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The algorithmic mine: Enhancing managerial effectiveness and organisational agility in the mining industry through artificial intelligence – A spatially aware predictive framework

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Background: This research critically examines the integration of artificial intelligence (AI) within the mining industry, focusing on their capacity to enhance both managerial effectiveness and organisational agility.

Aim: This article addresses the existing literature's limitations by introducing a novel, spatially aware predictive framework tailored to the unique challenges of mining operations.

Setting: While existing literature acknowledges the transformative potential of AI in mining, it often lacks concrete strategies for implementation and fails to address the inherent spatial variability of mining operations. This study proposes the spatially aware predictive framework, leveraging AI to optimise resource allocation, predictive maintenance and environmental management.

Method: A systematic literature review was conducted, employing Boolean logic across Web of Science, Scopus and IEEE Xplore databases, focusing on publications from 2019 to 2025.

Results: Managerial effectiveness and organisational agility are paramount for success in the increasingly complex and dynamic mining industry. The integration of advanced technologies such as AI offers a powerful means to enhance operational efficiency, improve decision-making and achieve sustainable growth. The spatially-aware predictive framework provides a practical roadmap for implementing these technologies, realising their full potential and moving beyond fragmented and spatially unaware applications.

Conclusion: This study proposes the spatially aware predictive framework, leveraging AI to optimise resource allocation, predictive maintenance and environmental management creating an AI-circular business model (AI-CBM).

Contribution: This study proposes a novel spatially aware predictive framework, leveraging AI to optimise resource allocation, predictive maintenance and environmental management, which creates an AI-CBM.

Keywords: artificial intelligence; machine learning; organisational agility; managerial effectiveness; mining industry; spatial analysis; predictive maintenance; optimisation algorithms; spatio-temporal regression; AI-circular business model.

Introduction

The mining industry, historically characterised by its reliance on traditional, often rigid operational methods, is undergoing a profound transformation driven by the integration of advanced technologies (Balasubramanian 2016). This shift is not merely about adopting new tools; it signifies a fundamental re-evaluation of how mining operations are managed, executed and sustained. The industry's traditional resistance to change has often resulted in significant production losses, heightened safety risks for personnel and substantial environmental impacts (Thonsen, Mikkelsen & Rasmussen 2011). As the industry embraces agile business models, leadership is compelled to adopt innovative methods for mineral extraction and processing. These changes have prompted a shift to transformational leadership, adoption of innovative methods of mining and processing of minerals.

In recent decades, the introduction of mechanised mining methods offered improvements but also introduced new challenges, particularly in terms of acquisition costs, maintenance demands, operational complexities and inherent risks. Consequently, the mining industry has increasingly turned to technological advancements, with artificial intelligence (AI) at the forefront. The effectiveness of mining operations management has been revolutionised by AI leading to considerable investment in these sectors (Nah et al. 2019). Artificial intelligence catalyses the empowerment of mining companies in implementing circular business models (CBMs). A CBM is one that has been designed so that there is minimisation in resource utilisation and leakages (Madanaguli et al. 2024). Where there is attainment of managerial efficiency and organisational agility that leads to efficient resource utilisation and leakage minimisation through the adoption of AI, an AI-CBM is created (Mehmood et al. 2019; Mor & Gupta 2021). This means that to achieve a proper CBM where efficiency is enhanced, AI must be adopted.

Artificial intelligence was coined in 1956 by a group that was organised by John MacCarthy, whose inspiration was to create an autonomous machine capable of human-like thinking (Lee et al. 2019). Although there is a plethora of definitions of AI, a more encompassing definition would be appropriate, such as the one coined by Madanaguli et al. (2024), which postulates AI as the family of technologies that enable machines to simulate human-like cognitive functions such as learning, thinking and making decisions based on current and past inputs and outputs. This definition clearly elucidates the three dimensions or functions that AI can perform to enhance managerial effectiveness and organisational agility in the mining industry, which firstly revolve around business analytics, which may take the form of descriptive analytics, diagnostic analytics, predictive analytics and prescriptive analytics (Sjodin et al. 2021). Artificial Intelligence can function through enhancing autonomous decision-making through expert systems, which enable companies to automate tasks that are time consuming and knowledge intensive such as production, processing planning, design and diagnosis (Lee et al. 2019). At the end, AI will harness both business analytics, which is augmentation AI, and autonomous systems, which is autonomous AI, to assist in human decision-making (Macthy 1955), which is assisted intelligence. In a mining firm where the business environment is in continuous state of flux and where there is need for efficiency in managerial effectiveness and organisational agility, there is need for enhancement through adopting AI which allows the company to close all the loops and adopt an AI-CBM.

The core of this article is to come up with a spatially aware predictive framework (SAPF) for adopting AI in the mining organisations to enhance managerial effectiveness and organisational agility. This ultimately shows that this article is skewed towards diagnostic AI which falls under business analytics but also leans towards harnessing the benefits of prescriptive analytics, which entails the prescription of the best option that mining companies can take to enjoy managerial effectiveness and organisational agility. Lepenioti et al. (2020) define business analytics as the extensive use of data that is acquired from various sources, statistical and quantitative analysis, explanatory and predictive models and fact-based management to drive decisions and actions to proper stakeholders. Three main stages of business analytics work together, including descriptive analytics, predictive analytics and prescriptive analytics. Descriptive analytics are diagnostic analytics by nature (Soltanpoor & Sellis 2016) because it focuses mainly on answering the question why it happened, whereas predictive analytics deals with what will happen and why it will happen. Ultimately, the results attained from both descriptive analytics and predictive analytics will help in prescriptive analytics (Lepenioti et al. 2020). Considered the next step towards data analytics, prescriptive analytics prescribes the best course of action and decision to take using large sums of data from predictive and descriptive analytics output (Siksnys & Pederse 2016).

This article elucidates the critical role of AI in bolstering managerial effectiveness and enhancing organisational agility within the mining industry. To achieve this, we conducted a systematic review of existing literature, focusing on the innovative role of AI in mining firms whose business operation model will be AI-CBMs to allow these mining companies to achieve managerial effectiveness and organisation agility. In addition to literature, grey literature from government agencies, consulting firms and mining industry associations was consulted. Studies included quantitative data suitable for meta-analysis or qualitative data providing in-depth case studies. Inclusion criteria focused on empirical studies, theoretical models and comprehensive reviews directly linking AI to operational improvements within mining. Our review will identify current gaps in research and introduce a novel SAPF designed to address the industry's unique spatial challenges.

Literature review

The discourse surrounding managerial effectiveness, organisational agility and AI within the mining sector is both multifaceted and expansive, encompassing a broad spectrum of theoretical perspectives, practical applications and critical case studies.

Theoretical frameworks

Understanding the foundations of this discussion requires exploring several key theoretical lenses:

Resource-based view

The resource-based view (RBV) provides a foundational framework for understanding how AI can drive competitive advantage in the mining industry. Resource-based view posits that a firm's resources and capabilities that are valuable, rare, inimitable and organised (VRIO) are the key determinants of its performance (Barney 1991). In the context of AI, these technologies represent strategic resources that can enhance a mining firm's capabilities and competitive position.

Dynamic capabilities view

The dynamic capabilities view (DCV) extends the RBV by focusing on an organisation's ability to adapt, integrate and reconfigure internal and external competencies to address rapidly changing environments (Teece, Pisano & Shuen 1997). In the mining industry, characterised by fluctuating commodity prices, evolving environmental regulations and technological advancements, DCV offers a critical perspective on how AI can enable firms to maintain competitiveness.

Managerial effectiveness in the mining industry

Managerial effectiveness is critical for the growth and survival of any firm, particularly in the high-stakes, capital-intensive mining industry (Rastogi 2018). Bartol and Martin (1991), as cited in Rastogi (2018), define managerial effectiveness as the ability of an organisation to set and achieve its goals. This definition emphasises the importance of both strategic planning and execution.

Managerial effectiveness is not only about achieving organisational goals but also about effectively utilising resources and skills. According to Anandan et al. (2017), managerial effectiveness involves using managerial skills and strategies through the workforce to meet organisational requirements. This perspective highlights the importance of leadership in driving productivity and fostering a collaborative work environment.

Organisational agility in the mining industry

Organisational agility is increasingly vital for maintaining a competitive advantage in today's dynamic market environment. Žitkienė and Deksnys (2018) note that globalisation, rapid technological advancements, competition, disruptive business models and evolving consumer preferences constantly challenge organisations. These challenges necessitate agile strategies to adapt and thrive.

Talbolt et al. (2015) argue that agility is no longer optional but a necessity for business organisations in the 21st century. The ability to respond swiftly to external environmental changes distinguishes successful organisations from those that struggle. This responsiveness is crucial for mining companies facing volatile commodity markets and regulatory landscapes.

Organisational agility is not a static state but an ongoing process of adaptation and innovation. Alzoubi (2011) suggests that while a firm can become increasingly agile, it can never be concretely agile because the business environment is continually evolving. This continuous evolution underscores the need for mining companies to embrace a culture of innovation and continuous improvement.

Organisational agility and innovation are closely linked, with agile organisations often characterised by a culture of innovation. Harraf (2013), as cited in Talbolt et al. (2015), defines a culture of innovation as one where the organisation is constantly evaluating its systems, structures, procedures and teams to find new and improved methods for performing functions and providing services.

The role of artificial intelligence in enhancing managerial effectiveness and organisational agility

Artificial intelligence is transforming how organisations are managed by enabling machines to perform tasks previously done by humans (Chewrnova & Chernov 2018). This technological shift has profound implications for managerial effectiveness and organisational agility. Scarcello (2019) notes that AI is becoming essential for the success of many organisations and is one of the most impactful technologies of the 21st century.

Machine learning (ML), which is a subset of AI, allows software applications to become more accurate at predicting outcomes. Burns (2023) defines ML as a type of AI that enables software applications to improve their accuracy in predicting outcomes. Similarly, Nilson (1998) views ML as the changes in systems that perform tasks associated with AI. This predictive capability can significantly enhance decision-making processes in the mining industry.

Artificial intelligence drives organisational agility by enabling companies to adapt quickly to changing conditions and make informed decisions based on data analysis. By adopting these technologies, mining companies can improve efficiency, reduce costs and enhance their overall performance. In addition to that, Scarcello (2019:42) asserted that 'Artificial Intelligence (AI) is proving to be essential for the success of many organisations and one of the most impactful technologies of the 21st century'. Other authors claim that AI has ushered in fourth industrial revolution. This means that for an organisation which is not agile, it will be difficult to compete because AI will bring with it a host of advantages, which include low cost of production, quicker production turnaround, quality output and many more benefits brought by AI whose name was postulated by McCarthy in 1956.

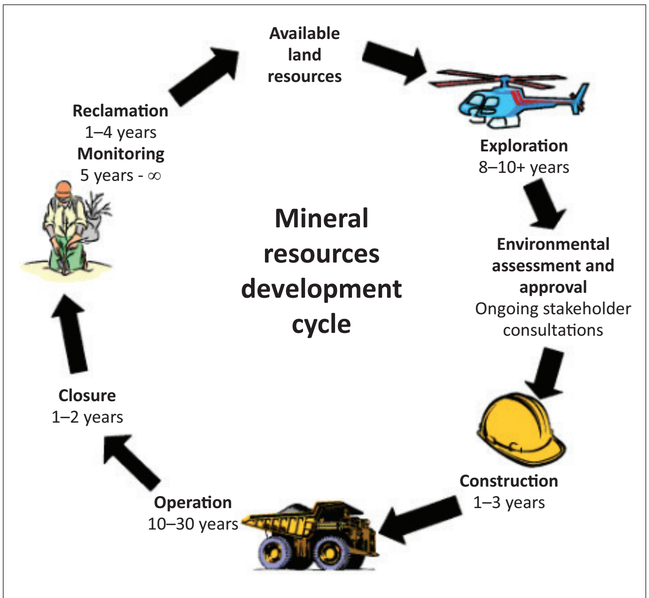
Burns (2023) explains that 'Machine learning (ML) is a type of AI that allows software applications to become more accurate at predicting outcomes'. This resonates with Nilson's (1998) view that 'Machine learning usually refers to the changes in systems that perform tasks associated with AI'.

Contemporary literature studies on the role of artificial intelligence in the mining industry

Because of the nature of mining operations, which are costly and unsafe as well as unpredictable in terms of the market variable, there has been a growing trend in the studies with regard to the evolution of the way mining operations should be managed through the adoption of AI. The studies have started from those who have to do with the definition of AI, forms of AI, application of AI and the effects of AI as well as ethical considerations with regard to AI use in the mining industry.

Defining artificial intelligence in the context of enhancement of managerial effectiveness and organisational agility in the mining industry

As was mentioned earlier, AI was coined in 1956 by a group that was organised by John MacCarthy, whose inspiration was to create an autonomous machine capable of human-like thinking (Lee et al. 2019). These autonomous machines were to be tailor-made for various sectors, that is, aviation, information technology, transportation, logistics, mining, hospitality, marketing (Davenport et al. 2019), agriculture and more. Although there is a plethora of definitions of AI, a more encompassing definition would be appropriate such as the one coined by Madanaguli et al. (2024), which postulates AI as the family of technologies that enable machines to simulate human-like cognitive functions such as learning, thinking and making decisions based on current and past inputs and outputs. This definition clearly elucidates the three dimensions or functions that AI can perform to enhance managerial effectiveness and organisational agility in the mining industry, which firstly revolve around business analytics, which may take form of descriptive analytics, diagnostic analytics, predictive analytics (Dubois 2023) and prescriptive analytics (Sjodin et al. 2021). Secondly, AI can function through enhancing autonomous decision-making through expert systems which enable companies to automate tasks that are time consuming and knowledge intensive such as production, processing planning, design and diagnosis (Lee et al. 2019). At the end, AI will harness both business analytics, which is augmentation AI, and autonomous systems, which is autonomous AI, to assist in human decision-making, which is assisted intelligence. In a mining firm where the business environment is in continuous state of flux and where there is need for efficiency in managerial effectiveness and organisational agility, there is need for enhancement through adopting AI, which allows the company to close all the loops and adopt an AI-CBM.



Source: Balasubramanian, S., 2016, 'Technology adoption in the mining industry: A literature review', *Journal of Mining Science* 52(3), 555–564

FIGURE 1: The mineral resource development life cycle.

Artificial intelligence application studies in the mining industry

The nature of mining business, which starts with exploration up to the reclamation of the mine as shown in Figure 1, resembles a CBM, which has so many loops that if not properly managed will lead to a lot of leakages. Adoption of new technologies such as AI together with the right application framework provides a panacea to the reduction of those leakages through the creation of an AI-based CBM. This model reduces waste, cost and time and increases return on investments and environmental sustainability.

Artificial intelligence adoption by mining companies directly results in the automation of the mining companies. Saleem (2025) highlighted technological changes, which lead to improvement in efficiency in mining operations and the changes include the adoption of autonomous mining methods. Table 1 shows some of the AI-based autonomous mining methods as compiled by Saleem (2025):

These new technologies can be used in ore transportations, ore drilling and use of robots in execution of work in confined areas. Artificial intelligence can also be used to predict machine failures, that is, under predictive

TABLE 1: Artificial intelligence – Based autonomous mining systems.

Application area	Technologies used	Benefits	Challenges	Refs.
Autonomous haulage systems (AHS)	GPS, sensors, AI algorithms	• Increased productivity through continuous operations • Reduced operational costs • Improved safety	• High initial investment • Complex infrastructure requirements • Need for skilled maintenance	(Kolapo et al., 2025; Wang et al., 2022)
Automated drilling and blasting	Precision control systems, robotics	• Greater accuracy in blast operations • Reduced over-break • Minimized environmental impact	• Technical complexity • Integration with existing systems • Training requirements	(Kokkinis et al., 2024; Onifade, Said, et al., 2023)
Robotic systems	Advanced vision systems, AI-powered sensors	• Enhanced inspection capabilities • Reduced human exposure to hazards • Lower maintenance costs	• High equipment costs • Limited flexibility in complex environments • Ongoing maintenance needs	(Onifade, Adebisi, et al., 2023)

Source: Saleem, H.A., 2025, 'Automation and artificial intelligence in enhancing mining efficiency and sustainability: A review', *Procedia Environmental Science, Engineering and Management* 12(1), 213–228

Note: Please see the full reference list of the article, Gosho, T. & Mpundu, M., 2026, 'The algorithmic mine: Enhancing managerial effectiveness and organisational agility in the mining industry through artificial intelligence – A spatially aware predictive framework', *South African Journal of Economic and Management Sciences* 29(1), a6538. https://doi.org/10.4102/sajems.v29i1.6538, for more information.

AI, artificial intelligence; GPS, global positioning system; Refs. references.

maintenance (Nunes, Santos & Rocha 2023; Odeyar et al. 2022) and in precision control systems that give greater accuracy in blasting and drilling (Kokkini et al. 2024; Said et al. 2023) as well as in advanced vision systems and AI-powered sensors, which enhance inspection capabilities and reduce human exposure hazards through robotic systems (Onifed & Adebis 2023).

Nah et al. (2019) also elucidate the roles that AI can play in a mining organisation that include prospecting and exploration, drilling, gases and hazard identification where AI can be used to detect dangerous gases such as nitrous fumes which may be harmful to humans.

Effects of artificial intelligence in the mining industry

Artificial intelligence adoption is driving a major revolution in mining and geology business (Bandi 2024), but its adoption has its own pros and cons. Artificial intelligence has revolutionised how exploration is done, mine optimisation and environmental impact reduction. This can be done through using AI to locate prospective mineral deposits (Franks 2020), using ML algorithms to analyse past successes and failures, using AI sensors to gather real-time data, predict machine failures, use autonomous robots to perform work and reduce waste in AI-circular business models in an AI-enabled closed business model (Madanaguli et al. 2024).

Artificial intelligence adoption in the mining industry has been used to improve process automation through two mechanisms, which are automation and augmentation of organisational tasks and routines (Raisck & Krakoswski 2020). This includes the use automated decision systems that can allow AI-enabled CBMs that can offer value by processing data through algorithms to make resource loops faster and more efficient (Thomson et al. 2022).

The rise of predictive analytics, which branches into probabilistic models, ML and data mining and statistical analysis (Madanaguli et al. 2024; Nasrabadi 2007), has positively impacted the role AI has been applied in the mining CBM. These predictive models can also be used as the basis for AI prescriptive analytics, which proffers the prescription of what is to be performed from the AI-generated data. However, prescriptive models take the form of probabilistic models, ML and data mining, mathematical programming, evolutionary computation, simulation and logic-based models. Both the predictive models and the prescriptive models are key and sometimes they intersect (Madanaguli et al. 2024; Shroft et al. 2024) making their use and adoption complementary.

Methods

To understand how AI impacts management and flexibility in the mining industry, we followed a structured research approach. This involved searching for relevant studies, selecting the most useful ones, extracting important information and analysing it using basic statistical methods.

Search strategy: Finding the right studies

We looked for studies in three major online libraries: Web of Science, Scopus and IEEE Xplore. These libraries cover a wide range of scientific and technical topics relevant to AI and mining. We chose these libraries to find as many useful studies as possible from different areas such as computer science, engineering, geology and business.

Web of Science: We used Web of Science because it has a good reputation for indexing important journals in many fields. This helped us to find key research and new trends in AI or ML for mining.

Scopus: Scopus covers even more journals and conference articles than Web of Science, so we used it to find a broader range of studies, including those from smaller journals and conferences.

IEEE Xplore: This library focuses on electrical engineering and computer science, so we used it to find specific technical details about AI algorithms and how they are used in mining.

Our search was designed to find different types of studies, including research with data, theoretical ideas, case studies and reviews. We started with a test search to make sure our search terms worked well. We adjusted the search terms as needed based on the test results and as we continued to monitor the available literature.

We used the following search terms:

- 'Artificial Intelligence' AND 'Mining'
- 'AI' AND 'Mining Industry'
- 'Predicting Breakdowns' AND 'Mining'
- 'Improving Efficiency' AND 'Mining'
- 'Location Analysis' AND 'Mining'
- 'Better Management' AND 'Mining' AND 'AI'
- 'Changing Quickly' AND 'Mining' AND 'AI'

We chose these terms to cover the different ways AI is used in the mining industry, including both technical and management aspects. Using the word 'AND' ensured that we only found studies that discussed both AI and mining. Terms such as 'Predicting Breakdowns' and 'Improving Efficiency' helped us find studies about specific AI applications in mining operations, while 'Location Analysis', 'Better Management' and 'Changing Quickly' helped us find studies about spatial analysis, management effectiveness and organisational flexibility.

We only looked at studies published between 2019 and 2025 to focus on the most recent developments. This timeframe ensured that we captured the most current research and applications of AI in the mining sector. We focused on this timeframe because technology is rapidly changing, and we wanted our findings to be relevant to current industry practices and challenges.

We also used backward and forward citation analysis to find articles that our main search might have missed. This involved checking the references of the studies we found and tracking who cited those studies in later publications. This helped us to make sure our review was as complete as possible.

Inclusion and exclusion criteria: Choosing the best studies

To make sure we only included the most relevant and high-quality studies, we used specific rules for including and excluding studies. These rules were based on our research goals and the scope of our review, ensuring that we selected studies that provided valuable information about the role and impact of AI on management and flexibility in the mining industry.

Inclusion criteria

Inclusion of studies was based on:

- Studies that focused on AI in the mining industry
- Studies that discussed management effectiveness or organisational flexibility as important results
- Studies that presented data, theoretical models or thorough reviews
- Studies published in well-respected journals, conference proceedings or government and industry reports
- Studies published in English between 2019 and 2025
- Studies that provided enough details about their methods so we could assess their validity and reliability
- Studies that specifically mentioned location information or spatial data analysis in the context of AI applications in mining.

Exclusion criteria

Exclusion of studies was based on:

- Studies about AI in other industries that were not directly relevant to mining
- Studies that lacked data or theoretical support
- Studies published in languages other than English
- Studies published outside the 2019–2025 timeframe
- Publications that lacked enough details about their methods or had methodological flaws
- Abstracts, editorials and opinion pieces without substantial content.

We applied these rules carefully to each study, using a two-stage screening process. Firstly, we screened the titles and abstracts to see if they were relevant to our research question. Secondly, we reviewed the full texts of the studies that passed the first stage to determine if they met all of our inclusion criteria. Any disagreements between the reviewers were resolved through discussion.

Data extraction and synthesis: Gathering and summarising information

After searching and screening the studies, we used a standard form to collect important information from each study. The form was designed to capture both numbers and descriptions, giving us a complete picture of the study's goals, methods, findings and limitations.

The form included details such as:

- Study goals and research questions
- Research methods (e.g. experiments, surveys, case studies, simulations)
- AI techniques used (e.g. regression models, neural networks, decision trees)
- Specific spatial analysis techniques (e.g. kriging, spatial autocorrelation, spatial regression)
- Important variables and measurements (e.g. productivity, safety incidents, environmental impact, cost savings)
- Sample size and characteristics (e.g. type of mine, geographical location, number of participants)
- Study location and context (e.g. underground mine, surface mine, processing plant)
- Main findings and conclusions
- Limitations and potential biases
- Data availability statements

We then summarised the data using descriptions and a simple *t*-test to compare mines that use AI versus those that do not. Descriptive synthesis gave us a general overview of the main ideas and findings across the studies. We identified common themes and insights related to AI applications, benefits, challenges and spatial considerations.

Comparing averages with a simple *t*-test: A quantitative comparison

To address the study objective assessing how AI-enabled, spatially informed decision-making enhances managerial effectiveness and organisational agility in mining, we begin with a foundational quantitative comparison of average outcomes. This quantitative comparison of average outcomes that is usually generated through the use of various AI models such as descriptive AI, predictive AI and prescriptive AI is a hallmark of enhancing mining companies to be effectively managed and responsive to the various variable in its environment. However, this comparison is intentionally embedded within the SAPF so that observed average differences are interpreted as manifestations of the mechanisms described by SAPF (spatial decision integration, rapid re-planning and cross-zone AI-enabled coordination), rather than as isolated statistical artefacts. The progression moves from a simple average comparison towards analyses that reveal spatial and causal links governing performance across the mine network. In essence, the quantitative comparison informs why AI should be adopted because they are a guide to the doubting mining companies who are laggards in adopting this new technology:

- **Selection of Metrics:** We identified key performance metrics relevant to managerial effectiveness and organisational agility, such as tonnes of ore extracted per

day, number of safety incidents per year or cost savings. These metrics were selected based on their relevance to the research questions and their availability in the included studies. The choice of metrics was guided by the existing literature and the input of industry experts, ensuring that the selected metrics were meaningful and representative of the key performance indicators in the mining industry.
- **Data Collection:** We collected data on these metrics from studies that reported outcomes for both AI-enabled and non-AI-enabled mining operations. The data collection process involved carefully extracting the relevant information from the included studies and organising it into a spreadsheet for analysis. The data were checked for accuracy and consistency to ensure the validity of the results.
- ***t*-Test Analysis:** We performed an independent samples *t*-test to determine if there was a statistically significant difference between the average values of the chosen metrics for the two groups. The *t*-test assumes that the data are normally distributed and have equal variances. These assumptions were checked using appropriate statistical tests (e.g. Shapiro–Wilk test for normality, Levene's test for equal variances). If the assumptions were violated, appropriate transformations were applied to the data or alternative non-parametric tests were used.

The *t*-test was chosen as a simple and widely used statistical test for comparing the means of two independent groups. The *t*-test provides a *p*-value, which indicates the probability of finding the observed difference in means (or a more extreme difference) if there is no true difference between the groups. A *p*-value less than a pre-determined significance level (e.g. 0.05) is typically considered statistically significant, indicating that there is strong evidence to reject the null hypothesis of no difference between the groups:

- **Spatial Regression Modelling:** This is used as a complementary tool to aid the *t*-test analysis to help explain what the *t*-test may have omitted.
- **Interpretation:** We interpreted the results of the *t*-test, considering the *p*-value and effect size, to assess the impact of AI on the chosen performance metrics. The effect size, such as Cohen's d, provides a measure of the magnitude of the difference between the groups, independent of the sample size. We acknowledged that other factors, such as mine size, ore type and worker skill, could also influence the outcomes.

The interpretation of the *t*-test results was conducted in the context of the specific metrics being analysed and the limitations of the data. We acknowledged that correlation does not equal causation and that the observed differences between the groups may be because of other factors not accounted for in the analysis. The interpretation was also guided by the existing literature and the input of industry experts, ensuring that the conclusions were meaningful and relevant to the mining industry.

Spatial regression modelling: Capturing spatial dependencies

The following is a more technical breakdown of the components (Equation 1):

$$Y(l) = X(l)\beta + \varepsilon(l) \qquad \text{[Eqn 1]}$$

where:

Y(l) is the outcome you are interested in at location *l* (e.g. ore grade)

X(l) are things that might affect Y at location *l* (e.g. distance to a fault line, type of rock)

β tells you how much each thing in X affects Y

ε(l) is the error, which includes everything else that affects Y at location *l*.

Now, the important part: because things close together are often more similar, the error ε(l) is related to the error at nearby locations. A simple way to model this is to say (Equation 2):

$$\varepsilon(l) = \rho \text{ (average } \varepsilon \text{ of nearby locations) + noise} \qquad \text{[Eqn 2]}$$

Here, ρ (rho) tells you how strong this relationship is. If *ρ* is close to 1, it means that if the error is high in one place, it is likely to be high in nearby places too. Noise is just random stuff that is not related to anything else.

Y(l): The dependent variable

This represents the outcome variable we are trying to predict or explain at a specific location *l* within the mining area. Examples include:

- **Ore Grade:** The concentration of valuable minerals within the ore at location *l.*
- **Extraction Rate:** The quantity of ore extracted per unit of time at location *l.*
- **Safety Incident Rate:** The number of safety incidents occurring per unit of time at location *l.*
- **Environmental Impact:** A measure of environmental degradation (e.g. air pollution, water contamination) at location *l*.

X(l): Independent variables (Explanatory variables)

These are the variables that are believed to influence or explain the variation in Y(l). They are measured at the same location *l* as the dependent variable. Examples include:

- **Geological Factors:**

  Rock Type: Categorical variable representing the type of rock formation at location *l*.

  Distance to Fault Line: Continuous variable measuring the distance from location *l* to the nearest geological fault line.

  Depth of Ore Body: Continuous variable representing the depth of the ore body at location *l*.

- **Operational Factors:**

  Equipment Type: Categorical variable representing the type of equipment used at location *l* (e.g. drilling rig, excavator).

  AI Implementation: Binary variable indicating whether AI technologies are implemented at location *l* (1 = yes, 0 = no).

  Operator Experience: Continuous variable representing the average experience level of equipment operators at location *l*.

- **Environmental Factors:**

  Precipitation: Continuous variable measuring the amount of rainfall at location *l*.

  Temperature: Continuous variable measuring the average temperature at location *l*.

  Vegetation Cover: Continuous variable representing the density of vegetation cover at location *l*.

β: Regression coefficients

These coefficients quantify the relationship between the independent variables X(l) and the dependent variable Y(l). Each coefficient represents the estimated change in Y(l) for a one-unit change in the corresponding independent variable, holding all other variables constant:

- **Positive Coefficient:** Indicates a positive relationship between the independent variable and the dependent variable. For example, a positive coefficient for 'AI Implementation' would suggest that implementing AI technologies is associated with higher ore grade or extraction rate.
- **Negative Coefficient:** Indicates a negative relationship between the independent variable and the dependent variable. For example, a negative coefficient for 'Distance to Fault Line' might suggest that locations closer to fault lines have lower ore grade because of geological instability.
- **Statistical Significance:** The statistical significance of each coefficient is assessed using *t*-tests or *p*-values. A statistically significant coefficient indicates that the relationship between the independent variable and the dependent variable is unlikely to have occurred by chance.

ε(l): Error term

This represents the unexplained variation in Y(l) that is not accounted for by the independent variables X(l). It includes factors such as measurement error, omitted variables and random noise. In traditional linear regression, it is assumed that the error terms are independent and identically distributed (i.i.d.). However, in spatial regression, this assumption is relaxed to account for spatial autocorrelation.

Spatial autocorrelation component: Modelling spatial dependence in the error term

To account for the spatial dependence among observations, the error term ε(l) is modelled as a function of the error terms at neighbouring locations. The spatial autoregressive model is defined as (Equation 3):

$$\varepsilon(l) = \rho W\varepsilon + u(l) \quad \text{[Eqn 3]}$$

where:

ρ (Rho): Spatial autoregressive coefficient

This coefficient measures the strength and direction of spatial autocorrelation. It ranges from −1 to 1.

Positive ρ: Indicates positive spatial autocorrelation, meaning that locations with similar values of the error term tend to cluster together.

Negative ρ: Indicates negative spatial autocorrelation, meaning that locations with dissimilar values of the error term tend to cluster together.

ρ = 0: Indicates no spatial autocorrelation.

W: Spatial weights matrix

This matrix defines the spatial relationships between locations. It specifies which locations are considered neighbours and the strength of their connections. Common types of spatial weights matrices include:

- **Contiguity-Based Weights:** Locations are considered neighbours if they share a common boundary (e.g. rook contiguity, queen contiguity).
- **Distance-Based Weights:** Locations are considered neighbours if they are within a certain distance of each other. The weights can be inversely proportional to the distance.
- **K-Nearest Neighbours Weights:** Each location is considered a neighbour of its k-nearest locations.

ε: Vector of error terms

This is a vector of error terms for each location.

u(l): Independent and identically distributed (i.i.d.) error term

This is the error term that is assumed to be independent and identically distributed (i.i.d.) with a mean of zero and constant variance.

Estimation of parameters

The parameters of the spatial regression model (β and ρ) are estimated using maximum likelihood estimation (MLE) or other appropriate estimation techniques.

Validity and reliability

To ensure our findings are trustworthy, we took several steps:

- **Clear and transparent methodology:** We clearly described our research methods, making it easy for others to understand and repeat our work.
- **Systematic search strategy:** We used a comprehensive and unbiased search strategy to minimise the risk of missing relevant studies.
- **Explicit inclusion and exclusion criteria:** We clearly defined our inclusion and exclusion criteria and applied them consistently to each study.
- **Standardised data extraction template:** We used a standard form to collect information from each study, ensuring consistency and accuracy.

- **Independent review and coding:** Two researchers independently extracted and coded data, resolving any disagreements through discussion.
- **Statistical analysis:** We used appropriate statistical techniques to analyse the data and assess the statistical significance of our findings.

Systematic review outcomes: A deep dive into artificial intelligence applications in mining

Our systematic review, conducted according to our methodology, identified 87 relevant studies published between 2019 and 2025. These studies provide a comprehensive overview of how AI is currently being used in the mining industry. Some of the selected studies are categorised by their description in Table 2.

To gain an in-depth understanding of the application of AI in the mining industry and how it may enhance managerial effectiveness and organisational agility, various studies regarding the origins of AI, how it is applied, the types of AI that mining firms can use, the impacts of the new technologies in the form of AI, ethical considerations with regard to the adoption of AI as well as the role played by AI to foster the adoption of a CBM were analysed. This was done to ensure that the novel SAPF for the use of AI will be designed based on the literature available on AI application in the mining industry. The idea was to eliminate all caveats and limitations that may arise because of lack of sufficient data.

TABLE 2: Selected studies about how artificial intelligence is used in the mining industry.

Study description	Selected studies	Reference authors
Emergence and definition of AI in the mining Industry	Prescriptive analytics, artificial intelligence capabilities, emerging technologies, artificial intelligence.	Davenport et al. (2020). Lee et al. (2019). Lepenioti et al. (2020). Madanaguli et al. (2024), Frimpong (2020)
AI types in the mining industry studies	Machine learning, deep learning, AI transformation in mining, AI, ML and autonomous technologies in mining industry.	Jafari et al. (2022), Boateng et al. (2024), Lee et al. (2019), Mining Industry White Paper Microsoft Corporation (2024), Hyder (2019)
AI application studies in the mining industry	AI integration in the mining industry, AI application, predictive maintenance, resource management, environmental monitoring.	Band (2024), Bui and Nguyen (2022), Kokkinis et al. (2024), Said et al. (2023), Adebisi et al. (2023) Nunes et al. (2023), Odeyar et al. (2022), Li (2022), Wu et al. (2022), Onifade et al. (2023), Singh et al. (2023)
Effects of AI in the mining industry	Impact of AI, promises and challenges of AI, automation and AI.	Mine Magazine (2020), Ghosh (2020), Saleem (2025), Kolapo et al. (2025), Wang et al. (2022), Rosa et al. (2019a)
AI ethical consideration	Use of AI in the mining industry and ethical considerations, ethical side effects of using AI, ethical implications of AI.	Laye and Corrogan (2022), Chavula and Kayusi (2025), Mishara and Allahabad (2020)
AI-circular business models	AI and circular business models, business value of AI.	Frishammar et al. (2018), Ångstrom et al. (2023), D'Amore et al. (2022), Nishant et al. (2020), Mikalef and Gupta (2021), Sjodin et al. (2023)

Note: Please see the full reference list of the article, Gosho, T. & Mpundu, M., 2026, 'The algorithmic mine: Enhancing managerial effectiveness and organisational agility in the mining industry through artificial intelligence – A spatially aware predictive framework', *South African Journal of Economic and Management Sciences* 29(1), a6538. https://doi.org/10.4102/sajems.v29i1.6538, for more information.
AI, artificial intelligence; ML, machine learning.

Artificial intelligence application domains in mining operations: A detailed exploration

Artificial intelligence-circular business model is important in mining companies, especially when it can help the company to create, capture and deliver value to improve resource efficiency by extending the lifespan of the mineral products and parts to improve environmental, social and economic benefits. Three roles must be played by AI in mining CBM, which are to slow, narrow and close the loops (Ritala, Bocken & Konietzko 2023). Mining companies must use AI to slow resource loops, that is, to increase the life of the mineral products and its components. A mining company can use AI-CBM to reduce resource flow that ultimately reduces costs, which is referred to as narrowing the business model, and this can be done through increasing efficiency in the value chain. Artificial intelligence–enabled closing business models focus on closing the loop of resources post consumptions of the resources and this can be done through reuse, remanufacture and recycle. The identified studies showed that AI is being applied in many different areas of mining. We will explore these areas in the next section:

Predictive and prescriptive maintenance and equipment health monitoring

This was the most common application, representing about 30% of the studies. Artificial intelligence is used to analyse sensor data (e.g. vibration, temperature) and predict when equipment might fail (Smith 2022). This helps mines avoid unexpected downtime and reduce maintenance costs. For example, one study used AI to predict failures in haul trucks, while another used AI to predict bearing failures in conveyor belts. Studies reported that predictive maintenance systems can reduce downtime by 15% – 20% and lower maintenance costs by 10% – 15%.

On prescriptive maintenance, AI-CBM can use AI to generate information that can guide in decision-making. The results generated from the predictions and diagnostics can be used to prescribe the course of action that can enhance managerial effectiveness and organisational agility in mining organisations.

Resource optimisation and production efficiency

Artificial intelligence is used to optimise how resources are allocated and improve production (Garcia 2024; Chen 2023). This includes estimating ore grade, planning mines, optimising blasting and handling materials. For instance, AI is used to create more accurate 3D models of ore deposits, helping with mine planning. Autonomous vehicles with AI are used to transport materials, reducing labour costs and improving safety. Studies indicated that AI helps to increase ore recovery by 5% – 10% and reduce operational costs by 5% – 8%.

Environmental monitoring and management

Artificial intelligence is used to monitor air and water quality, detect environmental hazards and optimise clean-up efforts. Remote sensing data (e.g. satellite images) and ML are used to track environmental conditions. For example, AI can predict the concentration of heavy metals in water based on geological and rainfall data.

Safety enhancement and risk mitigation

Artificial intelligence is used to enhance safety in mining environments, which are inherently hazardous (Clark 2022). These technologies are used to predict hazards, monitor safety conditions and prevent accidents. An AI-powered system was developed that monitors atmospheric conditions and provides early warnings. Machine learning can identify unstable slopes in open-pit mines, preventing landslides and protecting workers.

Spatial analysis and geological modelling

The review emphasised the importance of integrating spatial data and spatial analysis techniques with AI in mining. This is relevant for tasks such as ore grade estimation, resource modelling and environmental impact assessment. Traditional geostatistical methods, such as kriging, are being combined with ML algorithms to create more accurate and robust spatial models. Spatial data analysis can be used as a prescriptive analytical tool whose results inform decisions to be taken. This will ensure urgent decision outcomes and reduce lost time because AI technologies are usually real time and can handle large data. The decision prescribed can also be for specific locations, which ensures relevant decisions for relevant locations in a timely manner.

Benefits of adopting artificial intelligence technologies: Tangible and intangible gains

The reviewed studies consistently showed several benefits of using AI in mining:

- **Enhanced operational efficiency:** Improved resource allocation, reduced downtime and automated processes lead to increased production, lower costs and improved profitability.
- **Improved decision-making:** Real-time insights and data-driven recommendations help managers to make more informed decisions.
- **Cost reduction:** Predictive maintenance, optimised resource allocation and automated processes all contribute to lower costs.
- **Enhanced sustainability:** Improved environmental monitoring and optimised resource usage lead to more sustainable practices.
- **Improved safety:** Predicting hazards and monitoring safety conditions help to prevent accidents and protect workers.

Challenges and limitations: Navigating the hurdles to artificial intelligence adoption

Despite the benefits, there are also challenges to adopting AI in mining:

- **Data availability and quality:** A lack of high-quality, accessible data is a major barrier.
- **Integration challenges:** Integrating AI with existing mining systems can be complex and costly.
- **Interpretability and explainability:** The 'black box' nature of some AI models can make it difficult to understand how they work, hindering trust and adoption.
- **High initial investment:** Deploying AI requires significant upfront investment.
- **Ethical considerations:** Ethical concerns include algorithmic bias, data privacy and workforce displacement.
- **Skill gap:** There is a shortage of skilled professionals with expertise in AI and mining.

Location matters: A spatially aware predictive framework

The spatially aware predictive framework offers a robust and data-driven approach to enhancing managerial effectiveness and organisational agility in the mining industry. To simplify the SAPF, it is important to start by defining the concept of being spatially aware. A plethora of definitions exist in literature, which ranges from authors viewing spatial awareness as the understanding of the spatial dimensions and configurations of both the environment and the objects within it (Mihilewizic 1999). Ishikawa (2023) postulates that spatial awareness is the cognitive mapping, which involves acquiring, coding, recalling and decoding information about a relative location and attributes of phenomena in everyday spatial. While this definition by Ishikawa (2023) has managed to relate spatiality to place and location, a more comprehensive explication of spatial awareness would be to define it as the understanding of oneself and relationships within a given space (Gross et al. 2025). This means that from a circular mining business model, the concept of spatiality involves using new technologies such as AI in line with the attributes existing in that mining location. This eliminates a haphazard approach to implementation of AI. It addresses the limitations of current AI implementations by integrating spatial analysis techniques, providing a more comprehensive and nuanced understanding of the factors influencing mining performance. This allows managers to make more informed decisions, optimise resource allocation and improve overall operational efficiency. This framework moves beyond the theoretical by providing a practical roadmap for implementation. The integration of spatial awareness is not merely an add-on but a fundamental shift in how AI is applied, recognising that mining operations are inherently spatial processes.

Key components of the framework

This article is skewed towards diagnostic AI, which falls under business analytics but also leans towards harnessing the benefits of prescriptive analytics, which entails the prescription of the best option that mining companies can take to enjoy managerial effectiveness and organisational agility. Consequently, for effectiveness, the SAPF must have the following components:

- **Data Integration:** Combining data from different sources into a unified and spatially referenced dataset.
- **Spatial Data Analysis:** Exploring spatial relationships between variables using techniques such as geostatistics and spatial autocorrelation.

- **Predictive Modelling:** Building AI models that incorporate spatial variables to predict outcomes.
- **Optimisation Algorithms:** Identifying the best course of action based on model predictions, considering constraints.
- **Visualisation and Decision Support:** Presenting results in a user-friendly format to enable informed decisions.

The use of these components of data integration, spatial data analysis, predictive modelling, optimisation algorithms, visualisation and decision support gives room for an AI-CBM, which incorporates the benefits of predictive AI, descriptive AI and prescriptive AI. In this case, the AI-CBM mining organisation will be able to be managed effectively and as such be responsive to a dynamic business environment.

Spatial regression modelling: A deeper dive

Spatial regression models relationships between variables while accounting for spatial dependence. If you want to determine if AI adoption really improves mine output, you use the model to determine:

- Model specification
- Spatial dependence
- Model estimation
- Interpretation
- Model selection
- Practical implementation in mining
- Limitations

Illustrative example of *t*-test with spatial regression aid

Imagine there is a mining company that wants to understand how AI-driven predictive maintenance impacts its operational costs. They have divided their mining sites into two groups: those using AI-driven predictive maintenance (AI Group) and those using traditional methods (Traditional Group). Here is how they might use a *t*-test and spatial regression:

- ***t*-Test Analysis:**

  Metric: Annual Maintenance Costs (in millions).

  Data: The mining company collects data over a year.

  AI Group: $2M, $2.2M, $1.8M, $2.1M, $1.9M (Average: $2.0M).

  Traditional Group: $2.8M, $3.0M, $2.5M, $2.7M, $2.9M (Average: $2.8M).

Hypothesis testing

Null Hypothesis (H0): There is no significant difference in annual maintenance costs between the AI Group and the Traditional Group.

Alternative Hypothesis (H1): The AI Group has significantly lower maintenance costs than the Traditional Group.

t-test results

The *t*-test yields a *t*-statistic of −5.2 and a *p*-value of 0.001.

Interpretation

The *p*-value is less than the significance level ($\alpha = 0.05$), so we reject the null hypothesis. The AI Group shows significantly lower maintenance costs compared to the Traditional Group.

Spatial regression analysis

Variables:

- **Dependent Variable (Y):** Maintenance cost (cost).

Independent Variables (X):

- **AI Adoption (ai_adoption):** 1 if the site uses AI, 0 otherwise.
- **Distance to Equipment Supplier (distance_supplier):** Distance in kilometres.
- **Equipment Age (equipment_age):** Average age of equipment in years.
- **Geological Stability (geological_stability):** Index of site geological stability (1–10).

Model

cost = β0 + β1ai_adoption + β2distance_supplier + β3equipment_age + β4geological_stability + ε

- **Spatial Lag Component:** ε = ρ (average ε of nearby locations) + noise

Ethical considerations

Ethical clearance to conduct this study was obtained from the University of Zambia Biomedical Research Ethics Committee on 10 December 2024 (No. 6030-2024).

Results

- Coefficient for AI Adoption (β1): −0.75 ($p < 0.05$)
- Coefficient for Distance to Supplier (β2): 0.20 ($p < 0.05$)
- Coefficient for Equipment Age (β3): 0.30 ($p < 0.05$)
- Coefficient for Geological Stability (β4): −0.10 ($p < 0.10$)
- Spatial Autocorrelation (ρ): 0.45 ($p < 0.05$)

Interpretation

- **AI Adoption:** Sites using AI have maintenance costs that are approximately $750 000.00 lower than sites without AI, controlling for other variables.
- **Distance to Supplier:** Each additional kilometre from the supplier increases maintenance costs by $200 000, indicating that logistics and part availability are critical factors.
- **Equipment Age:** Each year increase in equipment age increases maintenance costs by $300 000.00.
- **Geological Stability:** More geologically stable sites tend to have slightly lower maintenance costs, although this effect is not as statistically strong ($p < 0.10$).
- **Spatial Autocorrelation:** The value of ρ = 0.45 indicates that maintenance costs at one site are positively correlated with maintenance costs at nearby sites. This could be

because of shared suppliers, similar geological conditions or shared management practices.

Integrating results

- ***t*-Test:** The *t*-test indicates a significant cost reduction with AI adoption.
- **Spatial Regression:** The regression confirms that AI adoption reduces costs even when controlling for other factors. It also highlights the importance of logistics (supplier proximity), equipment age and geological stability, which are not evident from the *t*-test alone.

Summary

The mining company concludes that AI-driven predictive maintenance is effective in reducing maintenance costs. Additionally, they learn that supplier relationships and equipment management strategies are critical.

Discussion

Bridging the gap between potential and reality

The SAPF offers a robust and data-driven approach to enhancing managerial effectiveness and organisational agility in the mining industry. It addresses the limitations of current AI implementations by integrating spatial analysis techniques, providing a more comprehensive and nuanced understanding of the factors influencing mining performance. This allows managers to make more informed decisions, optimise resource allocation and improve overall operational efficiency. This framework moves beyond the theoretical by providing a practical roadmap for implementation. The integration of spatial awareness is not merely an add-on but a fundamental shift in how AI is applied, recognising that mining operations are inherently spatial processes.

The success of the framework hinges on several key factors:

- **Data availability and quality:** Robust data governance policies, standardised data formats and investment in data infrastructure are essential to ensure the availability of high-quality data.
- **Interdisciplinary collaboration:** Effective implementation requires collaboration between data scientists, mining engineers, geologists and IT professionals.
- **Organisational change management:** Adopting the framework requires a shift in organisational culture, promoting data-driven decision-making and fostering a culture of innovation.
- **Ethical considerations:** Transparency, accountability and fairness must be prioritised in the design and deployment of AI systems, addressing concerns related to algorithmic bias, data privacy and workforce displacement.

The implementation of the framework should be phased, starting with pilot projects in specific areas of the mining operation. This allows for iterative refinement and adaptation of the framework to the specific needs of the organisation.

Conclusion

A path towards agile and effective mining

Managerial effectiveness and organisational agility are paramount for success in the increasingly complex and dynamic mining industry. The integration of advanced technologies such as AI offers a powerful means to enhance operational efficiency, improve decision-making and achieve sustainable growth. The SAPF provides a practical roadmap for implementing these technologies, realising their full potential and moving beyond fragmented and spatially unaware applications.

The framework's emphasis on spatial data analysis and integration addresses a critical gap in the current literature, recognising the inherent spatial nature of mining operations. By explicitly incorporating spatial considerations into the data integration, modelling and decision-making processes, the framework enables more informed and effective management of mining resources and operations.

While challenges remain, the potential benefits of the framework are substantial, including increased operational efficiency, improved decision-making, enhanced sustainability and improved safety. By embracing a data-driven and spatially-aware approach, mining companies can enhance their competitiveness, improve their environmental performance and create a safer and more sustainable working environment.

Limitations and future research: Charting the course for continued innovation

This study, while providing a comprehensive overview and a practical framework, is subject to certain limitations that warrant acknowledgement. These limitations also point towards promising avenues for future research:

- **Scope of the literature review:** As previously observed, the systematic review was restricted to English-language articles published between 2019 and 2025. This may have excluded relevant studies published in other languages or prior to this timeframe. Future research should broaden the scope of the literature review to encompass a wider range of sources, including grey literature and industry reports.
- **Generalisability of findings:** The findings of this study are based on a limited number of empirical studies and may not be generalisable to all mining contexts. Future research should conduct more empirical studies to validate the effectiveness of the SAPF in diverse mining contexts, considering different types of mines (surface vs. underground), different geological settings and different operational practices.
- **Data availability and quality:** The availability and quality of data continue to pose significant challenges for the implementation of AI in mining. Future research

should focus on developing methods for improving data quality and accessibility, including the use of data augmentation techniques, federated learning and data sharing initiatives.
- **Lack of longitudinal studies:** The reviewed studies are primarily cross-sectional, providing a snapshot of AI adoption at a particular point in time. Future research should conduct longitudinal studies to track the long-term impact of AI on managerial effectiveness, organisational agility and sustainability performance.
- **Complexity of the mining environment:** The mining environment is complex and influenced by a multitude of factors, many of which are difficult to quantify. Future research should explore the use of qualitative methods to capture the perspectives of mining professionals and gain a deeper understanding of the challenges and opportunities associated with AI adoption.
- **Integration of human factors:** The successful implementation of AI requires careful consideration of human factors, including user acceptance, trust and training. Future research should investigate the impact of AI on worker roles and responsibilities and develop strategies for promoting effective human–AI collaboration.
- **Ethical considerations:** The ethical implications of AI in mining warrant further investigation. Future research should examine issues related to algorithmic bias, data privacy, workforce displacement and the potential for misuse of AI technologies.
- **Development of practical tools and guidelines:** There is a need for practical tools and guidelines to support the implementation of the SAPF. Future research should focus on developing data collection and processing protocols, model selection criteria and decision support systems.
- **Exploration of advanced artificial intelligence techniques:** Future research should explore the application of advanced AI techniques, such as reinforcement learning, generative adversarial networks (GANs) and explainable AI (XAI), to address specific challenges in the mining industry.

Future research should be directed towards:

- Conducting more empirical studies to validate the effectiveness of the SAPF in diverse mining contexts.
- Developing practical tools and guidelines for implementing the framework, including data collection and processing protocols, model selection criteria and decision support systems.
- Investigating the ethical implications of AI in mining, including issues related to data privacy, algorithmic bias and workforce displacement.

Implications for practice: Guiding stakeholders towards responsible innovation

The findings of this study carry significant implications for various stakeholders in the mining ecosystem, including mining companies, government policymakers and technology providers.

Mining companies

- **Strategic investment in artificial intelligence:** Mining companies should prioritise strategic investments in AI technologies, recognising their potential to drive significant improvements in operational efficiency, sustainability and safety.
- **Data-driven culture:** Fostering a data-driven culture is crucial. This involves investing in data infrastructure, developing data governance policies and promoting data literacy throughout the organisation.
- **Skill development and training:** Companies should invest in training and development programmes to build internal expertise in AI and related fields.
- **Pilot projects and phased implementation:** Implementing AI should be approached in a phased manner, starting with pilot projects to demonstrate value and build internal capacity.
- **Collaboration and partnerships:** Collaborating with technology providers, research institutions and other mining companies can accelerate the adoption of AI and share best practices.
- **Ethical considerations:** Companies must address the ethical implications of AI, ensuring transparency, accountability and fairness in the design and deployment of AI systems.

Government policymakers

- **Funding for research and development:** Governments should provide funding for research and development in AI and related fields, supporting innovation and driving technological advancements.
- **Incentives for technology adoption:** Providing incentives for mining companies to adopt AI technologies can accelerate their deployment and promote economic growth.
- **Regulatory frameworks:** Developing regulatory frameworks that promote responsible and ethical use of AI in mining is essential, addressing concerns related to data privacy, algorithmic bias and workforce displacement.
- **Skills development initiatives:** Supporting skills development initiatives to train the workforce in AI and related fields is crucial to ensure a skilled workforce for the future.

Technology providers

- **Tailored solutions for mining:** Technology providers should develop AI solutions that are tailored to the specific needs of the mining industry, addressing its unique challenges and leveraging its unique data assets.
- **Data integration and interoperability:** Solutions should be designed to integrate seamlessly with existing mining

systems and data sources, promoting interoperability and reducing integration costs.

- **User-friendly interfaces:** Solutions should have user-friendly interfaces that are accessible to mining professionals with varying levels of technical expertise.
- **Transparency and explainability:** Transparency and explainability are crucial for building trust and promoting adoption. Technology providers should strive to develop AI models that are interpretable and explainable.
- **Ethical considerations:** Technology providers have a responsibility to ensure that their AI solutions are developed and deployed ethically, addressing concerns related to algorithmic bias, data privacy and workforce displacement.

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CRediT authorship contribution

Talent Gosho: Conceptualisation, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Visualisation, Writing – original draft, Writing – review & editing. Mubanga Mpundu: Supervision. All authors reviewed the article, contributed to the discussion of results, approved the final version for submission and publication, and take responsibility for the integrity of its findings.

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Data availability

The authors declare that all data that support this research article and findings are available in the article and its references.

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