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Review article

Human-machine collaboration in mining: A critical review of emerging frontiers of intelligence systems in the mining industry

Rosebella Osei [a,*], Samuel Frimpong [b], Allada Venkat [a]

[a] Engineering Management and Systems Engineering, Missouri University of Science and Technology, Rolla, MO, 65401, USA
[b] Mining Engineering, Missouri University of Science and Technology, Rolla, MO, 65401, USA

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ABSTRACT

Artificial Intelligence (AI) is driving significant transformations in numerous industries revolutionizing business processes, relationships, and engagements among individuals within organizations as well as with external service providers. These emerging smart technologies will also revolutionize the mining industry in significant ways. The future of AI in the mining industry will focus on autonomous equipment, drones and robots replacing humans in tasks performance. Mine automation is creating a new paradigm where technically savvy personnel are performing remote operations with improved workplace safety, health, and efficiencies. This study reviews the progress of mine automation, robotics, and other intelligent systems in the mining industry. We applied the technology, organization, and environment (TOE) framework to synthesize the various barriers associated with the implementation of these smart technologies in the various mining lifecycles. Using a preliminary literature review approach, we discuss enabling technologies facilitating human-machine collaboration along the mining life cycle, their impacts and synthesize the future of an industry where human and machine collaborate successfully to the benefit of humans. This review contributes to the best practices for managing change as an enabling factor to facilitate the smooth implementation of smart technologies in the mining industry.

1. Introduction

Mining plays an important role globally as a primary source of mineral commodities vital for sustaining and enhancing living standards worldwide. Mining is significant for the global community, as a catalyst for economic development by supplying raw materials crucial for industrial consumption and export (Sanda et al., 2011). Moreover, mining serves as a major employer, and it generates foreign exchange as a substantial portion of the gross domestic product. The dividends and taxes derived from mining operations further finance crucial infrastructure projects, such as hospitals, schools, roads, and other public amenities. Additionally, mining fosters the growth of various support industries, including equipment manufacturing, engineering, environmental services, research, and related sectors.

Mining operations are complex, capital-intensive, and are often located in remote and isolated geographical regions (Hall, 2017) with substantial direct and indirect socio-environmental impact on communities and the environment (Fordham et al., 2017). Both research and industry agree that the introduction of smart technologies is vital for the sustainability and transformation of the sector (Gruenhagen and Parker, 2020). The adoption and implementation of innovation offers the industry the opportunity to address most of its challenging obstacles. For instance, the finite nature of minerals and the challenges associated with accessing lower-grade deposits often situated in remote areas (Kurkkio et al., 2014), alongside the high operational expenses, including labor costs prevalent in developed mining economies (Bellamy and Pravica, 2011) makes some mining projects uneconomical. Introduction of smart technologies enhances organizational technological capabilities, enabling firms to attain competitive advantages and strengthen their market position (Ediriweera and Wiewiora, 2021). Consequently, technological innovations hold the promise of mitigating these numerous challenges encountered in mining operations, making the industry more sustainable. Artificial intelligence and machine learning represent the key technological innovation fields facilitating intelligent automation within mining operations through advanced learning algorithms (Ali and Frimpong, 2020). The Industrial Internet of Things presents unprecedented opportunities for mining and metals companies to achieve visibility, safety, and operational efficiency (Dehran et al., 2018). Therefore, many aspects of the mining industry make it an ideal candidate and ready for transformative technological integration.

* Corresponding author at: 600 W 14th Street, Rolla MO, 65409.
E-mail address: rodpn@mst.edu (R. Osei).

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Noteworthy among successful transformative technological applications in the mining industry are the utilization of artificial intelligence (AI), machine learning (ML), industrial internet of things (IIoT), virtual reality (VR), augmented reality (AR), drones, and autonomous driverless equipment (Dehran et al., 2018; Bellamy and Pravica, 2011). The benefits of these technologies are increased productivity, reduced operating costs, and improved health and safety conditions in hazardous mining environments.

Humans are at the center of the development and deployment of these intelligent systems. Successful partnerships between humans and machines have been showcased across various industries (Kinugawa et al., 2016; Wang et al., 2022; Wilson et al., 2017) including the mining industry (Abrahamsson, 2019). This research indicates that a collaborative human-AI approach outperformed both human-only and AI-only decision-making; demonstrating the potential for significant improvements in the mining industry through the power of collaboration between human expertise and deep learning capabilities. These studies underscore the effectiveness of a business model where humans and intelligent machines function as "co-workers," engaging in cooperative partnerships that promise more favorable outcomes for organizational success. Despite the potential benefits across the entire mine life cycle, from prospecting to reclamation, the mining and metals industry is considered to have lower digital utilization compared to other industries (Narendran and Weinelt, 2017). Technology adoption in machine and operation automation with intelligent technology has been extremely slow (Bellamy and Pravica, 2011; Bartos 2007, 2007).

Presently, there is a limited comprehensive review of literature focused on specifically examining the integration and adoption of smart technologies within the mining industry context (Gruenhagen and Parker, 2020), particularly concerning human-machine collaboration as a success factor. This paper aims to consolidate existing knowledge on the collaborative dynamics between humans and machines in the adoption of smart technologies within the mining industry, focusing on enabling technologies along the mining life cycle, impacts, human factors, and associated barriers. Our study seeks to advocate for a human-centered approach to the design and implementation of new technologies and automation in the mining industry. We aim to pinpoint the emerging frontiers in mining technology as well as the social and technological factors influencing human-machine collaborations in the development of newly automated systems pertinent to Mining Industry 4.0. The findings from this study are anticipated to contribute to existing guidelines for human-machine collaboration and offer insights for policymakers, industry stakeholders, and researchers regarding future directions.

This study is structured into four sections: Section 1 provides a brief introduction to the study and highlights the methodology. Section 2 presents the findings of the literature review, offering an overview of the historical context and theoretical frameworks pertinent to human-machine collaboration. Section 3 reviews emerging technologies that facilitate human-machine collaboration along the mining lifecycle. Lastly, Section 4 discusses various barriers influencing human-machine collaborations, addresses managing change as an enabling factor and suggests future research directions necessary for further exploring these dynamics.

1.1. Methodology

This research is part of a large-scale research program aimed at developing management tools to facilitate the seamless integration of smart technologies and address barriers to change within the mining industry.

(a) Employing a preliminary literature review approach, this study aims to map and align the consideration of human factors with the successful integration of enabling smart technologies in mining operations. The study seeks to ascertain the current landscape, identify gaps, propose opportunities through synthesis, and suggest potential avenues for future research.
(b) This research proposes a new framework to analyze the problem through a multidisciplinary lens which analyses the benefit of the introduction of smart technologies along the mining lifecycle particularly in the context of hazard elimination to make mining safer for humans.
(c) Finally, the researchers indicate plans in the near future to conduct industry engagement to validate the framework and prioritize recommendations.

2. Overview and historical context of human-machine collaboration in mining

2.1. Evolution of mining machinery and technology

The mining industry, despite its long history, has undergone substantial technological evolution. Over the past century, significant advancements have transformed equipment design and application, leading to higher productivity, enhanced worker safety, and improved environmental protection. (Evolutionary and Revolutionary Technologies for Mining, 2002). Evolutionary changes, such as the shift from compressed air to electricity and hydraulic drives, alongside revolutionary developments like millisecond blast ignition and the integration of GPS in surface mining operations, have propelled the industry forward. In mineral processing, innovations like radiometric density gauges and high-intensity magnetic separators have contributed to increased productivity (Figs. 1 and 2).

Industrial automation is an evolving paradigm that began in 1939-1945 during the “cold war” (Bennett, 2004). This interest and perceived need for automation led to rapid investment by both private and public entities in automatic control systems and their associated enabling technologies. The result was the development of technologies that supported missile and aerospace developments to support the ‘cold war’. Machine computing devices, both analogue and digital have proven their value as aids to military activity and as aids of economic growth to date; demonstrating their relevance as important areas of investment by the military, industry, academia, and governments. The mining industry has been no exception to these interests and investments. Recounting the timeline of evolution of automation in the mining industry, Bellamy and Pravica (2011) breaks it down into three stages as synthesized below emphasizing the contributing role of human operators in collaborating with machine in the safe and efficient execution of tasks;

These technologies made mining underground efficient and safer with the operator moved away from harm and elevated to supervise the performance of tasks by machines. Despite these advancements, the mining industry has been slower in adopting emerging technologies whilst other sectors have embraced these technologies for operational autonomy. Since the 2000’s, emerging fields such as machine learning and artificial intelligence have been inducing smart technology and automating complex tasks in operations with the promise of creating efficient, effective, and safe sustainable mining operations, (Ali and Frimpong, 2020). Hence the importance of focusing on the integration of human-machine collaboration concepts to assist with enhancing the acceptance and smooth integration of advanced automation into mining operations to reap the full benefits.

Human guidance utilizing intelligent interaction frameworks integrated in remote operation systems is vital in the performance of complex tasks in the mining industry. Robots, equipped with advanced capabilities, offer assistance in complex and hazardous environments although challenges such as stability and data transmission issues persist. Addressing these challenges requires a multifaceted approach to human factors considerations, encompassing operator perception, operation mode, and control decision-making (Du et al., 2022). Emerging visualization technologies like virtual reality (VR) and

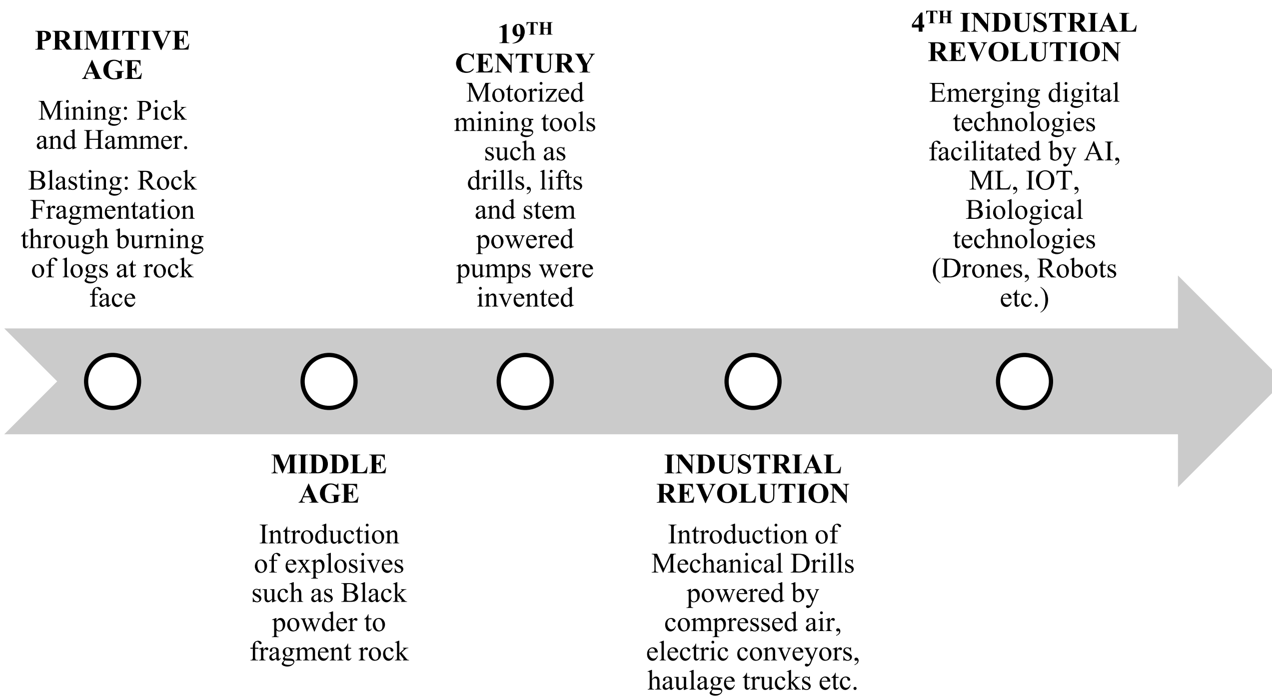

Fig. 1. A life cycle of mining technologies.

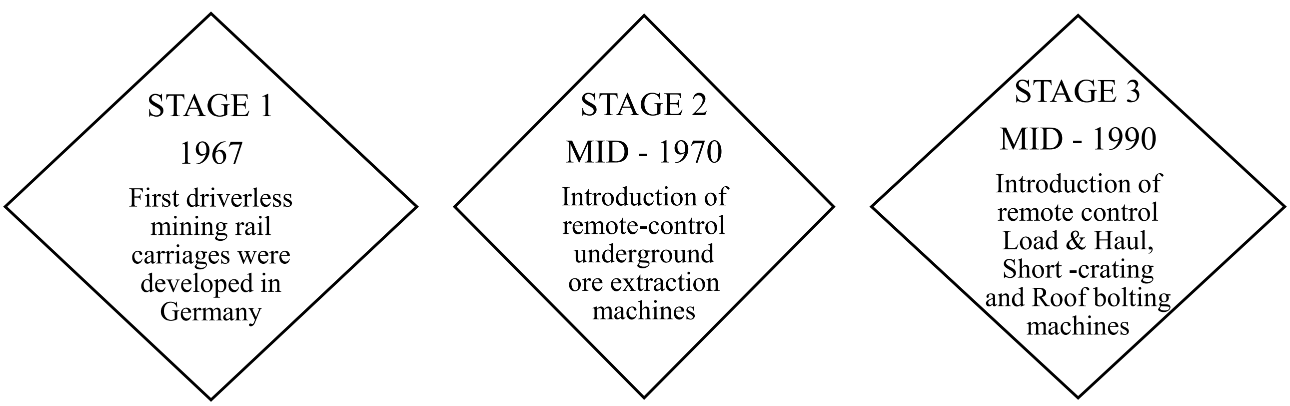

Fig. 2. Synthesis of the evolution of automation in mining before the industrial revolution.

augmented reality (AR) offer enhanced environmental feedback; while transitioning from machine-centric to human-centric operation modes reduces cognitive burdens on operators, thereby improving efficiency and accuracy. These emerging technologies encourage the natural interaction between humans and robots in "human-centric" mode which eliminates intermediate devices such as controllers. In this mode, the operator can interact with the robot in natural ways, such as voice and gestures which can be combined with augmented reality to change the display mode to further improve the naturalness of collaborating on performing the task (Liang and Wang, 2019). This operation mode reduces the cognitive burden of human interaction so that the operator no longer needs to vary their thinking and behavior to cope with the requirements of the machine; therefore, reducing learning costs, enhancing smooth collaboration, improving efficiency and ultimately safe execution of the process.

In organizational decision-making, the synergy between humans and machines is increasingly recognized as pivotal for performance improvements (Haesevoets et al., 2021). Therefore, the future of work entails a cooperative model where humans and machines collaborate synergistically, as evidenced by successful partnerships in various industries (Daugherty and Wilson, 2018; Haesevoets et al., 2021). Examples include Stitch Fix's utilization of AI in retail fashion, the development of collaborative robots in automobile assembly lines, and the combined human-AI approach in healthcare for improved pathological diagnoses (Kinugawa et al., 2016; Wang et al., 2022; Wilson et al., 2017). These industries demonstrate the consensus in the co-creation between humans and machines as the future of work relationships which underscore the potential benefits of integrating human and machine capabilities, paving the way for cooperative partnerships that drive future success in organizations.

2.2. Socio-technical systems perspective on human-machine collaboration in mining

The integration of human factors into the design of new technologies will undoubtedly facilitate smooth integration into existing processes where required. In their study, Joe-Asare et al. (2020) presents the significance of human factors within process design in the mining industry, emphasizing the complex interplay between humans and the sociotechnical components of systems. They advocate for optimizing human well-being to enhance overall system performance. In recent times, there has been a corresponding focus on Human Factor theories to understand the important role they play to significantly reduce the large proportion of total human errors (HEs) that occur during the operation and maintenance phase of implementing smart technologies. Yaghini et al. (2017) argue that compared to other industries; the risk of accidents is still relatively high and key performance indicators have not improved significantly although today's mining equipment and machinery are technologically advanced and highly reliable. They attribute this stagnation to the trivial importance given to the integration of human factors (HFs) as part of the planning, operation, and maintenance activities involved in the conception and deployment of these technologies. They argue that the current mining system is a people system, and inevitably Human factor (HF) theories should be considered prominently in all aspects of this industry to increase the success rate. The result will be the reduction of Human Errors (HE) which will invariably improve safety and productivity of the industry; thereby influencing the rate of adoption of smart technologies. Li et al. (2012) offer three case studies elucidating the role of human factors in risk reduction, emergency response management, and participatory ergonomics in equipment design. This underscores the integral nature of human factors within sustainability initiatives. Despite increased automation and technological advancements, Lynas and Horberry (2010) note a disparity between the rate of equipment technology development and the corresponding rate of development of human-related aspects, potentially leading to environments conducive to human errors and potential resistance.

Therefore, the importance of harmonizing human, technical, and social systems to achieve increased productivity cannot be over emphasized (Saadati et al., 2020). When new technologies and tools are introduced, there is an initial disruption to social relations in the way work is executed, however there is a gradual adaptation whereby these tools become surrogate social collaborative partners for employees. Therefore, they stress the imperative of understanding the social collaboration between miners and the technology they employ, advocating for its consideration in the development of digitized mining production systems to attain success.

This is critical in the evolving landscape of interactive technologies in the mining industry with a shift towards more automated systems involving computers, robots, and cyber-physical systems to enhance human performance and decision-making processes. While these automations hold the potential to augment performance and mitigate human errors, poorly designed interactive technologies can undermine user experience, leading to suboptimal performance and defeating the original objectives. Therefore, the advocate for meticulous design considerations in the development of future "smart mining operations," stressing the importance of involving users during the design phase to ensure the attainment of expected service quality goals for both end-users and employees (Saadati et al., 2020). In their examination, Saadati et al. (2020) delves into Human Work Interaction Design (HWID), a comprehensive framework aimed at bridging empirical work-domain studies with Human-Computer Interaction (HCI) designs to empower users by crafting smarter workplaces across various domains. HWID models, rooted in human characteristics, work domain contents, and task interactions, serve as a foundation for designing optimal interaction systems. They underscore the necessity of considering multifaceted factors such as theories, concepts, environmental contexts (e.g., national, cultural, social), and work-related elements (e.g., users' knowledge/skills, application domain, nature of tasks) in developing effective HWID models tailored to specific workplaces.

The potential of socio-technical systems for the adaptability of new technologies remains a compelling avenue for further research, promising improvements in efficiency, productivity, and safety within the mining industry.

3. Enabling technologies along the mining lifecycle

3.1. Enabling technologies and their impact on mining operations

Cutting-edge autonomation technology in the mining industry began in 1990 with Komatsu Mining using the Field Management Software for mines as a foundation. This autonomous technology has been used at mines for over 3 decades spurring the evolution and maturity of autonomous systems such as driverless vehicles powered by the Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), Big Data Analytics, and Wireless Connectivity among others. Undoubtedly this is a positive factor that can boost the safety and growth of the industry and make it more lucrative for investors. Artificial Intelligence is described as intelligent machines that can perform tasks similar to humans such as solving problems and making suggestions into decision making processes. Machine Learning on the other hand is a subset of AI that enables machines to learn patterns and make predictions or decisions based on data. ML are algorithms that adjust themselves to perform better as they are exposed to more data by helping gather, manage, clean, and analyze large datasets. Big Data set is a driving factor that makes machine learning a powerful tool; they refer to large data sets comprising many observations with many attributes or variables. The Internet of Things (IoT) is a system of interrelated devices connected to a network and/or to one another, exchanging data and services without necessarily requiring human-to-machine interaction. In other words, IoT is a collection of electronic devices that can share information among themselves. Examples includes; Smart homes, smart wearables, vehicular telematics etc. (Hyder et al., 2019; Ali and Frimpong, 2020; Rogers et al., 2019; Marr 2016; Wang and Siau, 2019).

The mining industry in general is currently experiencing increased application of AI and autonomous technologies. To assess the applications of some of these smart technologies, four major processes in mining operations will be reviewed using the Life Cycle approach. In addition, our study provides a conceptual framework which gives insight into the impact of smart technologies in reducing hazard and risk at the various stages of the mining life cycle. The mining industry is a high-risk sector made up of complex processes with a variety of obvious and hidden health and safety hazards along the life cycle of which recognition of these hazards is not simple. LaTourrette et al. (2023) describe the mining industry as a combination of harsh environment, heavy equipment, physical hazards, and potentially toxic and combustible atmospheres which creates a challenging operating environment and hazardous working conditions. Naeini and Badri (2023) identified the OHS hazards categories and hazard types in the mining industry. Table 1 has been developed in our study to highlight the importance of smart technologies along the mining life cycle processes in making mining safer for humans. This conceptual framework demonstrates at a glance the power of integrated OHS management with the introduction of smart technologies in the various stages of the Mining Life Cycle to make mining safer for humans.

3.2. Prospecting and exploration

Representing the initial stage of resource development, AI is making a significant impact in Prospecting and Exploration. An important development in the industry is the use of Big Data Analytics to drastically reduce exploration cost and time required for Exploration activities such as geochemical sampling and analysis. Traditionally, geochemical sampling has been done through collecting and analyzing samples of soil, rock, water, and vegetation to identify the presence and distribution of valuable minerals or elements that may indicate the presence of ore deposits. These activities expose humans to several physical, chemical, and biological hazards including accidents from rockfalls and falls from height. Advancements in AI technology have brought significant improvements to this process with the ability of remotely analyzing vast amounts of geological and geochemical data to identify patterns,

Table 1
A portrait showing a synthesis of the emerging frontiers of Mining Technology and their contribution to mitigating Occupational Health and Safety (OHS) Risk along the Mining Life Cycle. "Columns Hazard Category and Hazard Types" are referenced from Naeini and Badri, (2023): Naeini, S. A. B., and Badri, A. (2023). Identification and categorization of hazards in the mining industry: A systematic review of the literature. International Review of Applied Sciences and Engineering, 15(1), 1–19.

Mining Process	Activities	Hazard Category	Type of Hazard	Smart Technologies
Exploration	Geo Chemical Sampling Drilling	Physical Hazards Chemical Hazards Biological Hazards Accidents	Noise, Heat Stress Dust, Acids, Smoke Soil and Water borne infections, Fungal Infections, Mosquito Bites Falling Rocks, Falls from Heights	Real- time Monitoring with AI powered drones Data Fusion Predictive Modelling
Mining and Extraction	Manual Monitoring in Hazardous Environment Manually Operating Mining Equipment Drilling	Physical Hazards Chemical Hazards Biological Hazards Accidents Ergonomic Hazards Psychosocial Hazards	Noise, Vibration, Radiation, Temperature Dust, Poor Air Quality (Ammonia Gas, Methane, Carbon Monoxide, Hydrogen Sulfide, excess CO2 etc.) Bacteria, Viruses, Plants, Animals, Humans Collision, Injuries and Fatalities Physical Ergonomics: Prolong bending, sitting and handling of tools/equipment, repetitive muscular trauma, poor working postures Changes to Job Content, Poor Workload, Poor Shift Roster, Difficult Human Interaction, Poor Work Life Balance	Autonomous Vehicles and Drills Integrated Safety Systems (Air Quality Monitors, Fire detection and suppression systems etc.) Collision Avoidance and Human Detection Systems, Rescue Robots, Advance Dispatch Control Systems and Telematics, Remote Work Arrangements supported by AI Applications, AI-Powered Predictive Maintenance Systems
Mineral Processing (Gold)	Manual Operation and Sorting of Ore at the Rom Pad Process Monitoring in Hazardous Environment	Chemical Hazards Physical Hazards Accidents Biological Hazards Ergonomic Hazards	Dust, Cyanide, Mercury, Lead and Silica Noise, Heat Stress, Confined Spaces, Vibration, Radiation etc. Collision, Injuries and Fatalities Bacteria, Viruses, Contamination, Humans Physical, Organisational and Cognitive Ergonomics	AI - Powered Image Analysis Advanced Process Control and Dispatch Control Systems Autonomous Equipment (Rock breaker Systems etc.)
Reclamation	Soil Sampling Air Quality Monitoring Water Sampling Vegetation Survey	Accidents Biological Hazards Physical Hazards Chemical Hazards	Flooding, Fire Outbreaks, Falls from Height, Falling Rocks Bacteria, Viruses, Plants, Animals, Humans Heat Stress, Noise Dust, Smoke, Poisonous Gases	AI - Powered Remote Sensing Techniques Historical Data Analysis & Predictive Modeling powered by ML and Big Data Analytics

anomalies, and potential mineralization zones more efficiently than traditional methods making it safer for humans. By deploying AI, mining companies can optimize their operations by using data from various sources such as Geological, Operational and Environmental Data to make informed decisions on where to focus their exploration efforts. High performing companies such as BHP Billiton and Rio Tinto uses AI to optimize their drilling processes making the processes safer, cost effective and increasing efficiency (Sahota, 2023). With the help of ML, data collected during previous explorations and analyses can be used to identify new areas with similar patterns in terms of ground chemistry and mineral distribution, reducing multiple exposure of workers to these hazards. This approach also ensures that the right amount of material is extracted while reducing waste. Companies can precisely locate ore bodies, hard rocks, and regolith by collecting geophysical data from multiple remote sensors and leveraging Machine learning algorithms. By deploying AI-enabled applications, prospecting, and exploration tasks have become more accurate, and high-precision data analysis is now possible. Additionally, by incorporating AI into prospecting and exploration processes, companies are able to enhance the location of economically feasible mineable prospects, saving time and increasing their return on investment.

3.3. Mining and extraction

AI is greatly improving the productivity and efficiency of mining operations. Constraints such as confined workspaces, toxic substances and poisonous gases, radioactive materials, poor air quality, use of explosives, and unstable roofs are among the factors that make mining operations dangerous. Traditionally, mining operations have involved manual labor and conventional methods for extraction, transporting, and processing of minerals exposing mine workers to several physical, chemical, biological and ergonomic hazards as well as accidents and potential fatalities. Nonetheless, with the application of AI, machine learning, and autonomous technologies, the exposure of workers to dangerous underground and surface operations can be minimized. AI technologies can deploy autonomous machines and tools to monitor the atmosphere, send signals and warnings, locate hazardous conditions, and work continuously even in high-risk situations. Additionally, operational activities such as mine planning and design which were primarily based on geological knowledge, manual surveys, and engineering expertise have been optimized with AI-powered software which integrates geological data, mine geometry, and operational parameters to optimize the process. These AI software enables the creation of detailed 3D models, simulation of mining scenarios, and optimization of mine layouts to maximize resource recovery and minimize environmental impact. Therefore, the implementation of AI, machine learning, autonomous technologies and IoT is enhancing safety and increasing efficiency of mining operations (Hyder et al., 2019).

3.3.1. Autonomous equipment and maintenance

From production drilling to hauling, the mining industry can leverage AI technologies to provide end-to-end solutions for fully autonomous mining operations. Autonomous equipment in mining operations, also known as autonomous haulage systems (AHS) and Autonomous drill systems (ADS) are equipment that operate without direct human intervention, performing tasks such as drilling, hauling ore, waste material, and other commodities within a mine site (Ramani, 2012). These vehicles are equipped with sensors such as GPS, radar, lidar and other technologies to navigate, detect obstacles, and make decisions autonomously. Mining equipment manufacturers such as Komatsu, Caterpillar, Hitachi, Atlas Copco and Sandvick among others have been advancing the production of autonomous mining equipment over the past decade. The vital role of smart technologies has long been recognized in Australia as catalyst to improving safety and productivity in underground operations as well as reviving investment in surface mining operations maintaining Australia's competition in the global mining industry (Bellamy and Pravica, 2011). One of the most advanced projects in this area in the mining industry is Rio Tinto's Mine of the Future Program. Over the years, Rio Tinto has made several advancements in the development of autonomous drills and trucks, mine automation, robotics as well as the deployment of the world's first long haul driverless trains. The strategic intent of the Mine of the Future program is for employees to supervise automated production drills, loaders, and haul trucks from a remote operations center in Perth. This goes a long way to support the successful collaboration of humans and machines as "co-workers". Connecting sensors to a host of mining equipment helps gather real time data enabling mining companies to manage operations remotely. These sensors feed data to operators in a remote or above-ground control room to enhance visibility to enable users to make real time decisions to improve safety and productivity. Companies whose equipment has connectivity can take advantage of predictive maintenance and automatic spare-parts replacement, thereby reducing equipment's downtime while facilitating its life cycle management. In fact, these technologies promise to revolutionize the industry in almost unimaginable ways with smart technologies like both 3D and 4D printing eliminating the need to procure spare parts from afar. Other safety benefits come from LIDAR (light detection and ranging) sensors on autonomous trucks that measure range and recognize humans within range powering collision detection and avoidance systems (The New Technology Frontier in Mining, 2021).

3.3.2. Safety improvements

Workplace safety is another critical area where AI-enabled technologies are being deployed, addressing the complex and high-risk nature of mining operations due to factors such as confined workspaces, inadequate illumination, inhalation of particles, exposure to toxic waste and gases. In our work, emphasis has been given to the health and safety benefit of deploying smart technologies as well as the enhanced benefit of human-machine collaboration in improving efficiency. AI tools have been developed with the capability to autonomously monitor and report back through warnings and signals to eliminate these hazardous conditions (Corrigan and Ikonnikova, 2024). Rescue robots for underground rescue missions is another important area where AI technologies are successfully being deployed. Particularly in coal mines where accident zones become irespirable zones as a result of deficient levels of oxygen and increased levels of harmful gases such as carbon dioxide, carbon monoxide and explosive gases like methane; rescue mobile subterranean robots have proven to be invaluable in emergency response (Reddy et al., 2015). Regardless of the situation these robots can be deployed immediately an incident occurs irrespective of the atmosphere, to assist rescue personnel with surveillance of air quality, supporting trapped workers and executing other critically required tasks that cannot be executed by rescue workers at the time.

3.4. Metallurgy—Mineral processing

Another area of successful AI application is in Mineral processing. At the Run of mine production, ore sorting traditionally involves using a rock breaker to fragment larger rocks and facilitate the separation of valuable ore from waste material. This process relies on manual inspection and judgment by operators to identify and separate ore-bearing rocks from non-ore rocks which is labor intensive and can be time-consuming, especially for large volumes of material. The subjective nature of the process makes it ineffective and prone to errors. Additionally, the labor-intensive process of the mineral processing process exposes workers to physical (noise, heat stress), chemical (dust, reagents etc.), biological, ergonomic (cognitive stress involved in monitoring and data analysis as well as potential injuries / accidents. AI-based systems can be designed to sort useful minerals from waste material using applications such as color-sorting, x-ray transmission or near-infrared sensors. These technologies can be designed to detect differences in physical properties, mineralogical compositions, and chemical properties (Hyder et al., 2019). AI-powered ore sorting systems can operate continuously and efficiently process large volumes of material, resulting in higher ore recovery rates, improved workers safety and reduced processing costs. As the crushing and grinding processes are considered the least energy efficient processes in mineral processing, the application of intelligent systems before these processes can increase the efficiency of the comminution process and reduce energy cost (Jeswiet and Szekeres, 2016). The benefit of supporting humans to execute tasks are enormous including;

- **Improved Safety**: Operators can initiate and monitor the sorting process remotely from a control room, reducing the need for physical presence at the sorting site and allowing them to focus on other tasks and work more safely away from hazardous conditions such as excessive noise, dust, and interaction with heavy equipment.
- **Real-Time Decision Support**: Operators receive real-time feedback on ore quality and efficiency of the process (rate, speed, output), enabling them to make timely adjustments to sorting parameters and optimize the sorting process for maximum ore recovery. This reduces cognitive stress and excessive fatigue improving operators' health and safety. Operators can use insights from AI-powered sorting systems to optimize resource allocation, as well as allocate equipment and personnel more efficiently to improve the overall operational performance.

Therefore, AI-powered sorting systems in mineral processing provide efficient, and accurate ore separation, leading to improved productivity, resource recovery, health and safety enhancing the overall operational performance in mining operations.

3.5. Environmental monitoring and reclamation

Environmental monitoring and management are important for mining companies to be compliant with environmental regulations as well as minimize their impact improving their social reputation and regulatory license to operate. Sustainability is ever important in mining operations and requires several strategies to progress. However, it can get rather complex with diverse and critical stakeholders and requires a systematic approach to meet requirements (Batterham, 2017). Conventionally, environmental management and reclamation in mining operations involved various manual sampling and monitoring methods to assess and mitigate the impact of mining activities on soil, air, water, and vegetation. Soil sampling involves collecting soil samples manually from different locations within the mine operations. These samples are analyzed in a laboratory to assess soil quality, contamination levels, and potential impacts on vegetation and water resources. The labor-intensive nature of these activities exposes workers to hazards such as heat stress, bacterial and virus infections, exposure to poisonous and harmful animals and potential accidents (drowning, fire outbreak, fall from height etc.). AI-powered monitoring and sampling technologies use remote sensing technologies, such as satellite imagery and drones equipped with sensors, to collect and analyze soil data more efficiently and comprehensively. Machine learning algorithms are used to identify soil types, map soil properties, and detect contamination levels, enabling more targeted and cost-effective soil sampling strategies. Whilst air and water quality monitoring involves installing stationary air quality monitoring stations at strategic locations and picking water samples at mine discharge points within the mine operations to measure quality parameters (e.g. particulate matter, gases, contaminants, air and water pollutants) to assess compliance with regulatory standards and identify potential health risks; AI-powered air and water quality monitoring systems use sensors, drones, and IoT devices to continuously monitor air and water quality parameters in real-time. By utilizing Machine learning algorithms to analyze data patterns, identify trends, and predict air quality fluctuations, mining companies are able to implement proactive measures to mitigate air / water pollution and protect workers health and safety. AI has the potential to incorporate large amounts of data on the environment, land use, communities, and governance factors to improve decision-making in mining operations to make it more sustainable and reduce cognitive stress in humans involved in analyzing large data sets. By incorporating AI-enabled image detection for earth observation, companies are able to identify and protect biodiversity. The application in AI by integrating geologic, hydrologic, and other information on surface environment and characteristics helps with the analysis of impacts and thereby, management of water and land (Corrigan and Ikonnikova, 2024). These AI-enabled technologies assist regulatory bodies to detect environmental safety regulations such as identifying illegal mining activities and their impacts on communities. The benefit to supporting humans to execute environmental management tasks are enormous including;

- **Data Collection and Analysis**: AI-powered systems automate data collection processes by using sensors, drones, and other remote sensing technologies for environmental monitoring. This reduces the need for manual labor in samples collection and streamlines the data collection process. With the aid of Machine learning algorithms large volumes of environmental data are analyzed quickly and accurately, providing operators with valuable insights and actionable information in real-time. Thus, AI allows operators to focus on higher-level tasks such as decision-making and implementing environmental management strategies, leading to increased efficiency.
- **Early Detection of Environmental Risks**: AI – powered systems are able to detect environmental risks and anomalies in real-time, allowing operators to respond promptly to potential hazards to prevent accidents or environmental incidents. For example, in Underground operations AI-powered air quality monitoring systems can detect changes in air pollution levels or hazardous gas emissions in real time, triggering automated alerts and safety protocols to protect workers.
- **Decision Support**: AI – powered monitoring systems provides operators with complimentary decision support tools and dashboards that visualize environmental data, trends, and predictive analytics in an easily understandable and manipulable format for further analysis. Operators can then make informed decisions about environmental management strategies, resource allocation, and risk mitigation measures based on AI-generated insights, leading to more effective, proactive, and real-time environmental management practices.
- **Compliance and Reporting**: Environmental management and compliance involves the collection and analysis of large data. AI-powered systems continuously monitor environmental parameters, generate compliance reports, and identify areas of non-compliance in real-time to facilitate regulatory compliance. Management of mining companies can therefore use AI-generated reports and analytics to demonstrate compliance with environmental regulations, respond to regulatory enquiries, and communicate transparently with stakeholders. This may involve granting data access to stakeholders to facilitate real time reporting leading to the company integrated development partners (Batterham, 2017).

Ultimately, the use of AI in environmental management activities assists operators and mining operations to be more efficient and safer by automating monitoring, data collection and analysis, facilitating real-time detection of environmental hazards, optimizing sampling strategies, enhancing decision support, and ensuring regulatory compliance.

Researchers are encouraged to provide more comprehensive research in the contribution of the integration of health and safety management with new technologies making mining safer for humans. Our study is a preliminary review of literature and therefore limits its generalization and application. Our future research seeks to collect and analyze real data to practically understand pertinent issues uncovered in this preliminary literature review.

This study also makes substantial contributions in terms of highlighting Psychosocial hazards employees may face as a result of the introduction of new / smart technologies. These includes disturbance of their psychological well-being due to changes in job content, workload, work scheduling, process control, changes to equipment, organizational culture, workers interactions and roles within the organization, career development, personal relationships, and the interface between work and home. This is an important area which requires more research focus to support organizations to better manage changes associated with the introduction of new technologies and their impact on workers.

4. Technological, organizational & environmental barriers

4.1. Barriers to smart technologies adoption

Human labor has been the backbone of the mining industry for years, however, there is a growing integration of AI and other digital technologies to optimize the industry. Around the world, various centers of excellence with state-of-the-art research facilities are advancing research and achieving newest technological achievements to support human with mine automation (Ranjith et al., 2017). Investments in these technologies are increasing global competition and companies' technological capabilities in the industry. However, while research and practice agree that innovation is essential for the transformation and sustainability of the mining sector, its implementation is fraught with difficulties. As a sense of urgency, emerging digital technologies, such as artificial intelligence (AI), the Internet of Things (IoT), and new biological technologies are revolutionizing the industry in almost unimaginable ways as described earlier. These technologies are rapidly transforming existing business models and the traditional roles and relationships among mining companies and their employees, customers, suppliers, and even competitors; contributing to a safer and more sustainable industry. Regardless of these advances in technological innovations in the mining sector, barriers to the adoption of these smart technologies are present and hinder the transformation of the sector. Ediriweera and Wiewiora (2021), emphasizes the importance of identifying these barriers as well as potential enablers to technology adoption to help accelerate the adoption process to achieve both economical and sustainable goals of the industry. They argue that a better understanding of barriers and enablers to technological innovation can assist firms in fostering development of an environment that supports innovation in mining. In their work, they classified barriers to technology adoption as technological, organizational, and environmental (TOE). The TOE framework serves as a lens used to identify the determinants of how organizations adopt innovation. This study adopts the TOE framework as the theoretical underpinning to uncover barriers to adopting smart technologies in the mining industry. Below are some identified barriers to implementing smart technologies in the mining industry to achieve organizational excellence (Table 2).

4.2. Technological barriers to technology adoption in the mining industry

4.2.1. Unproven technology

A major risk related to the adoption of technology occurs when the technology is unproven. This is considered high risk for mining organizations since the outcomes of such technology adoption are unknown

Table 2
Synthesis of the sources, types and effect of barriers to the introduction of smart technologies in the mining industry using the TOE Framework.

Source of barrier	Types of barrier	Effects of barrier
Technological Barrier	Unproven Technology High Cost of New Technology Complexity and Compatibility	High Risk Investment High Cost of Investment
Organizational Barriers	Fear and Uncertainty Lack of Trust and Cultural Constraints Rewards and Recognition Systems Focused on Short-Term Incentives	Resistance Slow Adoption
Environmental Barriers	Regulatory Barriers Inadequate Engagement with External Stakeholders Negative Attitude of the Mining Sector towards Research Organisations Capital Intensive and Cyclical Nature of the Mining Industry	Limited Interoperability Slow Acceptance Limited Funding for Research

or cannot be predicted accurately. Employees particularly hesitate to accept unproven new technologies as these technologies could create negative impacts on individual performance. It is worth noting that although employees operating in an improvement culture may be willing to try small improvements; risk-related barriers to adoption of new technologies seem to be more applicable to disruptive innovations (Ediriweera and Wiewiora, 2021). The inability to predict their outcomes with certainty as well as to see more immediate results from these technologies makes them high risk.

4.2.2. High cost of new technology

The initial high investment cost in adopting new mining technologies creates barriers for both Mining companies and Manufacturers of these technologies. Decreasing revenue in particularly the coal mining industry is forcing most mining companies to cut costs (LaTourrette et al., 2023). The resultant effect is that mining companies have few resources to invest in new technology which decreases the available market size for technology manufacturers to deal with. On the other hand, the small size of the available market creates a disincentive to technology manufacturers to invest resources in innovation. Thus, therefore driving manufacturers to pursue new customers in other industries.

4.2.3. Complexity and compatibility

The level of complexity of new / smart technologies may pose as barriers for adoption by mining companies. Complex smart technologies requiring extensive training or significant alterations to current business operations will become demotivating and possibly become a barrier. Smart technologies may cause incompatibilities with pre-existing systems and may disrupt existing value chain necessitating further adjustments or outright replacements inducing additional cost and time (Ramdoo, 2019).

4.3. Organizational barriers to technology adoption in the mining industry

In this study, we review literature on the diffusion on innovation (DOI) model for technology adoption at the organizational level which is widely applied in the telecommunications industry (Rogers, 1995; Eder and Igbaria, 2001; Bradford and Florin, 2003; Li, 2008; Oliveira and Martins, 2011). Technological adoption process in organizations is much more complex and generally involves a number of individuals who may be supporters or opponents, each of whom plays a role in the adoption process. Oliveira and Martins (2011), describes DOI as a theory of how, why, and at what rate new ideas and technology spread through cultures operating at the individual and firm levels. Individuals are thus seen as possessing different degrees of willingness to adopt new technologies and innovations. To categorize and best understand the various adoptability levels Rogers (1995) segregates individuals into the following five categories (from earliest to latest adopters): innovators, early adopters, early majority, late majority, laggards. Findings suggest that earliness of adoption, top management support, lack of trust, risk – aversion, organizational size, technology flexibility, and competition significantly influences the rate of diffusion of new technology in an organization (Bradford and Florin, 2003). While diffusion generally refers to the spread of use of the new technology, it is much more important to also measure the level of infusion which refers specifically to the degree of integration with existing business processes (Eder and Igbaria, 2001). This model is to a large extent similar to the "Unified Theory of Acceptance and Use of Technology" (UTAUT) which is a potential area for research in the mining industry (Venkatesh et al., 2003).

4.3.1. Fear and uncertainty

Resistance to new technology by employees is the primary barrier to the widespread adoption of smart technologies particularly AI within organizations (Das and Datta, 2024). Employees must view smart technologies as tools that enhance their work rather than potential threats to replace or make them redundant. Employees' perception of these technologies is a critical aspect to successfully integrating them with 'legacy systems' which they have formed relationships and are familiar with executing tasks efficiently in a particular way (Chatterjee and Bhattacharjee, 2020). Fear and the lack of trust are two major contributions to developing resistance. According to (Winterton, 1983) when new technologies are introduced, miners face four problems which are; job contraction, job content, job control and health and safety. Job contraction simply means new technologies destroy jobs faster than they create them. Thus, the high potential of redundancies resulting from the introduction of new technologies unfortunately raises most controversies leading to the neglect of its impact on safety, productivity and sustainability of the organization. Where these concerns are real, there should be agreements secured specifying that no redundancies should result from the introduction of new technologies, with provisions for the redeployment or reskilling of displaced employees. Job content on the other hand is affected when the quantity of work performed by an employee is altered as a result of the introduction of new or smart technologies. In this context, Burns et al. (1983) argues that smart technologies have the potential to degrade jobs in two distinct ways: dehumanization and deskilling. Dehumanization occurs when robots are placed in between workers to speed up a production line thereby reducing social interaction. The dehumanization aspects of the degradation of work may often be an unintended consequence of new technology, a consequence that may be resultant and even be detrimental to the management objectives of increased productivity. Conversely, deskilling often is a central part of technological change, since automation or the introduction of smart technologies may result in skilled labor eventually replaced as overlookers or supervisors of machines. Deskilling as a result of smart technology has been witnessed in printing, banking, and engineering industries. Job control is a critical part of employees' bargaining power. Employee's skill is important for bargaining because it serves to maintain the worker's control over work especially when there is scarcity of such skills. Highly skilled workers have bargaining power in the labor market which in turn leads to higher earnings in recognition of this and technological change can remove this privilege. When we think about Health and Safety, our thinking is mostly confined to physical hazards than psychological ones, particularly when technology is so often mistakenly equated with physical or visible hazards (Naeini and Badri, 2023). Psychological hazards such as high workload, introduction of new work patterns particularly irregular shift may result from dehumanization, deskilling, work intensification and increased management control as a result of the introduction of new or smart technologies. These may be associated with a high incidence of stress-related illnesses and may have negative health effects on employees. Presently, there are enormous things that humans cannot imagine about how smart technologies, particularly AI and ML will change our future. However, fear can be subsided by knowledge on understanding how new jobs will be created (Tariq et al., 2021). To mitigate these barriers, the solution is to turn over to smart technology to enhance human's work by putting humans-in-the-loop instead of replacing humans with technology.

4.3.2. Lack of trust and cultural constraints

Most often limited trust between management and employees and between mine site employees and corporate office employees is a barrier to technology adoption. Retrenchment during difficult periods in the mining industry can create challenges in establishing trusting relationships between management and employees. Employees will focus on achieving short term targets to safeguard their job, rather than risking their position by engaging in unproven innovations or seeking out new / smart technologies. Long chains of command and geographical dispersion also act as a barrier for building trusting relationships between head office and mining sites. Mining sites are located in very remote areas with limited opportunities for interaction with the corporate office which affects trust building and potentially limits internal collaboration among departments which in turn affects technology adoption outcomes (Ediriweera and Wiewiora, 2021). Cultural constraints on the other hand refer to an organization's willingness to change. For most companies, it mainly requires some confidence in top management to decide on the potential to achieve enhanced profitability by introducing smart technology; over costs / losses involved in sticking to the status quo (Tarafdar et al., 2020). To overcome this barrier, organizations need to be educated to understand how advanced technologies can enhance productivity and lessen costs compared to existing processes. These factors may be classified together as the lack of strategic planning to the adoption of smart technologies (Tariq et al., 2021)

4.3.3. Rewards and recognition systems focused on short—Term incentives

Traditionally, the mining industry places low emphasis on idea generation and learning with much focus towards efficiency and effectiveness. This notwithstanding affects decisions on technology adoption in the industry. Mining companies tend to have a stance of seeking efficiency by day over employees and teams generating new and innovative ideas. The focus on efficiency impedes employees' creative abilities, resulting in an inadequate focus on adoption of new technology. This deters the ability of employees to be creative, to invest time to create and propose disruptive changes to impact their work. At the mine sites key performance indicators (KPIs) are set on production targets (tonnages / meters) and efficiency. Employees are therefore mainly rewarded for efficiency gains but not on creative ideas or degree of involvement in technology adoption (Ediriweera and Wiewiora, 2021). Tariq et al., (2021) encourage operational excellence as a management approach to mining firms to adopt new technologies and develop long-lasting improvement within their organizations. In their study, they demonstrate that organizations can achieve operational excellence when every individual in the firm can observe its value and is willing to contribute to the success. Firms are encouraged to diligently attempt to implement changes to seek the anticipated value. Operational excellence is a concept that in addition to encouraging idea generation also includes adopting appropriate techniques and technologies for the right procedures. The benefit is an organizational culture that prospers, motivates, and empowers employees (Sehnem et al., 2019).

4.4. Environmental barriers to technology adoption in the mining industry

4.4.1. Regulatory environment

In their study, LaTourrette et al. (2023) describes regulatory barriers as making up more than half of all barriers identified. The researchers identified 15 regulatory barriers which they classified into six subgroups, reflecting different aspects of the MSHA approval process: cost, duration, currency of regulations (i.e., how current the regulations are), prescriptiveness of standards, mine operator burden, and regulatory culture (meaning the prevalent attitudes and practices in the regulatory environment) among others. In the case of cost, obtaining approval for new technology, especially first-of-a-kind technology, may be unaffordable and demotivating for technology suppliers. Costs of certification may include the time required to prepare the initial application and revisions to the application in response to feedback from MSHA, the application fee, and the resources required to redesign the technology in response to feedback. These costs can discourage technology developers under certain conditions, making it a major barrier to the development of new technologies in the industry. Also, the conservative and risk-averse culture of the regulatory environment creates barriers to new technology adoption.

4.4.2. Inadequate engagement with external stakeholders

Insufficient communication with external stakeholders is one of the barriers to smart technology integration. Due to inadequate communication between external stakeholders and mining companies, limited information is shared with service providers (Mining Equipment, Technology and Services (METS) companies) to create new technology fit for purpose. As a result, technological solutions that are introduced may not fit with the entire system, making implementation difficult. Most of these systems are created as 'over the counter solutions' to generally improve and solve mining problems. Engaging external stakeholders takes a low priority in the mining development of new technologies, creating a barrier to optimizing opportunities for smooth adoption. This limits interoperability, making some technologies not efficient to invest in to achieve the required business and operational outcomes. Interoperability is an essential criterion in investing in smart technologies; thus, to avoid ambiguities adequate stakeholders' engagement must be a key priority in new technology development.

4.4.3. Negative attitudes of the mining sector towards research organizations

Another barrier identified by Ediriweera and Wiewiora (2021) is the negative attitude of the mining sector towards research organizations, with the belief that research organizations are not capable of creating new technologies that solves their problems. According to the authors, mining companies are hesitant to trust the capabilities, skills, and knowledge of external stakeholders and this creates obstacles to collaborating with research institutes to co-create solutions. It was revealed in their research the perception that research institutions were engaged not because they are competent but because of other reasons, such as personal relationships or the low cost of their services. This hinders the level of acceptance of technological solutions and slows its integration into business processes.

4.4.4. Capital intensive and cyclical nature of the mining industry

The capital-intensive nature of the mining industry presents significant barriers to the adoption of smart technologies and innovation. Mining companies are often under pressure to deliver short-term returns to satisfy shareholder expectations, making them reluctant to invest in long-term technological initiatives that may temporarily disrupt production and cash flow. Smart technology implementations, though beneficial in the long run, are frequently viewed as incompatible with short-term production targets, thereby limiting their investment. This short-termism fosters a narrow focus on immediate productivity at the expense of innovation. Furthermore, the industry's exposure to volatile economic conditions and the cyclical demand for commodities introduces uncertainty, reinforcing risk aversion among decision-makers. As a result, mining companies deprioritize long-term investments in emerging technologies in favor of operational continuity and cost control. These conditions collectively stifle the development of an innovative culture. Over time, organizational bandwidth for experimentation becomes constrained, and strategic innovation is sidelined by the need to protect margins. The result is a systemic challenge where the potential benefits of smart technologies are undermined by financial conservatism, limited time for innovation, and resistance to change (Fig. 3).

4.5. Managing change as an enabling factor

This study contributes to a better understanding of change management as an enabling factor of smart technology adoption in the mining industry. The results of this study are expected to be useful for contributing to best practices for smart technology adoption in the mining industry in order to overcome the identified barriers to adoption. Undoubtedly, the influx of smart technology and higher levels of automation is changing the role of human resources in the mining industry. Although applying automation can increase output and work efficiency, humans remain a critical component, because of the advantages that a human has over machine. In their research, Rogers et al., (2019) acknowledge the role of humans in the evolution of automation, from its design, implementation, and use to assure adequate performance, safety, and satisfaction. Therefore, the need to implement a dynamic balance between humans and automation to co-exist to handle new technological complexities particularly, human related issues cannot be overemphasized. As addressed earlier, the Human factors and ergonomics (HFE) theory has developed concepts and principles for work design, especially for human-technology interaction. These concepts are encouraged to be applied to the design and implementation of smart technology, particularly AI systems in terms of a division of functions between humans and AI. As part of the broader Human-Centered Artificial Intelligence (HCAI) framework these principles advocates prioritizing humans in designing, developing, and deploying intelligent systems, aiming to maximize the benefits of AI technology to humans and avoid its potential adverse effects (Makinde et al., 2015; Rogers et al., 2019; Xu et al., 2023). The basis is to inhibit a mutually reinforcing relationship between humans and AI based on capabilities and ethical design principles (Mazarakis et al., 2023). In most industries, end to end autonomy seems to be the goal for system developers; thus there are plans to move from manual (human controlled systems) to autonomous (no human required systems) (Battiste et al., 2018). However, as the industry move towards autonomous systems, there is the need to insert humans – in – the – loop to oversee automation. Leaving humans out of the loop creates its own problems as the automation with time may hand over problems that it cannot manage to the operator. To better handle these situations, (Battiste et al., 2018) proposed the development of human automation teams that have shared goals and objectives to support task performance. Their work introduces a model known as the Human Automation Teaming (HAT) which has three elements: transparency, bi-directional communications, and human-directed execution. HAT encourages that there must be cooperation and coordination between machines and humans in achieving goals.

Our synthesis revealed successful strategies developed by organizations including high performing mining companies to promote the successful adoption of smart technologies into their operations. Below are three main strategies for managing change in the introduction of smart technologies in the mining industry.

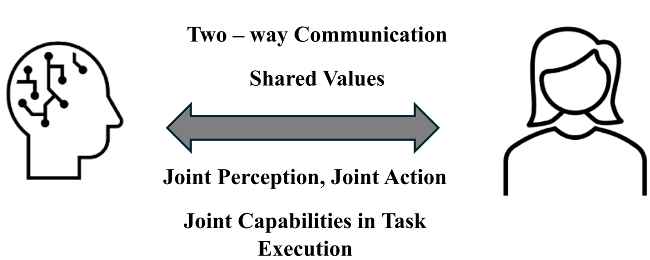

Fig. 3. A synthesis of human machine collaboration (teaming) framework.

4.5.1. Upskilling and new curriculum design

In Australia, mining giant Rio Tinto joined forces with the Western Australian Government and vocational training provider South Metropolitan College of TAFE in 2017, to develop a new curriculum to fill gaps associated with moving towards remote operations. Together, the team developed courses that will upskill potential and existing workers to undertake tasks in analytics, robotics, IT, and other technology related tasks. Rio Tinto operates a large autonomous truck and trains at its Pilbara iron ore mines and in the West Australian capital Perth respectively and workers in the remote operation center plan and make decisions in real-time through virtual monitoring. These vocational training courses which include a high school pathway program is made up of modules which ensures that employees can move between work and study. The strategic integration of AI and human to particular optimize fleet management systems in Rio Tinto is reducing downtime by up to 20 % (Sahota, 2023).

4.5.2. Top management support

A critical first step for achieving success in organizational change is to gain full commitment from senior executives. The active involvement, and direction of top management provides the key ingredient needed to sustain the implementation of smart technologies (Bradford and Florin, 2003). It is imperative that top management define the business case and send clear signals to various parts of the organization about the importance of the project, and the role of each employee in achieving success (O'Leary, 2000). This support from top management will guide and focus efforts toward the realization of organizational benefits and lend credibility to functional managers responsible for its implementation and use (Bradford and Florin, 2003).

4.5.3. Organizational culture

Tariq et al. (2021) encourages mining organizations to develop a continuous improvement culture. This is a continuous attempt to enhance organizational processes and occurs gradually instead of occurring instantly through some advanced innovation. Mining organization are encouraged to identify the required smart technologies and future vision required to achieve a step change and start small whilst carrying employees along, (*The New Technology Frontier in Mining*, 2021) As a start it is critical for an organization to assess their level of digital maturity and define the areas in which action is required. It is important to engage people across the business in this exploration while defining with them the monitoring metrics required to measure the evolving processes. Companies that embark on change with clear and systematic expectations of potential benefits will arguably realize greater organizational performance. Likewise, consensus across the business about the objectives of smart technologies implementation, and how these objectives will be monitored and measured will lead to higher employee satisfaction, reducing fear and building trust across the business (Fig. 4).

4.6. Conclusion

4.6.1. Conclusions and recommendations for future research

The main purpose of this study was to consolidate existing knowledge on the collaborative dynamics between humans and machines in the adoption of smart technologies within the mining sector; focusing on enabling technologies along the mining life cycle, impacts, human factors, and associated barriers. From our synthesis we have discussed enabling technologies facilitating human-machine collaboration along the mining life cycle making mining safer and more efficient for humans. These includes AI – powered Real time monitoring and predictive modelling systems shaping exploration and resource development as well as Autonomous Equipment, Predictive Maintenance Systems, Automated Process Control Systems and AI-Powered Remote Sensing and Data Analytics driving mining operations through to Reclamation. Adopting the TOE framework as the theoretical lens to uncover barriers to adopting smart technologies in the mining industry, this study

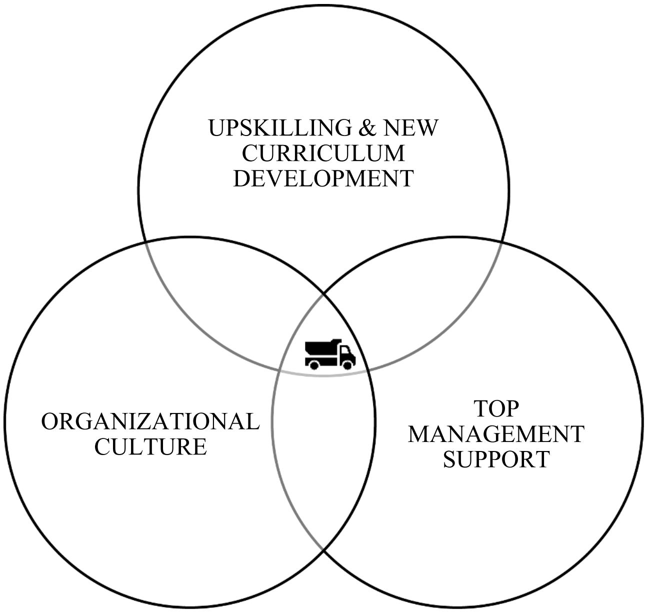

Fig. 4. Three key elements for successful change management for introducing smart technologies in the mining industry.

uncovers technological, organizational, and environmental barriers influencing the smooth integration of smart technologies in the mining industry. Other theoretical models for technology adoption at the organizational level such as DOI (diffusion of Innovation) is briefly discussed. The study also introduces a comprehensive framework demonstrating the enhanced benefit of making mining operations safer with the introduction of smart technologies. Lastly, this study contributes to a better understanding of change management as an enabling factor of smart technology adoption in the mining industry. The results of this study are expected to be useful for contributing to best practices for smart technology adoption in order to overcome the identified barriers. In view of this, emphasis has been given by reviewing frameworks and principles such as the Human-Centered Artificial Intelligence (HCAI) framework, Human Factors and Ergonomics (HFE) and Human Automation Teaming (HAT) models which advocates prioritizing humans in designing, developing, and deploying intelligent systems, aiming to maximize the benefits of AI technology to humans and avoid its potential adverse effects.

4.6.2. Future of work in the mining industry

The evolution of the mining industry towards smart technology and advanced automation seeks to create increasing opportunities for humans. Humans will increasingly move to a more supervisory role and will use advanced collaboration to solve complex problems throughout the mining value chain including collaboration with external support industries. Open collaboration and communication models instilled in today's workforce through the widespread use of social networking technologies will drive thought leadership far beyond current 'best practice' thinking. This will encourage the mining industry to rapidly collaborate and extract business value from rapidly converging fields of study such as environmental sciences, neuroscience, psychology, engineering, information technology and business finance among others. From a worker's perspective the impact of smart technologies on Mining Industry 4.0 provides an assurance of new possibilities of increased productivity with stimulating workplaces, safe working environment which provides opportunity for the utilization of employee's full expertise and creativity. Additionally, increased automation will ensure the sustainability of the industry as the present workforce is aging, and companies have difficulties recruiting talented young people that in general are not very interested in working in the mining industry in remote locations. The future of the industry promises the majority of the workforce to be located in remote operations centers in major urban centers. Therefore, a smart mining industry of the future will be an enabler for improved collaboration, increasing levels of integration between human and machine which will facilitate employee psychosocial safety whilst harnessing their full potential. Researchers are therefore encouraged to provide more comprehensive research in these areas.

CRediT authorship contribution statement

Rosebella Osei: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Samuel Frimpong:** Validation, Supervision, Resources, Project administration, Funding acquisition, Conceptualization. **Allada Venkat:** Writing – review & editing, Supervision, Formal analysis, Conceptualization.

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Supplementary materials

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Rosebella Osei.

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TO : Seyedeh Arezoo Baghaei Naeini
Email: Naelni@uqtr.ca
COMPANY : Industrial Engineering Department, School of Engineering, Université du Québec à Trois-Rivières, Trois-Rivières, Québec, Canada

FROM/RETURN TO : Rosebella Osei
EMAIL : rodpn@mst.edu
PHONE : +15732028190
ADDRESS : Engineering Management and Systems Engineering Department, Missouri University of Science & Technology, Rolla – Missouri - USA

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