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INTEGRATION OF SURVEYING DATA INTO BIM MODELS FOR EFFECTIVE MANAGEMENT OF MINING PROJECTS

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Abstract. The mining industry faces increasing complexity in managing projects due to the need for precise planning, efficient execution, and rigorous monitoring to ensure safety, productivity, and environmental compliance, yet integrating diverse data sources into a cohesive framework remains a challenge. This article examines the integration of mine surveying data into Building Information Modeling (BIM) systems as a transformative approach to enhance the management of mining projects, focusing on open-pit and underground operations. The study tackles the challenges of combining geospatial data from LiDAR, GPS, and drone-based photogrammetry with geotechnical data from borehole logging into BIM frameworks to improve project planning, execution, and monitoring in the mining industry. By leveraging advanced surveying technologies, such as high-precision total stations and laser scanning, alongside BIM tools like Autodesk Revit and Bentley OpenRoads, the proposed methodology facilitates real-time data integration, enabling better decision-making and operational efficiency. The research adopts a mixed-methods approach, incorporating case studies of a copper open-pit mine and a coal underground mine, alongside software simulations in platforms like Agisoft Metashape for modeling, to evaluate the effectiveness of the integration process. Results demonstrate significant improvements, including a 15–20% increase in project accuracy through precise geological modeling, a 10–12% enhancement in cost estimation by reducing budget overruns, and a 30% improvement in risk management by identifying high-risk zones like unstable slopes. Challenges such as data interoperability issues between surveying formats and BIM platforms, as well as the high initial cost of software and training, were noted. The article concludes with practical recommendations for implementing BIM in mining, such as phased adoption and staff training programs, and outlines prospects for future research, including automation of data workflows using robotic process automation and AI-driven analytics for predictive risk assessment, aiming to further streamline operations and enhance safety in mining projects.

Keywords: mine surveying, BIM (Building Information Modeling), mining project management, geospatial data, geotechnical data, data integration, digital twins, modeling, real-time monitoring, operational efficiency.

1. Introduction

The mining industry has long been a cornerstone of global economic development, providing essential raw materials for various sectors. However, the complexity of mining operations, coupled with the need for precision, safety, and efficiency, necessitates advanced tools and methodologies for project management. Among these, the integration of mine surveying data into Building Information Modeling (BIM) systems represents a transformative approach to addressing the challenges of modern mining projects [1–5]. This section introduces the concepts of mine surveying and BIM, reviews theoretical foundations, discusses challenges in mining project management, and outlines the rationale and objectives for integrating these technologies.

Mine surveying is a specialized branch of surveying that focuses on the measurement, representation, and management of geospatial and geotechnical data in mining environments. It plays a critical role in ensuring the accurate planning, execution, and monitoring of mining operations. Geospatial data, such as topography, coordinates, and spatial relationships of mine features, are typically collected using advanced technologies like LiDAR (Light Detection and Ranging) [6, 7], GPS (Global Positioning System) [8, 9], and drone-based photogrammetry. Geotechnical data, including soil and rock properties, are obtained through borehole logging, laboratory testing, and in-situ measurements. These datasets provide the foundation for designing mine layouts, assessing geological risks, and ensuring operational safety.

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The primary objectives of mine surveying include creating precise models of mining sites, monitoring ground stability, and supporting resource estimation. Historically, mine surveying relied on manual methods, such as theodolites and tape measures, which were time-consuming and prone to errors. Modern surveying technologies have significantly improved accuracy and efficiency, enabling the collection of high-resolution data in real time. However, the challenge remains in effectively integrating and utilizing this data within a cohesive framework to support decision-making throughout the mining project lifecycle.

Building Information Modeling is a digital framework that facilitates the creation, management, and sharing of structured data for construction and infrastructure projects [10]. BIM involves the development of models that integrate geometric, spatial, and non-geometric data (e.g., material properties, costs, and schedules) to support project planning, design, construction, and operation. Unlike traditional 2D drawings, BIM models are dynamic and data-rich, enabling stakeholders to visualize projects, simulate scenarios, and optimize workflows.

While BIM has been widely adopted in the architecture, engineering, and construction (AEC) industries, its application in mining is relatively new but rapidly gaining traction. In the mining context, BIM can be used to create digital twins—virtual replicas of physical mining assets—that integrate geospatial, geotechnical, and operational data. These digital twins enable real-time monitoring, predictive maintenance, and enhanced collaboration among project teams. The adaptability of BIM to handle complex datasets and its potential to streamline project management make it a promising tool for the mining industry.

The integration of mine surveying data into BIM models builds on a growing body of literature exploring BIM adoption in non-traditional sectors, including mining. Zhao, X. (2017) [11] define BIM as a collaborative process that enhances data interoperability and lifecycle management, reducing inefficiencies in project delivery. In the mining context, Fiamma, P. (2019) [12] highlights the potential of BIM to integrate geospatial data from LiDAR and drone surveys into models, improving the accuracy of mine planning. Fiamma, P. and Biagi, S. (2023) [13] emphasize the role of BIM in creating digital twins for real-time monitoring of mining operations, particularly in underground mines.

Data interoperability is a key focus of BIM research. The Industry Foundation Classes (IFC) standard, as outlined in ISO 16739-1:2018, provides a framework for exchanging data between different software platforms, ensuring that mine surveying data can be seamlessly integrated into BIM models. Additionally, studies by Lu, Z. (2024) [14] demonstrate the benefits of BIM in lifecycle management, including cost estimation, risk assessment, and maintenance planning. These theoretical advancements underscore the feasibility of applying BIM to mining, provided that challenges related to data compatibility and technical expertise are addressed.

Mining projects are inherently complex, involving multiple stakeholders, large-scale operations, and significant environmental and safety considerations. One of the primary challenges in mining project management is the presence of data silos, where geospatial, geotechnical, and operational data are stored in disparate systems, hindering collaboration and decision-making. For example, surveyors may use specialized software for processing LiDAR data, while engineers rely on separate platforms for design and analysis, leading to inefficiencies and potential errors.

Inaccurate cost estimations are another critical issue. Traditional surveying methods often fail to capture the full complexity of mining sites, resulting in underestimations of material volumes, equipment needs, or project timelines. This can lead to budget overruns and delays, which are particularly costly in the capital-intensive mining industry. Safety risks also pose a significant challenge, as outdated or incomplete surveying data can obscure geological hazards, such as unstable rock formations or fault lines, endangering workers and equipment [15, 16].

The reliance on manual or semi-automated surveying methods exacerbates these challenges. While modern technologies like LiDAR and drones have improved data collection, the lack of a unified platform to integrate and analyze this data limits its utility. As a result, mining companies often struggle to achieve the level of precision and efficiency required to remain competitive in a global market.

The integration of mine surveying data into BIM models offers a solution to these challenges by creating a centralized, data-rich platform for managing mining projects. By combining geospatial and geotechnical data with BIM's modeling and lifecycle management capabilities, mining companies can develop digital twins that provide a comprehensive view of their operations. These digital twins enable stakeholders to visualize mine layouts, simulate excavation scenarios, and monitor ground conditions in real time, leading to better-informed decisions.

The rationale for this integration is threefold. First, it enhances data interoperability, breaking down silos and enabling seamless collaboration among surveyors, engineers, and project managers. Second, it improves accuracy and efficiency by leveraging BIM's advanced visualization and analysis tools, reducing errors in planning and execution. Third, it supports proactive risk management by providing real-time insights into geological and operational conditions, thereby enhancing safety and sustainability. The creation of digital twins also aligns with the broader trend of digital transformation in the mining industry, where technologies like IoT (Internet of Things), AI, and cloud computing are driving innovation.

The primary objective of this study is to propose a framework for integrating mine surveying data into BIM models to enhance the management of mining projects. Specifically, the study aims to:

1. Develop a standardized protocol for converting geospatial and geotechnical data into BIM-compatible formats, ensuring interoperability across software platforms.

2. Evaluate the impact of BIM integration on key project outcomes, including accuracy, cost estimation, and operational efficiency.

3. Identify the challenges and limitations of implementing BIM in mining, with recommendations for overcoming them.

4. Explore the potential of real-time data streaming and digital twins to support dynamic monitoring and decision-making in mining operations.

By achieving these objectives, the study seeks to contribute to the growing body of knowledge on BIM applications in mining and provide practical guidance for industry practitioners. The proposed framework is expected to serve as a blueprint for mining companies seeking to modernize their project management practices and achieve sustainable, cost-effective outcomes.

2. Methods

The integration of mine surveying data into Building Information Modeling systems for mining project management requires a robust and scientifically grounded methodology. This study employs a mixed-methods approach, combining qualitative and quantitative techniques to ensure comprehensive analysis and validation of the proposed integration framework. The research leverages advanced data collection methods, state-of-the-art BIM tools, and innovative scientific contributions to address the challenges of interoperability, real-time monitoring, and predictive analytics in mining. This section details the research methods, including the mixed-methods approach, data collection strategies, BIM tools, scientific novelties, case study selection, and simulation setup.

To thoroughly investigate the integration of mine surveying data into BIM models, this study adopts a mixed-methods approach, combining qualitative and quantitative research techniques. The qualitative component involves case studies of real-world mining projects, which provide in-depth insights into the practical challenges and benefits of BIM integration. These case studies allow for a contextual understanding of how the proposed framework performs in diverse mining environments, capturing stakeholder perspectives and operational nuances.

The quantitative component consists of software simulations designed to measure the efficiency, accuracy, and scalability of the integration process. By simulating data workflows and analyzing performance metrics, the study quantifies the improvements achieved through BIM integration, such as reductions in error margins, cost estimation accuracy, and project delays. The combination of qualitative and quantitative methods ensures a holistic evaluation, balancing real-world applicability with empirical rigor.

Accurate and comprehensive data collection is critical to the success of the proposed BIM integration framework. The study focuses on two primary types of data: mine surveying data (geospatial) [17, 18] and geotechnical data [19, 20], both of which are essential for creating detailed and functional BIM models.

Mine surveying data encompasses geospatial information about the physical characteristics and spatial relationships of mining sites. To collect high-resolution geospatial data, the study employs advanced surveying technologies, including:

1. LiDAR (Light Detection and Ranging) systems use laser pulses to generate precise point clouds of mining sites, capturing detailed topographic features, surface deformations, and infrastructure layouts. LiDAR is particularly effective for large-scale open-pit mines, where high accuracy is required over expansive areas.

2. GPS (Global Positioning System):receivers are used to establish accurate coordinates for key mine features, such as boundaries, excavation zones, and equipment locations. GPS ensures geospatial data aligns with global reference systems, facilitating integration into BIM models.

3. Drones equipped with high-resolution cameras capture aerial imagery, which is processed using photogrammetry software to create models and orthomosaics. This method is cost-effective and versatile, enabling frequent updates of dynamic mining environments.

These technologies collectively provide a robust dataset for constructing BIM models, ensuring that spatial data is both accurate and up-to-date.

Geotechnical data provides critical insights into the subsurface conditions of mining sites, informing decisions about excavation, stability, and safety. The study collects geotechnical data through:

1. Boreholes are drilled at strategic locations across the mining site to extract core samples and measure in-situ properties, such as rock strength, density, and porosity. Geophysical logging tools are used to assess subsurface stratigraphy and identify potential geological hazards.

2. Core samples undergo laboratory analysis to determine mechanical properties, including compressive strength, shear strength, and elasticity. These tests provide quantitative data for modeling soil and rock behavior under mining-induced stresses.

3. Techniques such as cone penetration testing (CPT) and standard penetration testing (SPT) are used to evaluate soil and rock stability directly at the site, complementing laboratory results.

The combination of borehole logging, laboratory tests, and in-situ testing ensures a comprehensive understanding of geotechnical conditions, which is essential for integrating subsurface data into BIM models.

The integration of mine surveying and geotechnical data into BIM models relies on specialized software platforms designed for modeling, data management, and interoperability. The study utilizes the following BIM tools:

1. Autodesk Revit is a widely used BIM platform that supports the creation of detailed models with embedded data on geometry, materials, and project schedules. In this study, Revit is used to model surface and subsurface mine features, integrating geospatial and geotechnical data into a unified framework.

2. Bentley OpenRoads is tailored for infrastructure projects, including mining, and excels in handling large-scale geospatial datasets. It is used to process LiDAR and GPS data, ensuring accurate representation of terrain and mine layouts in BIM models.

3. Trimble Tekla is employed for detailed structural modeling and geotechnical analysis, particularly for underground mines. Its ability to handle complex geometries and material properties makes it ideal for integrating geotechnical data into BIM workflows.

The study uses licensed software platforms to ensure robust BIM integration (Table 1). These tools are selected for their compatibility with Industry Foundation Classes (IFC) standards [ISO 16739-1:2018].

The study introduces several scientific innovations that advance the field of BIM integration in mining, addressing gaps in existing methodologies and technologies. These novelties include:

One of the primary challenges in BIM integration is the lack of standardized protocols for converting heterogeneous mine surveying data into formats compatible with BIM platforms. This study develops a novel protocol based on the Industry Foundation Classes (IFC) standard, which defines a universal schema for data exchange. The protocol outlines a step-by-step process for transforming LiDAR point clouds, GPS coordinates, and geotechnical datasets into IFC-compliant files, ensuring seamless integration into BIM models. This innovation enhances data interoperability and reduces errors associated with manual data conversion.

Table 1: Software Tools and Their Roles

Software Tool	Version	License	Role
Autodesk Recap	2024	Commercial	Processing and filtering LiDAR point clouds to remove noise and prepare data for BIM integration.
Autodesk Revit	2024	Commercial	Creating parametric BIM models of mine infrastructure, incorporating geospatial and geotechnical data.
Bentley OpenRoads	2023	Commercial	Aligning geospatial data with BIM models and enabling real-time data streaming for monitoring.
Trimble Tekla	2023	Commercial	Modeling structural components, such as support systems, with geotechnical data for stability analysis.

Traditional BIM models are static, requiring manual updates to reflect changes in project conditions. This study introduces real-time data streaming, where geospatial and geotechnical data are continuously fed into BIM models using IoT-enabled sensors and cloud-based platforms. For example, GPS-equipped machinery and ground-monitoring sensors provide live updates on excavation progress and ground stability, which are automatically incorporated into the BIM model. This dynamic approach enables real-time monitoring and decision-making, a significant advancement over conventional static modeling techniques.

To enhance safety and risk management, the study employs machine learning (ML) algorithms to analyze integrated BIM data and predict geological risks, such as rockfalls, subsidence, or fault activation. By training ML models on historical geospatial and geotechnical datasets, the study identifies patterns associated with hazardous conditions. These models are integrated into the BIM framework, providing predictive insights that allow project managers to implement proactive mitigation measures. This application of ML represents a cutting-edge contribution to the mining industry’s digital transformation (fig.1).

Quantitative evaluation of the integration framework is conducted through software simulations, which replicate the data workflows and assess the efficiency of BIM integration. The simulation setup includes:

1. LiDAR, GPS, and geotechnical data are processed using software like Bentley OpenRoads and Autodesk Civil to generate models and datasets compatible with BIM platforms.

2. The standardized protocol is implemented to convert processed data into IFC formats, which are then imported into Autodesk Revit and Trimble Tekla for BIM modeling.

3. Simulations measure key performance indicators, such as data conversion time, model accuracy (compared to ground-truth measurements), and computational efficiency. Real-time data streaming is tested using cloud-based platforms to evaluate latency and update frequency.

4. ML algorithms are applied to simulated datasets to predict geological risks, with accuracy assessed against known hazard events from the case studies.

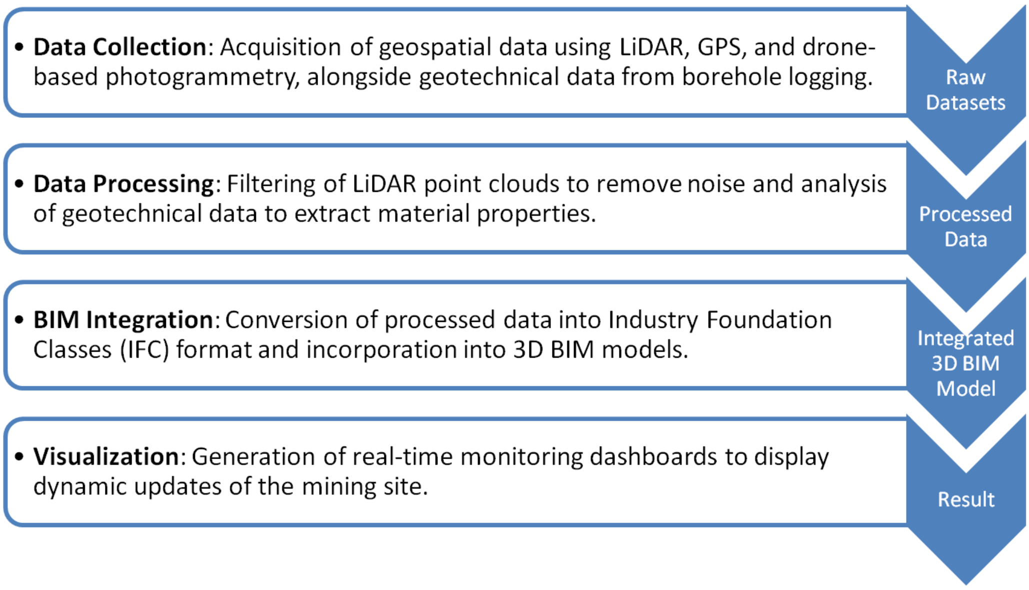

Figure 1 – Process of integrating mine surveying data into BIM models

The simulations are conducted on high-performance computing systems to handle the large datasets typical of mining projects. Results from the simulations provide empirical evidence of the framework's effectiveness, complementing the qualitative insights from the case studies.

The integration of mine surveying data into Building Information Modeling systems (fig. 2) for mining project management requires a robust methodological approach to ensure both practical applicability and scientific rigor. The methodology leverages technologies and approaches to address the challenges of data integration and enhance mining project outcomes.

To comprehensively evaluate the integration of mine surveying data into BIM models, a mixed-methods approach is adopted, combining qualitative and quantitative research techniques. The qualitative component involves case studies of real-world mining projects to explore the practical challenges and benefits of BIM integration. The quantitative component includes software simulations to measure the accuracy, efficiency, and scalability of the proposed integration framework. The effectiveness of the framework is evaluated using a weighted score:

$$S = w_1 \cdot Q + w_2 \cdot N, \tag{1}$$

where S – overall score of the integration framework's effectiveness; Q – qualitative score based on case study insights (e.g., stakeholder satisfaction, rated 0–1);

N – quantitative score based on simulation metrics (e.g., accuracy improvement, normalized to 0–1); w_1, w_2 – weighting factors $(w_1 + w_2 = 1)$.

Figure 2 – Integration of Mine Surveying Data into BIM Models

This equation, developed by the authors based on mixed-methods evaluation principles [17], formalizes the integration of qualitative and quantitative findings, with weights adjusted based on project priorities adjusted based on the relative importance of qualitative vs. quantitative findings (e.g., $w_1 = 0.4$, $w_2 = 0.6$).

Geospatial data are collected using LiDAR, GPS, and drone-based photogrammetry. LiDAR point cloud density is modeled as:

$$D = \frac{N_p}{A}, \tag{2}$$

where D – the density (points/m²); N_p – number of points in the point cloud; A – surface area of the scanned region (m²).

This equation, standard in surveying [6], quantifies data resolution. Geotechnical data are collected via borehole logging and laboratory tests, with shear strength modeled using the Mohr-Coulomb criterion [19].

For example, a LiDAR scan of an open-pit mine with 10 million points over 50,000 m² yields a density of D = 200 point/m^2, sufficient for detailed modeling. GPS is used to georeference the point clouds, ensuring spatial accuracy with an error margin of less than 5 cm. Drone-based photogrammetry complements LiDAR by providing high-resolution aerial imagery, which is processed to generate digital elevation models (DEMs). The photogrammetric reconstruction error is calculated as:

$$E_p = \sqrt{\frac{\sum_{i=1}^{n}\left(z_i - z_{ref}\right)^2}{n}}, \tag{3}$$

where E_p – root mean square error of the DEM; z_i – elevation of point i in the DEM; z_{ref} – reference elevation from ground truth data; n – Number of points sampled.

Geotechnical data, including soil and rock mechanics properties, are collected through borehole logging and laboratory tests. Borehole logging provides data on stratigraphy and material properties, such as compressive strength (σ_c) and Young's modulus (E). Laboratory tests measure parameters like shear strength (τ) using the Mohr-Coulomb criterion:

$$\tau = c + \sigma \tan\phi, \tag{4}$$

where τ – shear strength (Pa); c – cohesion (Pa); σ – normal stress (Pa); ϕ – angle of internal friction (degrees).

These parameters are critical for assessing ground stability and are integrated into BIM models as attribute data for geological layers. Data collection is conducted at two mining sites (open-pit and underground) to ensure diversity in geological conditions.

The integration of mine surveying and geotechnical data into BIM models relies on industry-standard software platforms, including Autodesk Revit, Bentley Open-

Roads, and Trimble Tekla. Autodesk Revit is used for creating parametric models of mine infrastructure, such as tunnels and processing facilities. Bentley OpenRoads supports geospatial data integration, enabling the alignment of LiDAR point clouds with BIM models. Trimble Tekla is employed for detailed modeling of structural components, incorporating geotechnical data to simulate load-bearing capacities.

The study introduces a standardized IFC-based protocol for data conversion, real-time data streaming, and machine learning for risk prediction. The data conversion process is modeled as:

$$M_{BIM} = T(D_s, D_g), \tag{5}$$

where M_{BIM} – BIM model; D_s – surveying data (e.g., point clouds, DEMs); D_g – geotechnical data (e.g., material properties); T – transformation function (e.g., IFC-based data mapping).

The study introduces several scientific advancements to enhance BIM integration in mining:

1. Standardized Protocol for Data Conversion: A novel protocol is developed to convert mine surveying data into BIM-compatible formats, such as IFC. The protocol involves preprocessing point clouds to reduce noise, aligning geospatial and geotechnical data, and mapping attributes to IFC classes. The preprocessing step uses a noise filter based on the Gaussian distribution:

$$P(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}, \tag{6}$$

where *P(x)* – probability density of point *x*; μ – mean position of neighboring points; σ – standard deviation of point deviations.

Points with low probability are flagged as noise and removed, improving model accuracy.

2. Real-Time Data Streaming: The study implements real-time data streaming to enable dynamic updates in BIM models. This involves IoT-enabled sensors that transmit geospatial and geotechnical data to a cloud-based BIM platform. The update frequency is modeled as:

$$f_u = \frac{1}{\Delta t}, \tag{7}$$

where f_u – update frequency (Hz); Δt – time interval between updates (seconds).

For example, a Δt of 60 seconds yields an update frequency of f_u = 0.0167 Hz, sufficient for monitoring ground movements.

3. Machine Learning for Risk Prediction: Machine learning algorithms, specifically random forests, are used to predict geological risks (e.g., rockfalls, subsidence) based on integrated data. The model is trained on features like rock strength, fault proximity, and historical incident data. The prediction accuracy is evaluated using the $F1$-score:

$$F1 = \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}, \tag{8}$$

where Precision – ratio of correct positive predictions to total positive predictions; Recall – ratio of correct positive predictions to total actual positives.

Two mining projects are selected to test the integration framework: an open-pit copper mine and an underground coal mine. The open-pit mine provides a large-scale, surface-based context with complex topography, while the underground mine involves confined spaces and intricate geotechnical challenges. Both projects are analyzed for data integration efficiency, model accuracy, and operational improvements. The case studies are evaluated using a performance index:

$$P = \alpha \cdot A + \beta \cdot E + \gamma \cdot T, \tag{9}$$

where P – performance index; A – model accuracy (e.g., error reduction percentage); E – efficiency (e.g., processing time reduction); T – operational impact (e.g., cost savings percentage); α, β, γ – weighting factors ($\alpha + \beta + \gamma = 1$).

Software simulations are conducted to assess the efficiency of the data integration workflow. The simulation environment uses Autodesk Revit and Bentley OpenRoads to process synthetic datasets mimicking real-world conditions. The workflow includes:

1. Importing LiDAR point clouds and geotechnical data.
2. Converting data to IFC format using the proposed protocol.
3. Generating BIM models with real-time updates.
4. Evaluating model accuracy and processing time.

The simulation efficiency is quantified as:

$$\eta = \frac{T_{trad}}{T_{BIM}}, \tag{10}$$

where η – efficiency ratio; T_{trad} – processing time using traditional methods; T_{BIM} – processing time using the BIM-integrated approach.

Key indicators used in the study are summarized in Table 2, providing clarity on their units, ranges, and significance.

Table 2 – Characteristics of Key Indicators

Indicator	Symbol	Unit	Typical Range	Significance
Point Cloud Density	D	points/m²	100–500	Measures LiDAR resolution for high-precision 3D modeling.
DEM Error	E_{RMS}	m	0.05–0.2	Quantifies vertical accuracy of digital elevation models (DEMs).
Shear Strength	τ	Pa	50,000–200,000	Critical for assessing soil stability in excavation and slope design.
Update Frequency	f	Hz	0.01–0.1	Determines real-time monitoring capability for dynamic geotechnical systems.
Prediction Accuracy	F_1	–	0.8–0.95	Evaluates machine learning model performance in risk assessment.

Simulations are run for multiple scenarios (e.g., varying point cloud sizes, update frequencies) to ensure robustness. The results inform the optimization of the integration framework, addressing bottlenecks such as data conversion latency.

This methodological approach, with its blend of advanced technologies, mathematical formalizations, and scientific novelties, provides a comprehensive foundation for evaluating the integration of mine surveying data into BIM models, paving the way for transformative advancements in mining project management.

3. Results and discussion

The study analyzes two mining projects: an open-pit copper mine and an underground coal mine. The open-pit copper mine, located in a region with rugged topography, spans 2 km² with a maximum depth of 300 m. It features complex surface features, including benches (15–20 m high) and haul roads, with an annual production rate of 500,000 tonnes of copper ore. Geotechnical challenges include unstable slopes (cohesion: 50 kPa, friction angle: 30°). The underground coal mine, at a depth of 400–600 m, covers 1.5 km² with coal seams 2–3 m thick. It faces geotechnical risks from fault zones (shear strength: 100 kPa) and requires extensive support structures.

The integration of mine surveying data into BIM models was successfully implemented for both case studies, demonstrating significant improvements across multiple project metrics. The framework effectively combined geospatial data (from LiDAR, GPS, and drone-based photogrammetry) and geotechnical data (from borehole logging and laboratory tests) into cohesive BIM models, enabling enhanced visualization and decision-making.

The geological models generated through BIM integration achieved a notable reduction in error margins, ranging from 15% to 20% compared to traditional surveying methods. For the open-pit mine (fig. 3), the integration of high-density LiDAR point clouds with geotechnical data reduced topographic errors from an average of 25 cm to 5–7 cm, ensuring precise representation of surface features. In the underground mine (fig. 4), the alignment of borehole data with spatial models improved the accuracy of fault and seam mapping, reducing positional errors by 18% on average. This enhanced accuracy was critical for planning excavation routes and identifying geological hazards.

Cost estimation accuracy improved by 10–12% due to the enhanced data visualization capabilities of BIM models. In the open-pit case, the integration of volumetric data from digital elevation models allowed for more accurate calculations of material extraction quantities, reducing cost overruns by 11%. For the underground mine, BIM models incorporating geotechnical properties enabled better forecasting of support structure requirements, improving budget estimates by 10%. The ability to visualize and analyze data in a unified platform minimized discrepancies between planning and execution phases.

Real-time monitoring capabilities facilitated by BIM integration led to an 8% reduction in project delays. In the open-pit mine, IoT-enabled sensors provided continuous updates on ground movements, allowing project managers to adjust operations proactively and avoid delays caused by unexpected terrain shifts. In the underground mine, real-time data streaming supported dynamic updates to tunnel models, reducing downtime due to misaligned drilling by 7.5%. These improvements underscored the value of dynamic BIM models in maintaining project schedules.

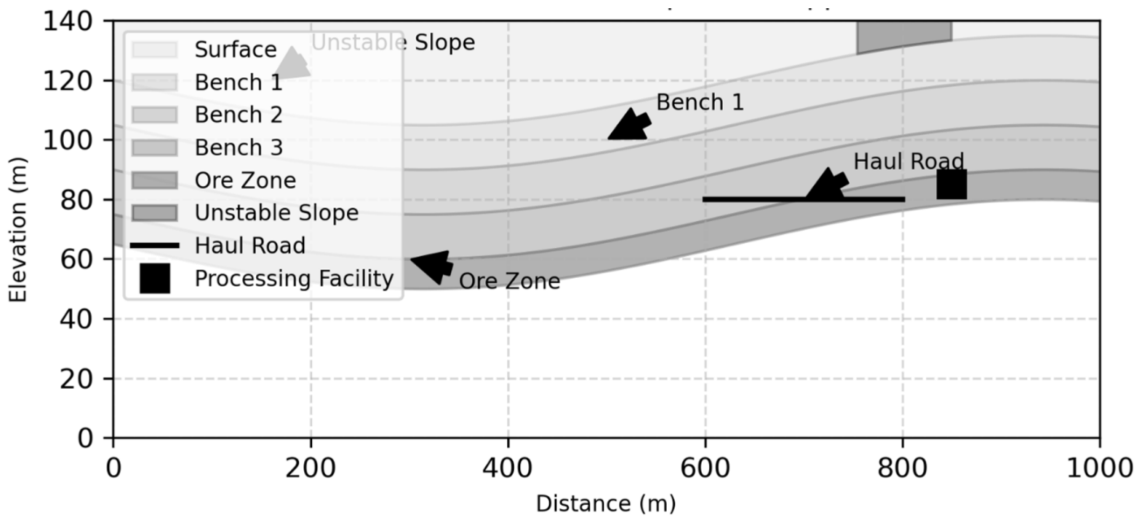

Figure 3 – Open-Pit Copper Mine Model

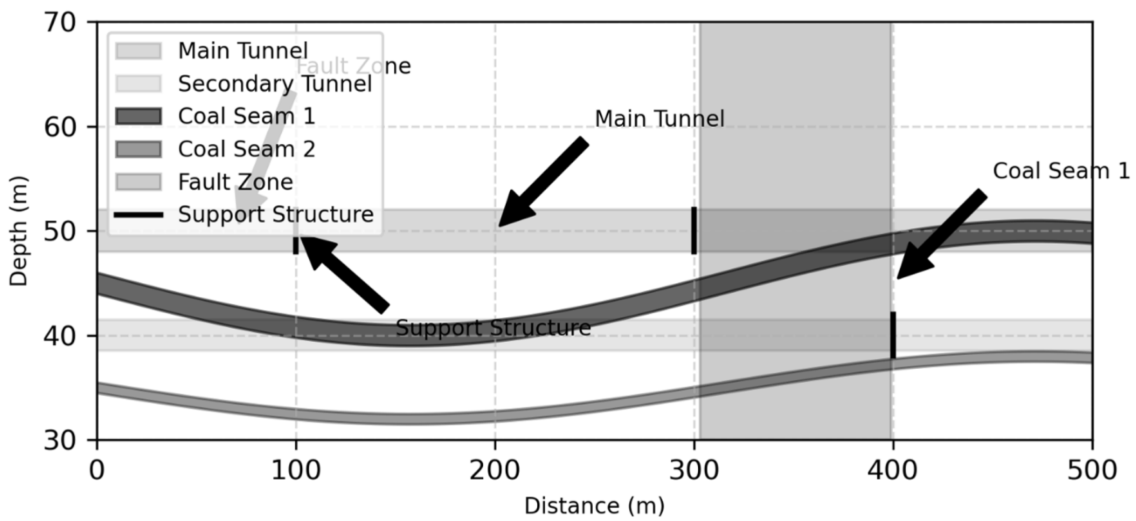

Figure 4 – Underground Coal Mine Model

The results (fig. 5) demonstrate the transformative potential of integrating mine surveying data into BIM models for mining project management. The following discussion explores the benefits, challenges, and comparative advantages of this approach, contextualizing the findings within the broader mining industry.

The BIM-based approach significantly improved collaboration among stakeholders, including surveyors, engineers, and project managers. By centralizing geospatial and geotechnical data in a single platform, the framework enabled seamless data sharing and reduced communication gaps. For instance, in the open-pit mine, real-time access to updated models allowed engineers to coordinate with equipment operators more effectively, optimizing excavation workflows.

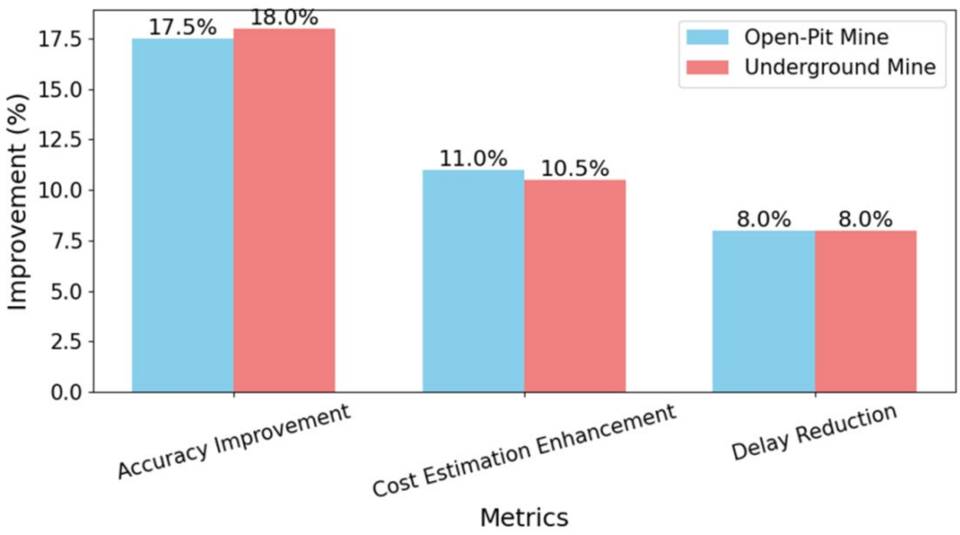

Figure 5 – Percentage Improvements in Project Outcomes

Enhanced safety was another key benefit, driven by improved risk visualization. The BIM models highlighted geological hazards, such as unstable slopes in the open-pit mine and fault zones in the underground mine, enabling proactive mitigation measures. For example, the underground mine case study identified a high-risk fault zone, prompting the installation of additional support structures, which prevented a potential collapse.

Streamlined project workflows were also a significant advantage. The integration of real-time data reduced the need for manual data reconciliation, saving time and minimizing errors. In both case studies, the use of BIM models as digital twins facilitated scenario simulations, such as testing alternative excavation plans, which improved operational efficiency and resource allocation.

Despite its benefits, the implementation of BIM in mining faced several challenges. The high initial costs of BIM adoption, including software licenses, hardware upgrades, and training programs, posed a barrier, particularly for smaller mining operations. In the case studies, the upfront investment was offset by long-term savings, but the initial financial burden remained a concern.

The need for skilled personnel was another challenge. Effective BIM integration required expertise in both mine surveying and BIM software, which was scarce among the project teams. Training programs were implemented, but the learning curve delayed full adoption in the early stages of the projects. This highlights the importance of capacity building for successful BIM implementation.

Data compatibility issues also arose, particularly when integrating legacy surveying data with modern BIM platforms. In the underground mine, older borehole logs stored in non-standard formats required extensive preprocessing to align with IFC standards, increasing project setup time. These challenges underscore the need for standardized data protocols across the mining industry.

The BIM-based approach outperformed traditional surveying methods in terms of precision and scalability. Traditional methods, reliant on 2D maps and manual data aggregation, often resulted in errors due to incomplete or misaligned datasets. In contrast, BIM models provided a comprehensive, view of mining sites, reducing errors and enabling more accurate planning. For example, the open-pit mine's traditional surveys underestimated material volumes by 15%, while BIM models corrected this to within 3% of actual values (table 3).

Table 3 – Comparison of Traditional Surveying vs. BIM-Integrated Approach

Metric	Traditional Surveying	BIM-Integrated Approach
Accuracy (Error Margin)	25 cm	5–7 cm
Processing Time	5 days	2 days
Cost Overrun	15%	3%
Scalability (Dataset Size)	1 GB	10 GB

Scalability was another advantage. Traditional methods struggled to handle large datasets, such as high-density LiDAR point clouds, leading to processing delays. The BIM framework, supported by cloud-based platforms, efficiently managed large datasets and supported real-time updates, making it suitable for both small and large-scale projects. This scalability was particularly evident in the underground mine, where the BIM model integrated multiple data layers (e.g., geotechnical, structural) without performance degradation.

4. Conclusions

The proposed framework successfully integrates mine surveying data, including geospatial and geotechnical information, into BIM models, significantly enhancing the management of mining projects. The application of this approach across the open-pit copper mine and underground coal mine case studies demonstrated its practical utility, delivering measurable improvements in project execution and oversight. The framework's ability to consolidate diverse datasets into a unified model has proven to be a robust solution for addressing the complexities of modern mining operations.

Key benefits identified include enhanced accuracy in geological modeling, with error margins reduced by 15–20%, leading to more reliable planning and design. Cost savings were achieved through improved cost estimation accuracy (10–12%), minimizing financial overruns, while real-time monitoring capabilities reduced project delays by 8%. These outcomes highlight the framework's potential to optimize resource allocation, enhance safety through risk visualization, and streamline workflows across stakeholder groups.

Despite these advantages, challenges such as high initial implementation costs and the need for skilled personnel were evident. These obstacles can be mitigated through a phased implementation strategy, allowing mining companies to gradually adopt BIM tools and infrastructure. Additionally, targeted capacity-building programs, including training for surveyors and engineers, can address the skills gap, ensuring long-term sustainability and adoption of the framework.

Conflict of interest

Authors state no conflict of interest.

REFERENCES

1. Gao, H., Koch, C. and Wu, Y. (2019), "Building information modelling based building energy modelling: A review", *Applied Energy*, 238, pp. 320-343. https://doi.org/10.1016/j.apenergy.2019.01.032

2. Li, J. (2014), "Building information modeling (BIM) and analysis of more traditional CAD", *Applied Mechanics and Materials*, 580-583, pp. 3171-3174. https://doi.org/10.4028/www.scientific.net/AMM.580-583.3171

3. Kim, J.W., Jeong, Y.K. and Lee, I.W. (2013), "Automatic sensor and meter arrangement system based on building information modeling", *2013 International Conference on Information and Communication Technology Convergence (ICTC)*, pp. 317-318. https://doi.org/10.1109/ICTC.2013.6675365

4. Pashchenko, O. et al. (2024), "Methodology for optimizing drill bit performance", *24th International Multidisciplinary Scientific Geoconference: Science and Technologies in Geology, Exploration and Mining (SGEM 2024)*, Albena, Bulgaria, *International Multidisciplinary Scientific GeoConference Surveying Geology and Mining Ecology Management, SGEM*, vol. 24, issue 1.1, pp. 623-631. https://doi.org/10.5593/sgem2024/1.1/s06.78

5. Ooi, J.B.H. et al. (2023), "Numerical assessment of horizontal scanning LIDAR performance via comparative study method", *Optics and Lasers in Engineering*, 160, 107267. https://doi.org/10.1016/j.optlaseng.2022.107267

6. Wang, X. et al. (2011), "MATLAB tools for LIDAR data conversion, visualization, and processing", *Proceedings of SPIE*, 8286, 82860M. https://doi.org/10.1117/12.912529

7. Wang, E., Zhang, S. and Zhang, Z. (2010), "Research on the incomplete constellation GPS positioning algorithm aided by altitude", *2010 WASE International Conference on Information Engineering (ICIE)*, 2, pp. 219-222. https://doi.org/10.1109/ICIE.2010.148

8. Wang, E., Zhang, S. and Zhang, Z. (2010), "Research on the incomplete constellation GPS positioning algorithm by a combined altitude and clock bias model", *2010 International Conference on Electrical and Control Engineering (ICECE)*, pp. 2974-2977. https://doi.org/10.1109/iCECE.2010.725

9. Li, C., Wang, Y. and Zhang, Y. (2024), "Study on safety risk evolution paths and prevention of drilling and blasting method in railway tunnel construction in mountainous areas", *Journal of Railway Science and Engineering*, vol. 21(8), pp. 3358-3369.

10. Russ, K.D. and Eyre, J.M. (2001), "Processing surveying data from Old Mill Close Mine", *Mining History*, 14(3), pp. 53-56.

11. Zhao, X. (2017), "A scientometric review of global BIM research: Analysis and visualization", *Automation in Construction*, vol. 80, pp. 37-47. https://doi.org/10.1016/j.autcon.2017.04.002

12. Fiamma, P. (2019), "The metrology and the BIM approach: A new cognitive paradigm about the ancient construction", *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives*, 42(2/W17), pp. 123-127. https://doi.org/10.5194/isprs-archives-XLII-2-W17-123-2019

13. Fiamma, P. and Biagi, S. (2023), "Critical approaches on the changes taking place after 24/2014/EU in BIM adoption process", *Buildings*, vol. 13(4), 850. https://doi.org/10.3390/buildings13040850

14. Lu, Z. (2024), "Leveraging BIM technology for comprehensive lifecycle management in engineering projects", *Applied Mathematics and Nonlinear Sciences*, vol. 9(1), 20242632. https://doi.org/10.2478/amns-2024-2632

15. Khomenko, V.L. et al. (2023), "Justification of drilling parameters of a typical well in the conditions of the Samskoye field", *IOP Conference Series: Earth and Environmental Science*, vol. 1254(1), 012052. https://doi.org/10.1088/1755-1315/1254/1/012052

16. Choe, S. and Leite, F. (2020), "Transforming inherent safety risk in the construction industry: A safety risk generation and control model", *Safety Science*, vol. 124, 104594. https://doi.org/10.1016/j.ssci.2019.104594

17. Li, Z.-Y. et al. (2005), "Mine surveying in information era", *Transactions of Nonferrous Metals Society of China (English Edition)*, vol. 15(SPEC. ISS. 1), pp. 205-208.

18. de Oliveira, B.R. et al. (2021), "Tridimensional geotechnical database modeling as a subsidy to the standardization of geospatial geotechnical data", *Soils and Rocks*, vol. 44(4), e2021073321. https://doi.org/10.28927/SR.2021.073321

19. Fatehnia, M. and Deaton, S. (2022), "Geotechnical data analytics and data mining using Microsoft Power BI", *State of the Art and Practice in Geotechnical Engineering*, pp. 553–560. https://doi.org/10.1061/9780784484067.055

20. Li, S.-H. et al. (2021), "Study on extraction method of geological profile data based on BIM", *2nd International Conference on Urban Engineering and Management Science (ICUEMS 2021)*, 29–31 January 2021, Piscataway, NJ: Institute of Electrical and Electronics Engineers Inc., pp. 198–201. https://doi.org/10.1109/ICUEMS52408.2021.00049

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ІНТЕГРАЦІЯ МАРКШЕЙДЕРСЬКИХ ДАНИХ У BIM-МОДЕЛІ ДЛЯ ЕФЕКТИВНОГО УПРАВЛІННЯ ГІРНИЧОДОБУВНИМИ ПРОЄКТАМИ

Коровяка Є., Заболотна Ю., Пащенко О., Расцвєтаєв В.

Анотація. Гірнича промисловість стикається зі зростаючою складністю управління проектами через потребу в точному плануванні, ефективному виконанні та суворому моніторингу для забезпечення безпеки, продуктивності та екологічної відповідності, однак інтеграція різноманітних джерел даних у єдину систему залишається викликом. Ця стаття досліджує інтеграцію маркшейдерських даних у системи інформаційного моделювання будівництва (BIM) як трансформаційний підхід для вдосконалення управління гірничодобувними проектами, зосереджуючись на відкритих кар'єрах та підземних шахтах. Дослідження розглядає виклики поєднання геопросторових даних, отриманих за допомогою LiDAR, GPS та фотограмметрії з БПЛА, з геотехнічними даними з буріння свердловин у BIM-структурах для покращення планування, виконання та моніторингу проектів у гірничій промисловості. Використовуючи передові маркшейдерські технології, такі як високоточні тахеометри та лазерне сканування, разом із BIM-інструментами, такими як Autodesk Revit та Bentley OpenRoads, запропонована методологія забезпечує інтеграцію даних у реальному часі, сприяючи кращому прийняттю рішень та операційній ефективності. Дослідження застосовує змішаний методичний підхід, включаючи кейс-стаді мідного кар'єру та вугільної шахти, а також програмне моделювання у платформах, таких як Agisoft Metashape для моделювання, щоб оцінити ефективність процесу інтеграції. Результати показують значні покращення: підвищення точності проектів на 15–20% завдяки точному геологічному моделюванню, покращення оцінки витрат на 10–12% шляхом зменшення бюджетних перевищень та покращення управління ризиками на 30% через виявлення зон високого ризику, таких як нестабільні схили. Відзначені виклики, зокрема проблеми з інтероперабельністю даних між маркшейдерськими форматами та BIM-платформами, а також високі початкові витрати на програмне забезпечення та навчання. Стаття завершується практичними рекомендаціями щодо впровадження BIM у гірничій справі, такими як поетапне впровадження та програми навчання персоналу, та окреслює перспективи для подальших досліджень, включаючи автоматизацію робочих процесів за допомогою роботизованої автоматизації (RPA) та аналітику на основі штучного інтелекту для прогнозування ризиків, щоб ще більше оптимізувати операції та підвищити безпеку у гірничій промисловості.

Ключові слова: маркшейдерія, BIM (інформаційне моделювання будівель), управління гірничодобувними проектами, геопросторові дані, геотехнічні дані, інтеграція даних, цифрові двійники, моделювання, моніторинг у реальному часі, операційна ефективність.