprovedHealthSafety), predict()
dy/dx w.r.t. : AI_Awareness_Score AI_Acceptance SafetyPracticeRating Awareness_x_Acceptance Gender AgeGroup Experience
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
AI_Awareness_Score	.1882834	.1235777	1.52	0.128	-.0539243	.4304912
AI_Acceptance	.188326	.0776931	2.42	0.015	.0360504	.3406016
SafetyPracticeRating	-.0434602	.0288061	-1.51	0.131	-.0999191	.0129986
Awareness_x_Acceptance	-.0877561	.0362368	-2.42	0.015	-.1587789	-.0167333
Gender	.1168957	.0924327	1.26	0.206	-.064269	.2980603
AgeGroup	-.0069776	.0397049	-0.18	0.861	-.0847979	.0708426
Experience	-.0143788	.0467863	-0.31	0.759	-.1060783	.0773207

Marginal Effects

```
. mfx

Marginal effects after probit
      y  = Pr(ImprovedHealthSafety) (predict)
         =  .61109944
```

variable	dy/dx	Std. Err.	z	P>|z|	[95% C.I.	]	X
AI_Awa~e	.2022665	.13639	1.48	0.138	-.065048	.469581	1.85833
AI_Acc~e	.2023123	.0888	2.28	0.023	.02827	.376355	3.05
Safety~g	-.0466879	.03173	-1.47	0.141	-.108874	.015498	2.7
Awaren~e	-.0942734	.04149	-2.27	0.023	-.175588	-.012959	5.725
Gender*	.1227598	.09601	1.28	0.201	-.065423	.310943	.316667
AgeGroup	-.0074958	.04267	-0.18	0.861	-.091118	.076126	2.66667
Experi~e	-.0154467	.05032	-0.31	0.759	-.114069	.083176	2.61667

(*) dy/dx is for discrete change of dummy variable from 0 to 1

Link Test

```
Probit regression                               Number of obs     =        120
                                                LR chi2(2)        =      11.58
                                                Prob > chi2       =     0.0031
Log likelihood = -74.968983                     Pseudo R2         =     0.0717
```

ImprovedHealthSafety	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_hat	.9110957	.4474811	2.04	0.042	.0340488	1.788143
_hatsq	.1408813	.5181662	0.27	0.786	-.8747058	1.156468
_cons	-.0074585	.142688	-0.05	0.958	-.2871218	.2722048

Test for Multicollinearity

```
===========================================================================
* Farrar-Glauber Multicollinearity Tests
===========================================================================
  Ho: No Multicollinearity - Ha: Multicollinearity

* (1) Farrar-Glauber Multicollinearity Chi2-Test:
    Chi2 Test =   295.1956     P-Value > Chi2(6) 0.0000
```

Test for Heteroscedasticity

```
Heteroskedastic probit model                    Number of obs     =        120
                                                Zero outcomes     =         48
                                                Nonzero outcomes  =         72

                                                Wald chi2(4)      =       0.77
Log likelihood = -75.76875                      Prob > chi2       =     0.9426
```

ImprovedHealthSafety	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
ImprovedHealthSafety						
AI_Awareness_Score	.869662	1.108856	0.78	0.433	-1.303657	3.042981
AI_Acceptance	.8469541	1.035482	0.82	0.413	-1.182554	2.876462
SafetyPracticeRating	-.2071856	.2578079	-0.80	0.422	-.7124798	.2981086
Awareness_x_Acceptance	-.4062766	.5119715	-0.79	0.427	-1.409722	.5971692
_cons	-.8930109	1.428614	-0.63	0.532	-3.693043	1.907021
lnsigma2						
AI_Awareness_Score	.0831441	.5367114	0.15	0.877	-.968791	1.135079
AI_Acceptance	.0976798	.2779771	0.35	0.725	-.4471453	.6425048

```
Likelihood-ratio test of lnsigma2=0: chi2(2) =      0.17    Prob > chi2 = 0.9177
```