BAŞKENT UNIVERSITY
INSTITUTE OF SOCIAL SCIENCE
DEPARTMENT OF BUSINESS ADMINISTRATION
MASTER'S OF BUSINESS ADMINISTRATION (MBA)WITH THESIS

NAVIGATING THE DIGITAL TRANSITION IN THE MINING INDUSTRY: TECHNOLOGY ADOPTION CHALLENGES AND OPPORTUNITIES FOR SUSTAINABLE MINING PRACTICES

PREPARED BY

JAVAD PAKDEL

MASTER'S THESIS

THESIS ADVISOR

PROF. DR. İSMAİL EROL

ANKARA – 2025

BAŞKENT ÜNİVERSİTESİ
SOSYAL BİLİMLERİ ENSTİTÜSÜ
YÜKSEK LİSANS TEZ ÇALIŞMASI ORİJİNALLİK RAPORU

Tarih:28/05/2025

Öğrencinin Adı, Soyadı: Javad PAKDEL

Öğrencinin Numarası: 22310150

Anabilim Dalı: İşletme Anabilim Dalı

Programı: İşletme Yönetimi Tezli Yüksek Lisans

Danışmanın Unvanı/Adı,Soyadı: Prof. Dr. İsmail EROL

Tez Başlığı: Madencilik Endüstrisinde Dijital Dönüşümün Yönetilmesi: Sürdürülebilir Madencilik Uygulamalarında Yıkıcı Teknolojilerin Benimsemesine İlişkin Engeller ve Fırsatların Analizi”

Yukarıda başlığı belirtilen Yüksek Lisans tez çalışmamın; Giriş, Ana Bölümler ve Sonuç Bölümünden oluşan, toplam 86 sayfalık kısmına ilişkin, 28/05/2025 tarihinde tez danışmanım tarafından Turnitin adlı intihal tespit programından aşağıda belirtilen filtrelemeler uygulanarak alınmış olan orijinallik raporuna göre, tezimin benzerlik oranı % 12’dir. Uygulanan filtrelemeler:

1. Kaynakça hariç

2.Alıntılar hariç

3.Beş (5) kelimeden daha az örtüşme içeren metin kısımları hariç

“Başkent Üniversitesi Enstitüleri Tez Çalışması Orijinallik Raporu Alınması ve Kullanılması Usul ve Esaslarını” inceledim ve bu uygulama esaslarında belirtilen azami benzerlik oranlarına tez çalışmamın herhangi bir intihal içermediğini; aksinin tespit edileceği muhtemel durumda doğabilecek her türlü hukuki sorumluluğu kabul ettiğimi ve yukarıda vermiş olduğum bilgilerin doğru olduğunu beyan ederim.

Öğrenci İmzası:

ONAY

Tarih: 28/05/2025

Prof. Dr. İsmail EROL

ACKNOWLEDGEMENTS

This thesis is not merely the culmination of an academic journey—it is a personal testament to the unwavering support, belief, and love I have been fortunate to receive.

First and foremost, I would like to express my deepest and most heartfelt gratitude to **Prof. Dr. İsmail Erol**, my supervisor and mentor. From the very beginning of this research, your guidance has been my anchor. Your insightful feedback, tireless encouragement, and academic integrity have not only shaped the quality of this thesis but have also profoundly influenced my growth as a researcher and as a person. You have been more than a supervisor—you have been a source of inspiration, and I will carry the lessons I have learned from you throughout my academic and professional life. Your patience, wisdom, and unwavering belief in my potential gave me the courage to push boundaries and strive for excellence. I owe this achievement, in no small part, to your generous and steadfast support.

To my beloved wife, **Parastoo** — no words can truly capture what you mean to me. This thesis would not have been possible without your love, strength, and boundless devotion. You have been my light in the darkest hours, the quiet calm when I felt overwhelmed, and the voice that reminded me of who I am when I began to doubt myself. Your sacrifices, your faith in my dreams, and your infinite patience are woven into every page of this work. If I have reached this point, it is because you stood by me with your heart wide open, lifting me when I fell, and walking beside me every step of the way. You are the reason I dared to begin this journey—and the reason I was able to finish it.

Javad PAKDEL

Ankara 2025

ÖZET

Javad PAKDEL. Madencilik Endüstrisinde Dijital Dönüşümün Yönetilmesi: Sürdürülebilir Madencilik Uygulamalarında Yıkıcı Teknolojilerin Benimsemesine İlişkin Engeller ve Fırsatların Analizi, Başkent Üniversitesi, Sosyal Bilimler Enstitüsü, İşletme Yönetimi Tezli Yüksek Lisans Programı, 2025.

Madencilik endüstrisi (ME), altyapı gelişimi, enerji dönüşümü ve ileri üretim için vazgeçilmez olan kritik hammaddelerin sağlanmasını temellendiren, küresel ekonomik mimarinin kurucu bir sütununu oluşturmaktadır. Stratejik önemine rağmen, sektör kökleşmiş verimsizlikler, güvenlik riskleri, düzenleyici katılıklar ve artan çevresel zorunluluklarla yük altındadır. Bu bağlamda, yapay zekâ ve otomasyondan Nesnelerin İnterneti (IoT) mimarilerine ve veri analitiğine kadar uzanan dijital teknolojilerin yaygınlaşması, eşi benzeri görülmemiş bir operasyonel dönüşüm vadetmektedir. Ancak bu tür teknolojilerin benimsenmesi, sıklıkla birbirinden bağımsız ya da doğrusal olmayan değil, derinlemesine sistemik ve karşılıklı olarak pekişen çok boyutlu engeller dizisi tarafından sekteye uğratılmaktadır. Bu tez, ME’de dijital dönüşümün önündeki başlıca engelleri sistematik olarak tanımlamak, doğrulamak ve nedensel olarak haritalandırmak için titiz, çok yöntemli bir araştırma yürütmektedir. PRISMA rehberliğinde yürütülen sistematik literatür taraması, bibliyometrik analiz ve klasik DEMATEL metodolojisinin entegre edildiği ardışık bir çerçeve kullanılarak, araştırma on altı kritik engeli damıtarak tanımlamakta ve uzman görüşlerine dayalı etki matrisleri aracılığıyla bunların karşılıklı bağımlılıklarını açıklığa kavuşturmaktadır. Ampirik bulgular, Yüksek Başlangıç Yatırımı, Üst Yönetim Taahhüdü Eksikliği ve Etkisiz Düzenleyici Çerçeveler gibi üst düzey nedensel unsurların; Değişime Direnç, İş Gücü Yetenek Açıkları ve Siber Güvenlik Açıkları gibi aşağı akıştaki kısıtlamaları tetiklediği hiyerarşik bir yapı ortaya koymaktadır. Öncelik düzeyi $(D+R)$ ve net nedensellik $(D-R)$ teşhisleri yoluyla, çalışma dönüşüm ekosistemi içerisinde müdahale noktalarının önceliklendirilmesini sağlayan bir karar destek mimarisi sunmaktadır. Bu tez böylelikle, hem akademik hem de uygulayıcı kesimler için metodolojik açıdan sağlam ve pratik olarak uygulanabilir bir çerçeve sunmakta; ME’de sistemik, aşamalı ve sürdürülebilir dijital geçişi kolaylaştırmaya yönelik paydaşlara özel stratejik çıkarımlar sağlamaktadır.

Anahtar Kelimeler: Dijital dönüşüm, madencilik endüstrisi, teknoloji benimseme, sürdürülebilirlik, uygulama engelleri

ABSTRACT

Javad PAKDEL. Navigating the Digital Transition in the Mining Industry: Technology Adoption Challenges and Opportunities for Sustainable Mining Practices, Başkent University, Institute of Social Sciences, Master's of Business Administration with Thesis, 2025.

The mining industry (MI) constitutes a foundational pillar of global economic architecture, underpinning the provision of critical raw materials indispensable for infrastructural development, energy transition, and advanced manufacturing. Notwithstanding its strategic relevance, the sector remains encumbered by entrenched inefficiencies, safety risks, regulatory rigidity, and escalating environmental imperatives. In this context, the proliferation of digital technologies—ranging from artificial intelligence and automation to Internet of Things (IoT) architectures and data analytics—promises unprecedented operational transformation. However, the uptake of such technologies is frequently stymied by a constellation of multidimensional barriers that are neither isolated nor linear, but deeply systemic and mutually reinforcing. This dissertation undertakes a rigorous, multi-method inquiry to systematically identify, validate, and causally map the key impediments to digital transformation in the MI. Employing a sequential framework that integrates a PRISMA-guided systematic literature review, bibliometric analysis, and classical DEMATEL methodology, the research distills sixteen critical barriers and elucidates their interdependencies through expert-informed influence matrices. The empirical findings of this study delineate a hierarchical structure wherein High Initial Investment, Lack of Top Management Commitment, and Ineffective Regulatory Frameworks emerge as dominant causal antecedents, precipitating downstream constraints such as Resistance to Change, Workforce Skill Gaps, and Cybersecurity Vulnerabilities. Through prominence *(D+R)* and net causality *(D−R)* diagnostics, the study furnishes a decision-support architecture that enables prioritization of intervention points within the transformation ecosystem. This thesis thus contributes a methodologically robust and practically actionable framework for both academic and practitioner audiences, offering stakeholder-specific strategic implications to facilitate systemic, phased, and sustainable digital transition in the MI.

Keywords: Digital transformation, mining industry, technology adoption, sustainability, implementation barrier

TABLE OF CONTENTS

ACKNOWLEDGEMENTS i
ÖZET ii
ABSTRACT iii
LIST OF TABLES v
LIST OF FIGURES vi
LIST OF SYMBOLS AND ABBREVIATIONS vii
1. INTRODUCTION 1
2. CONCEPTUAL BACKGROUND 13
  2.1. The Mining Industry 13
  2.2. Digital Transformation in the Mining Industry 16
3. LITERATURE REVIEW 21
  3.1. PRISMA 23
  3.2. Bibliometric Analysis 27
  3.3. Barriers to Digital Transformation in the MI 33
4. METHODOLOGY 44
5. Application and Findings 52
  5.1. The results of DEMATEL Analysis 55
6. Discussion and Implictions 73
  6.1. Managerial and Policy Implications 75
  6.2. Research and Theoretical Implications 80
7. Conclusions 82
  7.1. Research Contributions 83
  7.2. Limitations of the Study 83
  7.3. Future Research Opportunities 84
REFERENCE 87
APPENDICES 93
  Appendix 1: Relevant Research 93
  Appendix 2: Expert Survey Questionnaire 108

LIST OF TABLES

Page

Table 3.1. Search string and Filtering Criteria 25
Table 3.2. Inclusıon and exclusıon crıterıa 26
Table 3.3. The list of barriers and their descriptions 34
Table 5.1. Barriers and their codes 52
Table 5.2. Expert Group 54
Table 5.3. Average direct-relation matrix constructed from expert panel consensus (16 × 16) 57
Table 5.4. Normalized direct-relation matrix 59
Table 5.5. Identity matrix 61
Table 5.6. Matrix $I - D$, obtained by subtracting the normalized direct-relation matrix from the identity matrix 62
Table 5.7. Inverse matrix $I - D - 1$ 63
Table 5.8. Total relation matrix $T = D \cdot I - D - 1$ 64
Table 5.9. Summary of dispatching (*D*), receiving (*R*), prominence (*D* + *R*), and net causality (*D* - *R*) values for the Sixteen barriers 66
Table 6.1. Summarizes stakeholder-specific strategies for addressing key barriers 79
Table 7.1. Future Research Opportunities 86

LIST OF FIGURES

Page

Figure 2.1. Mining Supply Chain 15
Figure 3.1. Systematic Review 21
Figure 3.2. Scientific article selection process according to PRISMA methodology 24
Figure 3.3. Search STRING 24
Figure 3.4. Information resources 27
Figure 3.5. Number of Publıcatıons per Journal 28
Figure 3.6. Number of Citations per Journal 28
Figure 3.7. Journals Citation Network 29
Figure 3.8. Keyword co-occurrence network 29
Figure 3.9. Number of Publication per Country 30
Figure 3.10. Number of Citations per Country 30
Figure 3.11. Country collaboration network 31
Figure 3.12. Yearly Distribution of the Relevant Literature 31
Figure 3.13. Number of Citations per Article 32
Figure 3.14. Article citation network 32
Figure 4.1. Methodological Framework 44
Figure 5.1. Causal relationship diagram 67
Figure 5.2. Scatter Plot Based on D – R and D + R Values 69
Figure 5.3. Classification of the Identified Barriers into Cause-and-Effect Group 69
Figure 5.4. Prominence Scores of Barriers with Threshold Highlight (D + R ≥ 2.0) 70

LIST OF SYMBOLS AND ABBREVIATIONS

AHS	Autonomous Haul Truck Systems
AI	Artificial Intelligence
CNN	Convolutional Neural Networks
CSR	Corporate Social Responsibility
DEMATEL	The Decision Making Trial and Evaluation Laboratory
DT	Digital Twins
ESG	Environmental, Social, and Governance
IOT	Internet Of Things
MI	Mining Industry
ML	Machine Learning
NGO	Non-Governmental Organizations
OT	Operational Technology
PDM	Product Data Management
PPPs	Public–Private Partnerships
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RNN	Recurrent Neural Networks
SMEs	Small and Medium-sized Enterprises

1. INTRODUCTION

The Mining Industry (MI) constitutes a foundational pillar of the global economy, supplying indispensable raw materials that underpin technological advancement, industrial expansion, and infrastructure development (Mokganya et al., 2024). These resources are integral across a multitude of sectors—from energy and construction to high-tech manufacturing—where their unavailability would critically impair productivity and innovation capacities (Long et al., 2024; Philo & Webber-Youngman, 2024). In particular, the resilience of global supply chains for strategic commodities such as steel, aluminum, copper, and rare earth elements remains inextricably tied to the stability and output of mining operations. The strategic importance of the MI has been further underscored by escalating geopolitical rivalries between leading global powers, particularly the United States and China. As both nations intensify their competition over technological supremacy and economic resilience, critical minerals—especially rare earth elements (REEs)—have become pivotal tools of resource diplomacy and industrial sovereignty. China's long-standing predominance in the rare earth supply chain, covering over 90% of refined rare earth magnet production, has provoked widespread concern in Western capitals regarding supply continuity, national security, and technological independence (Reuters, 2025; The Verge, 2025). In response, the United States and China have agreed on a provisional trade framework to ease rare earths export restrictions, signaling both markets' sensitivity to REE supply tensions (Reuters, 2025). Meanwhile, the U.S. is making concerted efforts to build a fully domestic rare earths supply chain, with initiatives supported by bipartisan industry-policymaker coalitions aimed at reducing dependence on China (Axios, 2025). Similarly, supranational entities like the European Union have begun institutionalizing measures through the Critical Raw Materials Act to secure access to strategically vital minerals via diversification and supply chain traceability. This evolving landscape highlights a broader transformation in the role of mining—from economic activity to a strategic lever of geopolitical influence—emphasizing the urgent need for resilient and ethically governed mineral supply architectures.

Beyond its economic centrality, the MI occupies a critical geopolitical position, primarily due to its control over strategic minerals such as lithium, cobalt, and nickel—

resources indispensable to contemporary technologies including semiconductors, aerospace systems, and electric vehicle batteries (Lund et al., 2024; Onifade et al., 2024). As global demand for these minerals continues to surge, both nation-states and multinational corporations are intensifying efforts to secure long-term and ethically sourced access, underscoring the MI's integral role in resource diplomacy and international trade policy (Gruenhagen et al., 2022). Concurrently, the industry serves as a backbone for the transition to low-carbon energy systems, as minerals extracted through mining underpin key technologies such as wind turbines, photovoltaic panels, and grid-scale storage units (Abdellah et al., 2022; Qi, 2020). Although extractive activities related to fossil fuels face mounting environmental and social scrutiny, the rising demand for energy-transition metals reinforces the sector's indispensability in achieving global decarbonization objectives (Tahir et al., 2024; Barnewold & Lottermoser, 2020).

Despite its indispensable economic and geopolitical role, the MI continues to face deep-rooted structural challenges that threaten its long-term sustainability, efficiency, and adaptive capacity. These include persistent issues such as environmental degradation, local community opposition, volatile commodity markets, and the slow pace of technological modernization. Together, these multifaceted challenges necessitate a paradigm shift toward more socially responsible, environmentally sustainable, and innovation-driven operational frameworks (Delibalta, 2022).

Among the most pressing sustainability concerns is the MI's substantial ecological footprint. The extraction and processing of raw materials often result in extensive land disruption, the depletion of local water sources, and considerable greenhouse gas emissions—all of which contribute to ecosystem degradation and climatic destabilization (Sánchez & Hartlieb, 2020). Recent studies have placed the MI among the top contributors to global CO_2 emissions, with mineral processing alone accounting for approximately 4–7% of the total (Vargas et al., 2022). These environmental challenges are further exacerbated by the industry's ongoing reliance on a linear economic model predicated on the "take-make-dispose" paradigm, which generates excessive waste and fosters inefficient resource utilization (Vargas et al., 2022). This model stands in sharp contrast to the circular economy principles, which advocate for regenerative and closed-loop material flows (Duarte et al., 2021).

With global material consumption now exceeding the planet's natural regenerative capacity by a factor of 1.75, there is an urgent need to transition mining operations toward more sustainable frameworks (Vargas et al., 2022).

Operating under inherently challenging environmental and logistical conditions, the industry is increasingly leaning on digital transformation to reconcile productivity with sustainability imperatives. In light of escalating ecological burdens, digital technologies offer promising avenues for mitigating the adverse environmental externalities associated with mining operations. By enabling real-time monitoring, automated control systems, and data-driven process optimization, digital tools enhance operational efficiency and support more sustainable extraction practices (Fang et al., 2024). Technologies such as remote sensing, IoT-based equipment diagnostics, and AI-driven predictive analytics facilitate early detection of environmental anomalies and enable preemptive mitigation strategies. As sustainability benchmarks become progressively more demanding, these digital enablers are no longer optional—but essential instruments for ensuring regulatory compliance, reputational legitimacy, and long-term environmental stewardship.

Yet, despite the demonstrated potential of digital technologies, their adoption across the MI remains uneven and sporadic. Infrastructural deficiencies, fragmented data ecosystems, and insufficient technological maturity—particularly in developing economies—continue to hinder effective implementation (Fang et al., 2024). These limitations obstruct the deployment of advanced digital solutions designed to enhance resource recovery, reduce waste, and facilitate circular operational models. The continued underutilization of such innovations stems not only from technical hurdles, but also from persistent financial and organizational constraints (Ediriweera & Wiewiora, 2021; Lund et al., 2024; Onifade et al., 2024).

Beyond its environmental ramifications, the MI also faces intensifying societal opposition, particularly in regions where extractive activities intersect with ecologically or culturally sensitive territories. In recent years, tensions have escalated between mining corporations and Indigenous or local communities over disputes concerning land ownership, territorial rights, and resource governance. These sociocultural frictions pose significant reputational and operational risks that digital innovation alone cannot resolve (Holcombe &

Kemp, 2019). These sociopolitical tensions are often exacerbated by substandard labor conditions, negligible socioeconomic benefits for host communities, and the involuntary displacement of populations caused by large-scale mining operations. Such conditions frequently catalyze legal disputes, civil unrest, and heightened regulatory scrutiny across diverse jurisdictions (Gruenhagen et al., 2022). Similar tensions have been reported in Türkiye, particularly in mining regions where operations encroach upon environmentally vulnerable or culturally sensitive areas, often resulting in public protests and community-led legal actions (Koç et al., 2022; Delibalta, 2022). In response to mounting public pressure, many mining corporations have adopted Corporate Social Responsibility (CSR) frameworks. However, these initiatives are frequently critiqued for lacking transparency, enforceable accountability, and substantive engagement with the underlying ethical and social dimensions of mining activities (Bhattacharyya & Shah, 2022; Dayo-Olupona et al., 2020).

While digital technologies are frequently introduced to enhance operational efficiency, their deployment must be situated within ethical frameworks that uphold community rights, labor protections, and cultural heritage (Koç et al., 2022). The shift toward digital mining should be evaluated not only through the lens of technical feasibility, but also through its potential sociocultural ramifications—particularly in regions where mining is deeply intertwined with local livelihoods and identity (Delibalta, 2022). Addressing the multifaceted challenges embedded within the MI therefore necessitates an integrated strategy that synthesizes technological innovation, regulatory support, and cross-sectoral cooperation. Recent scholarship has increasingly underscored digital transformation as a strategic lever not only for boosting operational performance, but also for advancing environmental stewardship and long-term sustainability objectives (Jianing et al., 2024; Onifade et al., 2024; Zvarivadza et al., 2024; Barnewold & Lottermoser, 2020; Dayo-Olupona et al., 2020).

Technological advancements, particularly in automation, artificial intelligence (AI), and the Internet of Things (IoT), have substantially redefined operational paradigms within the MI by reducing human error, enhancing precision, and facilitating real-time monitoring across production cycles (Onifade et al., 2023). One of the most significant breakthroughs has been the integration of AI-powered automation systems in mineral extraction, logistics coordination, and ore processing. For example, the deployment of Autonomous Haul Truck

Systems (AHS) in surface mining has yielded measurable improvements in operational safety, navigational accuracy, and throughput efficiency (Long et al., 2024). Similarly, predictive maintenance supported by machine learning and sensor analytics has emerged as a critical approach to reducing equipment downtime and improving asset reliability in underground mining (Patil et al., 2021). Through the combination of big data analytics and real-time sensing technologies, AI algorithms now enable early-stage fault detection, empowering maintenance teams to execute proactive interventions that minimize cost-intensive disruptions (Duarte et al., 2022).

Moreover, the convergence of AI and IoT is strengthening data-driven decision-making within mining operations, thereby facilitating more effective resource allocation and equipment utilization (Zvarivadza et al., 2024). The integration of IoT, digital twin systems, and cyber-physical infrastructures into Product Data Management (PDM) architectures enables real-time diagnostics and predictive maintenance, which significantly enhance equipment availability and performance (Dayo-Olupona et al., 2023). Among these technologies, digital twins have emerged as particularly promising tools for improving operational transparency, process optimization, and system-wide productivity. Blockchain technology is increasingly being recognized as a valuable enabler of transparency and ethical governance within mineral supply chains. By leveraging decentralized ledgers, blockchain systems can trace the full lifecycle of minerals—from extraction to end use—thereby supporting compliance with international sustainability protocols and responsible sourcing standards (Tahir et al., 2024). In addition, blockchain-enabled smart contracts automate regulatory reporting, facilitate secure financial exchanges, and streamline mineral certification procedures, reducing both fraud and bureaucratic inefficiencies. Empirical studies reveal that mining firms employing blockchain-based solutions have achieved higher traceability, mitigated illicit mining practices, and fostered improved stakeholder trust (Onifade et al., 2024). However, the lack of standardized implementation protocols continues to pose a major challenge for industry-wide adoption (Don et al., 2025).

Beyond equipment maintenance, AI-powered systems have also been increasingly applied in geological exploration and orebody modeling, where they enhance the precision of subsurface analyses and reduce both geological uncertainty and ecological disturbance

(Philo & Webber-Youngman, 2024). Digital twin technologies, similarly, have demonstrated high potential in enabling real-time simulations of mining operations, facilitating predictive control, and supporting remote oversight (Hazrathosseini & Moradi Afrapoli, 2023). As the sector accelerates toward Industry 4.0, the convergence of AI, IoT, and digital twins promises a more sustainable, automated, and insight-driven mining ecosystem. However, despite the proven advantages of these technologies, their large-scale implementation remains constrained by a complex web of barriers—ranging from infrastructural gaps and financial constraints to regulatory fragmentation and cultural inertia. Understanding and addressing the systemic barriers to digital transformation in the MI is not only a technical endeavor but also a strategic necessity for achieving industrial resilience, sustainability, and competitiveness. As mining operations become increasingly complex and capital-intensive, failure to identify and prioritize interrelated challenges can lead to fragmented digital initiatives, wasted resources, and missed opportunities for innovation. This study contributes by offering a structured, system-level anal”ysis of these barriers, providing stakeholders with actionable insights for targeted and high-impact interventions.

Recent research indicates that safety enhancement, risk management, and workforce training remain the most common application areas for digital twin and related enabling technologies in the MI (Don et al., 2025). Nevertheless, the development of fully functional digital twin ecosystems continues to be hampered by the lack of coherent data governance frameworks and the chronic underutilization of collected sensor data—industry reports suggest that as little as 1% of available data is actually leveraged for decision-making (Don et al., 2025). Moving forward, meaningful progress in mining digitalization will depend on addressing interoperability constraints, strengthening cyber-physical system integration, and cultivating more effective collaboration between IT and operational technology (OT) teams.

Despite the operational and strategic advantages associated with digital transformation, its diffusion across the MI remains sporadic and uneven. Core barriers include prohibitively high initial investment costs, cybersecurity vulnerabilities, integration challenges with legacy systems, and persistent organizational resistance to change (Long et al., 2024; Onifade et al., 2024; Jianing et al., 2024). These obstacles are particularly acute for small and medium-sized enterprises (SMEs), which often lack access to capital and digital infrastructure, thereby constraining their ability to invest in advanced technologies (Lund et al., 2024; Bhattacharyya & Shah, 2022). Moreover, the absence of strong leadership vision and commitment at the executive level often leads to fragmented or short-lived transformation efforts (Mokganya et al., 2024; Philo & Webber-Youngman, 2024). Cultural inertia, combined with low digital literacy among the workforce and insufficient training programs, further inhibits technology adoption (Don et al., 2025; Zvarivadza et al., 2024). Regulatory ambiguity and the lack of universally accepted standards also exacerbate implementation risks, deterring long-term investment and cross-functional integration (Tahir et al., 2024; Duarte et al., 2022).

A significant disparity exists between large multinational corporations and smaller mining operators in their capacity to adopt digital technologies. While the former can afford to pilot advanced systems such as AI-driven platforms, IoT-based monitoring, and autonomous machinery, the latter often lack the financial resources and organizational readiness required for such transitions (Jianing et al., 2024). The acquisition, implementation, and long-term maintenance of tools like automated vehicles, predictive analytics software, and real-time data platforms demand capital-intensive investments that many firms find prohibitive, forcing continued reliance on labor-intensive methods (Bhattacharyya & Shah, 2022). This pattern is especially pronounced in Türkiye, where the MI is dominated by SMEs that often struggle with limited capital reserves and insufficient digital infrastructure (Koç et al., 2022; Delibalta, 2022). Moreover, integrating these technologies into legacy mining infrastructures frequently necessitates complex reengineering of operational systems, thereby increasing implementation costs and risks (Gruenhagen et al., 2022; Lund et al., 2024; Onifade et al., 2024). These financial and technical constraints are compounded by organizational inertia, outdated IT infrastructure, and limited digital literacy among the workforce, all of which continue to impede the scalable adoption of technologies such as digital twins (Don et al., 2025).

Furthermore, predictive maintenance remains particularly challenging to scale due to heterogeneous data environments, gaps in specialized expertise, and the lack of mature analytic infrastructures across many mining operations (Dayo-Olupona et al., 2023). Compared to more digitally advanced resource sectors such as oil and gas, the MI continues to lag in digital maturity, characterized by limited diffusion of best practices and minimal intersectoral learning (Don et al., 2025). Beyond these technical limitations, concerns over workforce displacement persist as a major socio-cultural barrier to digital adoption. The rapid deployment of automation and AI systems has heightened anxiety among mining personnel—particularly those in labor-intensive roles such as drilling, hauling, and mineral processing—who fear redundancy and loss of livelihood (Young & Rogers, 2019; Jianing et al., 2024). These fears are especially acute in mono-industrial regions where employment alternatives are scarce, making digitalization socially and politically sensitive (Duarte et al., 2022). Yet, despite growing evidence of these concerns, many mining companies have failed to invest in systematic reskilling or workforce adaptation programs, thereby exacerbating employee resistance and further decelerating the pace of transformation (Jianing et al., 2024).

The shift toward digital mining necessitates a fundamental reconfiguration not only of infrastructure and capital allocation but also of organizational mindset—requiring the reengineering of business models and the cultivation of a digitally competent workforce (Koç et al., 2022). Alongside these structural changes, digitalization introduces an additional layer of vulnerability in the form of cybersecurity threats. As mining operations become increasingly reliant on interconnected networks of IoT devices, AI-driven platforms, and cloud-based systems, they expose themselves to a wide spectrum of cyber risks, including hacking, ransomware, and industrial espionage (Gaber et al., 2021; Abdellah et al., 2022). The decentralized and real-time nature of these systems expands the number of potential entry points for malicious intrusions. Addressing such vulnerabilities requires more than conventional firewalls—it demands encrypted communication protocols, real-time network monitoring, and a dedicated cybersecurity team equipped with specialized expertise (Bi et al., 2022). However, many mining organizations lack the personnel, resources, and operational maturity to establish these protective measures effectively, which continues to constrain their digital transformation efforts (Ulewicz et al., 2022).

The growing reliance on cyber-physical systems in mining has elevated cybersecurity from a purely technical concern to a central pillar of operational risk management (Don et al., 2025). Concurrently, regulatory and policy uncertainties remain among the most critical external barriers to digital transformation. In many jurisdictions, there is a striking lack of clear legal and institutional frameworks specifying how digital technologies—such as AI, blockchain, and automation—should be governed, regulated, and ethically deployed within mining operations (Bhattacharyya & Shah, 2022). Türkiye exemplifies this regulatory gap, as its MI currently lacks dedicated legal provisions for governing the deployment of advanced digital systems, resulting in significant uncertainty for both domestic operators and potential technology investors (Delibalta, 2022). Legal ambiguities surrounding data privacy, liability for system failures, and alignment with environmental compliance standards create considerable hesitation among decision-makers (Gruenhagen et al., 2022; Duarte et al., 2022). Moreover, outdated legislative instruments that fail to reflect the operational complexities and innovation trajectories of Industry 4.0 continue to deter investment and impede strategic digital adoption (Philo & Webber-Youngman, 2024).

Achieving meaningful digital transformation in the MI necessitates not only advanced technological solutions, but also coherent policy frameworks, cross-regional collaboration, and sustained investment in digital infrastructure and workforce development (Fang et al., 2024). Although recent scholarship increasingly acknowledges the strategic importance of digitalization in mining, the existing literature remains largely fragmented, descriptive, and lacking in analytical depth (Lund et al., 2024; Onifade et al., 2023). This gap is especially evident in countries like Türkiye, where digital transformation in the MI has received limited scholarly attention and is rarely examined through system-oriented frameworks (Koç et al., 2022). While numerous studies have cataloged various barriers to digital adoption, relatively few have examined the interdependencies and directional influences among these obstacles in a systematic manner. Yet such understanding is critical, as certain barriers may function as root causes that activate or reinforce others. Addressing surface-level symptoms without identifying and mitigating their underlying drivers risks producing ineffective strategies and misdirected resource allocations.

To address this gap, this study adopts an integrated methodological approach combining qualitative and quantitative techniques. The first phase involves a systematic literature review guided by *PRISMA* protocols and supplemented by bibliometric analysis to identify and structure the prevailing barriers to digital transformation in the MI. In the second phase, the Decision-Making Trial and Evaluation Laboratory *(DEMATEL)* method—originally developed by Fontela and Gabus (1976)—is employed to model the complex interrelationships among these barriers. As a structured multi-criteria decision-making tool, *DEMATEL* enables the construction of a causal diagram that classifies factors based on their degree of influence and dependence, offering both visual and quantitative insights into systemic dynamics. This approach is particularly suited for the MI, where transformation barriers rarely exist in isolation and are often interwoven through feedback loops and latent structural linkages. By applying *DEMATEL,* this study systematically identifies which barriers operate as foundational "*cause*" factors requiring early intervention, and which are consequential "*effect*" factors reflective of deeper systemic constraints.

Beyond distinguishing which barriers function as root causes and which emerge as downstream effects, the proposed analytical framework also assesses the structural centrality of each factor within the broader digital transformation system. This dual-layered perspective—capturing both directional influence and systemic prominence—enables not only causal classification but also strategic prioritization of barriers based on their relative leverage within the network. By integrating influence mapping with assessments of structural relevance, this study advances a systems-informed lens that deepens interpretive insight while enhancing practical applicability. This framework synthesizes otherwise fragmented insights into a coherent decision-support model tailored to the mining context. In doing so, it provides actionable guidance for mining enterprises, digital solution providers, and policymakers by illuminating high-impact intervention points that can accelerate digital adoption and mitigate resistance. The approach thus transcends static barrier lists, offering a nuanced understanding of the interdependencies, feedback loops, and leverage dynamics that shape the trajectory of digital transformation in the MI.

Building upon this analytical foundation, the study seeks to answer the following research questions in order to clarify the underlying structure of digital transformation barriers in the MI.

***RQ*$_{1}$**. What are the key barriers that hinder the adoption of digital technologies in the MI?

***RQ*$_{2}$**. How are these barriers interrelated, and which ones act as primary causal drivers within the digital transformation process?

RQ_3. How can the *DEMATEL* method be used to model and visualize the cause-effect relationships among these barriers?

RQ_4. Based on the integrated findings from bibliometric analysis and causal modeling, what strategic recommendations can be proposed to accelerate digital transformation in the MI?

This study makes a multifaceted contribution to the literature on digital transformation in the MI by combining systematic review, bibliometric mapping, and causal modeling within a single research framework. First, using the *PRISMA* method, the study conducts a rigorous and transparent selection of academic sources to ensure the comprehensiveness and reproducibility of the literature review. In addition, bibliometric analysis is employed to systematically examine co-citation networks, intellectual structures, and emerging research themes related to barriers in mining digitalization. This dual approach helps to map the evolution of knowledge and identify fragmented areas that require further investigation.

Second, to move beyond descriptive categorizations and capture the complex interdependencies among barriers, the study utilizes the *DEMATEL* method. This analytical tool enables the construction of a cause-effect relationship model that distinguishes between "driving" and "dependent" barriers, offering a deeper understanding of how digital transformation obstacles interact within mining systems. By combining these methods, the study shifts from simple enumeration toward strategic prioritization, which is crucial for designing effective interventions. As such, the research contributes both methodologically and practically. Methodologically, it demonstrates how bibliometric and causal analysis can be integrated to generate actionable insights. Practically, it delivers targeted recommendations to mining companies, policy makers, and digital solution providers by clarifying which barriers should be addressed first to unlock broader systemic change. This integrated approach not only fills gaps in the existing literature but also supports evidence-based decision-making in the MI transition toward digital maturity.

The remainder of this thesis is structured as follows: Section 2 outlines the conceptual background, covering the MI from global and national perspectives, its role in the supply chain, and the concept of digital transformation as Section 3 presents the systematic literature review using *PRISMA* and bibliometric analysis, leading to the identification and explanation of sixteen key barriers. Section 4 introduces the methodological framework, explaining the theoretical foundations of the *DEMATEL* method followed by Section 5 detailing the application of *DEMATEL* and presenting the findings on the causal relationships among the barriers. Finally, while Section 6 discusses the results, compares them with existing literature, and provides managerial, policy, and theoretical implications, Section 7 concludes the study with a summary of contributions, limitations, and directions for future research.

2. CONCEPTUAL BACKGROUND

This section establishes the conceptual underpinnings of the research by addressing two interrelated thematic domains. The first pertains to the MI, examined through both global and national (Turkish) lenses, with particular attention to its structural characteristics and its embeddedness within broader supply chain networks. The second concerns the notion of digital transformation as it applies to the mining context, elucidating its underlying drivers, prevailing constraints, and the multifaceted implications it holds for industrial modernization and strategic renewal.

2.1. The Mining Industry

The MI serves as a critical backbone of the global economy, supplying raw materials indispensable for infrastructure development, manufacturing, and energy production (Zhang et al., 2024; Fang et al., 2024). Over centuries, the sector has evolved in tandem with industrial revolutions, moving from labor-intensive manual operations to mechanized systems and, more recently, toward increasing automation and digitalization (Long et al., 2024; Barnewold & Lottermoser, 2020). In recent decades, global mining has encountered profound structural challenges, including the depletion of easily accessible ore bodies, the necessity of mining at greater depths, escalating production costs, and the imposition of stringent environmental regulations (Mokganya et al., 2024; Don et al., 2025). These dynamics have intensified the pressure on mining companies to embrace innovation, improve operational efficiencies, and mitigate their environmental and social impacts (Zvarivadza et al., 2024; Xie et al., 2022).

Moreover, the accelerating demand for critical minerals such as lithium, cobalt, and rare earth elements—largely driven by clean energy transitions and digital technologies—has positioned the MI as a key enabler of sustainable global development (Fang et al., 2024; Don et al., 2025). For instance, Australia and Canada, both rich in critical minerals, have increasingly invested in advanced mining technologies and sustainable extraction practices, setting global benchmarks in responsible mining (Long et al., 2024). Despite these advancements, significant issues persist. The sector faces rising scrutiny over environmental degradation, including deforestation, water contamination, and greenhouse gas emissions (Sánchez & Hartlieb, 2020; Holcombe & Kemp, 2019). The COVID-19 pandemic further exposed vulnerabilities in the industry, causing supply chain disruptions, labor shortages, and operational shutdowns, which underscored the urgent need for resilient and adaptive mining strategies (Agbehadji et al., 2021).

Furthermore, the MI's conservative culture and its historically slow adoption of disruptive innovations have created inertia that hampers rapid technological integration (Gruenhagen et al., 2022). Nonetheless, the advent of Industry 4.0 technologies—including automation, IoT, AI, and blockchain—is progressively transforming mining operations into more efficient, transparent, and sustainable systems (Mokganya et al., 2024; Barnewold & Lottermoser, 2020).

Türkiye, endowed with significant mineral wealth, holds a strategic position in the global mining landscape. However, despite its potential, the MI in Türkiye has struggled with systemic challenges such as regulatory uncertainty, limited digital infrastructure, fragmented supply chains, and insufficient technological innovation (Koç et al., 2022; Delibalta, 2022). Recent studies indicate that, while Türkiye's mining exports have consistently contributed between 0.82% and 1.17% to national GDP over several decades, the sector has yet to achieve full industrial integration or maximize value-added production (Delibalta, 2022). Unlike global leaders such as Australia or Canada, where mining has evolved toward high-tech, sustainable models, Türkiye's MI remains heavily reliant on traditional extraction methods (Zhang et al., 2024).

Additionally, the MI faces operational inefficiencies stemming from high production costs and fluctuating global commodity prices, which have contributed to a reported 28% decline in productivity over the past decade (Delibalta, 2022). The slow pace of digital transformation, combined with infrastructural limitations, hampers the industry's ability to compete effectively in the global market. To address these issues, Turkish mining companies are increasingly being encouraged to integrate automation technologies, remote sensing systems, and big data analytics into their operations (Koç et al., 2022). Moreover, the application of circular economy principles—emphasizing resource efficiency, waste minimization, and environmental stewardship—has emerged as a critical priority for the future sustainability of Turkish MI (Delibalta, 2022). Several initiatives, including pilot projects in smart mining and mineral traceability, have been launched to promote digitalization, though widespread adoption remains limited. The development of a comprehensive national mining digitalization strategy, supported by public-private partnerships and regulatory reforms, is essential to unlock the full potential of Türkiye's mineral resources.

Mining supply chains represent a complex web of interconnected activities, encompassing exploration, extraction, processing, transportation, and marketing of mineral resources (Long et al., 2024; Noriega & Pourrahimian, 2022). *Figure 2.1.* visualizes the traditional mining supply chain, spanning from resource exploration to final delivery. Historically characterized by fragmented and siloed operations, mining supply chains are increasingly undergoing digital transformation to enhance efficiency, transparency, and resilience (Zvarivadza et al., 2024). The integration of advanced technologies such as IoT, blockchain, and real-time analytics is revolutionizing how mining companies manage logistics, asset tracking, and environmental compliance (Philo & Webber-Youngman, 2024). Blockchain-based traceability systems, for instance, enable secure and tamper-evident recording of mineral provenance, helping companies meet rising Environmental, Social, and Governance (ESG) expectations (Philo & Webber-Youngman, 2024).

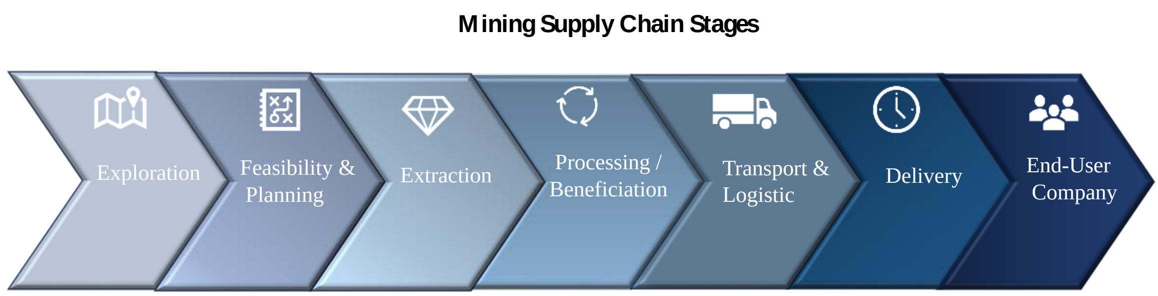

Figure 2.1. Mining Supply Chain

Furthermore, decentralized information systems and cloud-based collaboration platforms are facilitating greater agility and responsiveness across geographically dispersed mining operations (Bi et al., 2022). These systems allow for seamless data sharing among stakeholders, from exploration teams to logistics managers, thereby reducing bottlenecks and improving decision-making. In Türkiye, the mining supply chain remains relatively underdeveloped, with limited technological integration across operational stages (Delibalta, 2022). However, the growing global emphasis on sustainable and responsible sourcing presents an opportunity for Turkish mining enterprises to modernize their supply chains, thereby enhancing competitiveness in international markets (Jianing et al., 2024). Emerging global trends indicate that future mining supply chains will increasingly leverage predictive maintenance, autonomous logistics, smart inventory management, and carbon footprint tracking, transforming the sector into a digitally orchestrated ecosystem (Mokganya et al., 2024; Lund et al., 2024). Building resilient and intelligent supply chains will be essential not only for operational success but also for aligning mining practices with broader sustainability and societal goals.

2.2. Digital Transformation in the Mining Industry

The MI, long characterized by mechanistic production models and labor-intensive operations, is experiencing a paradigmatic shift driven by the convergence of digital technologies and industrial innovation. As the global demand for efficiency, transparency, and sustainability intensifies, digital transformation has emerged as a structural imperative rather than a supplementary trend. Under the broader umbrella of Industry 4.0, advanced technologies such as IoT, AI, digital twins (DT), machine learning (ML), neural networks, big data analytics, blockchain, and cloud-based infrastructures are increasingly integrated into core mining operations, including exploration, ore extraction, processing, logistics, and safety management (Onifade et al., 2023; Don et al., 2025). These interconnected systems offer transformative potential by enabling real-time visibility, predictive maintenance, data-driven decision-making, and process optimization, ultimately enhancing the industry's resilience, environmental performance, and competitiveness (Zvarivadza et al., 2024; Duarte et al., 2022).

IoT infrastructures form the digital backbone of modern mining environments by connecting distributed equipment, environmental sensors, and mobile assets. In open-pit mines, IoT sensors track vehicle performance indicators such as tire pressure, fuel consumption, and payload weight, contributing to dynamic fleet management systems that optimize haulage cycles. In underground operations, smart sensors monitor geomechanical pressure, air quality, and ventilation efficiency, ensuring worker safety and compliance with regulatory standards (Dayo-Olupona et al., 2023). When integrated with AI algorithms, IoT-generated telemetry supports predictive maintenance strategies capable of detecting anomalous vibration patterns or thermal deviations in critical machinery. For example, predictive maintenance frameworks deployed in subterranean haulage systems have been shown to reduce unplanned equipment failures by over 20%, thereby improving equipment availability and reducing operational costs (Liu et al., 2023; Duarte et al., 2022).

DT technologies complement IoT systems by providing high-fidelity, real-time simulations of physical mining environments. By virtually replicating entire plants, production systems, or even geological formations, DTs allow engineers to conduct "what-if" scenario analyses, optimize production schedules, and anticipate equipment degradation without disrupting actual operations (Hazrathosseini & Moradi Afrapoli, 2023). In mineral processing, digital twins of flotation circuits and crushing lines integrate live data from sensors to model throughput, particle size distribution, and reagent usage. These simulations help fine-tune operational parameters to minimize waste and maximize recovery. In geotechnical monitoring, DTs track slope stability in open-pit settings or support integrity in underground stopes, significantly reducing the risk of structural failure (Duarte et al., 2021). Despite these advantages, challenges such as fragmented data systems, limited interoperability with legacy infrastructure, and high development costs remain critical barriers to widespread DT deployment (Don et al., 2025).

AI technologies have rapidly become integral to mineral exploration, orebody modeling, and process control. Machine learning algorithms analyze high-dimensional datasets—from hyperspectral satellite images to drilling assay logs—to identify mineral anomalies and estimate ore grades with improved precision (Philo & Webber-Youngman, 2024). In production environments, AI-driven control systems dynamically adjust variables such as flotation aeration, mill rotation speed, or leaching temperature based on real-time feedback, reducing energy consumption and improving process consistency (Long et al., 2024). Furthermore, AI applications extend to safety and logistics: AHS guided by AI frameworks are now deployed in large-scale mines across Australia and Canada, resulting in reduced human exposure to hazardous conditions and increased fuel efficiency (Jianing et al., 2024).

Embedded within the broader AI framework, ML models offer scalable tools for predictive analytics, pattern recognition, and anomaly detection. Supervised ML techniques support orebody classification by learning from historical geochemical data, while unsupervised models uncover hidden correlations in equipment performance or environmental variables. For instance, ML models have been applied to forecast pump failures based on sensor readings, enabling proactive intervention and minimizing water management disruptions (Duarte et al., 2022; Mishra, 2021). In exploration, ML-driven predictive mapping enhances targeting accuracy by assimilating multisource geological, structural, and geophysical datasets. The effectiveness of ML-based systems lies in their ability to adapt to evolving operational contexts and integrate new data streams without human intervention.

Neural networks, particularly deep learning architectures such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have expanded the frontiers of automation and interpretation in mining. CNNs are utilized to process core scan imagery, classifying lithological patterns or detecting mineral inclusions with higher objectivity than traditional visual logging (Shetty et al., 2023). In drilling automation, RNNs process time-series data from bit torque, rotation speed, and penetration rate to infer rock properties and optimize drilling strategies on the fly. Moreover, neural networks are embedded in vision-based safety systems to identify human presence near autonomous vehicles, further reducing the risk of workplace accidents (Don et al., 2025).

Big data analytics serves as the overarching layer that consolidates, analyzes, and visualizes vast quantities of information generated throughout the mining lifecycle. From real-time sensor feeds and geological surveys to maintenance logs and market data, mining firms now face the challenge—and opportunity—of managing terabytes of structured and unstructured data (Mishra, 2021). Advanced analytics platforms powered by big data technologies synthesize these inputs to generate actionable insights, enabling closed-loop control systems and integrated decision support. However, studies show that less than 1% of collected mining data is currently utilized, highlighting the urgent need for improved data governance, interoperability standards, and analytical capacity (Duarte et al., 2021). Real-world applications include centralized dashboards for multi-site performance comparison, AI-assisted dispatch systems, and automated compliance monitoring. Cloud-based architectures underpin much of this digital ecosystem, allowing for scalable data storage, remote access, and cross-functional collaboration. Cloud mining platforms, in particular, support real-time synchronization of data from geographically dispersed operations, enabling centralized oversight and rapid decision-making. These platforms also facilitate remote equipment control, centralized maintenance scheduling, and cross-site benchmarking, all of which contribute to a more agile and adaptive mining enterprise (Don et al., 2025). Moreover, cloud integration reduces the burden of on-site IT infrastructure and enhances disaster recovery capabilities, making digital transformation more accessible to mid-sized operators.

Blockchain technology further reinforces the credibility and transparency of digital mining operations by enabling tamper-proof, decentralized records of mineral origin, processing history, and contractual compliance. This is particularly crucial in the traceability of conflict minerals and rare earth elements, where regulatory bodies and consumers increasingly demand verifiable sourcing data (Onifade et al., 2024). Blockchain-enabled smart contracts streamline procurement, automate ESG reporting, and facilitate secure cross-border transactions. Empirical evidence suggests that companies employing blockchain frameworks in their supply chains experience higher stakeholder trust, faster transaction resolution, and improved resilience against regulatory scrutiny (Onifade et al., 2024; Zvarivadza et al., 2024).

Despite these technological advancements, the global MI remains characterized by digital asymmetries. Large multinational enterprises with access to capital and talent pools are progressing rapidly, while small and medium-sized enterprises (SMEs), particularly in developing countries, continue to face structural obstacles. These include outdated infrastructure, insufficient broadband coverage, lack of digital literacy, fragmented regulatory environments, and workforce resistance due to job security concerns (Jianing et al., 2024; Bhattacharyya & Shah, 2022). The case of Türkiye is illustrative: while several large-scale mining firms have initiated pilot programs in GIS-based process monitoring, automated drilling, and blockchain traceability, the broader industry landscape remains constrained by institutional inertia, limited innovation incentives, and an underdeveloped digital workforce (Delibalta, 2022; Koç et al., 2022). In sum, digital transformation in the MI signifies a systemic and strategic reconfiguration of how resources are explored, extracted, processed, and governed. The synergistic integration of IoT, AI, ML, DT, cloud computing, blockchain, and big data analytics is redefining operational excellence, safety norms, and sustainability benchmarks across the sector. However, realizing the full potential of this transformation requires more than technological capability—it demands coherent regulatory frameworks, inclusive innovation policies, sustained infrastructure investment, and a digitally skilled workforce. As mining operations become more complex, data-intensive, and globally integrated, the strategic deployment of digital technologies will be essential not only for maintaining competitiveness but also for securing the environmental and social license to operate in the 21st century.

3. LITERATURE REVIEW

This study judiciously locates, evaluates, and synthesizes the body of the literature on the barriers to the digital technology adoption in the MI using systematic review approach. Based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses *(PRISMA 2020)* guidelines and bibliometric analysis as shown in *Figure 3.1.*, systematic review methodology ensures legitimacy, accuracy, and robustness. A mixed-methods strategy integrates qualitative synthesis (to thematically evaluate barriers and contextual factors) with quantitative bibliometric analysis (to map trends, authorship networks, and topic clusters). This dual approach also enables a holistic understanding of the research landscape, reduces the risk of subjectivity, enhances the reliability of findings, and facilitates the identification of research gaps that warrant further investigation.

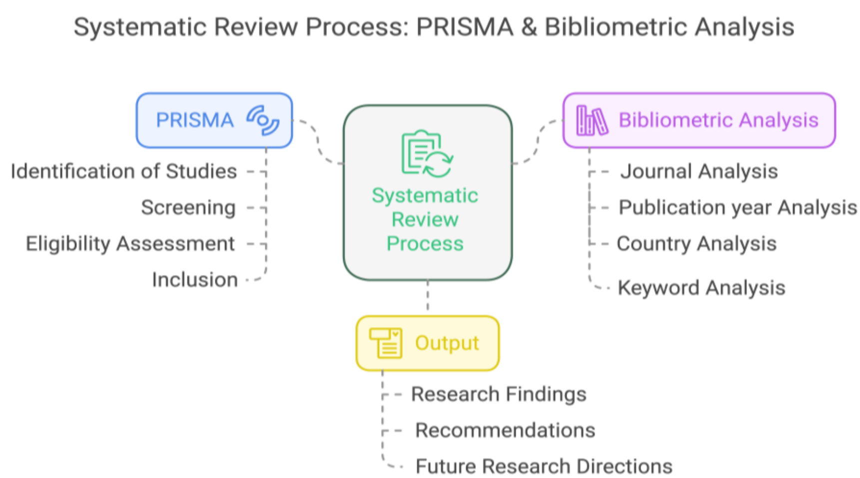

Figure 3.1. Systematic Review

Systematic reviews emerged as a key method for synthesizing scientific knowledge across disciplines. The concept was first formalized in the 1970s, evolving through different phases: the foundation period (1970–1989), the institutionalization period (1990–2000), and the diversification period (2001–present) (Hong & Pluye, 2018). Initially developed in health sciences, systematic reviews have since expanded into social sciences, engineering, and business research. Their structured approach ensures objectivity and reproducibility, making them essential for consolidating and evaluating existing research in a given field. The need for systematic reviews arose due to concerns over bias in traditional literature reviews, which often lacked structured methodologies. By contrast, systematic reviews adopt a transparent, rigorous, and replicable methodology to collate, evaluate, and synthesize evidence from multiple studies (Chalmers et al., 2002). They follow a pre-defined protocol, ensuring objectivity, and reproducibility in research synthesis (Hong & Pluye, 2018).

To enhance the transparency and completeness of systematic reviews, the *PRISMA* guideline was originally proposed by Moher et al. (2009). It was developed to address inadequate reporting practices by providing a structured checklist that promotes clarity, replicability, and consistency. The guideline underwent a major update in 2020, incorporating advancements in systematic review methodology, such as automated literature screening and enhanced synthesis techniques. Unlike systematic review methodologies that dictate research design, *PRISMA* functions as a reporting standard, providing a framework that ensures systematic reviews provide clear, reproducible, and high-quality findings. *PRISMA* includes a 27-item checklist covering critical elements such as study selection, data extraction, and risk of bias assessment (Page et al., 2021). This review was conducted in accordance with the *PRISMA 2020* guidelines to ensure a transparent and comprehensive systematic review process. The methodology, study selection, and data synthesis were structured following the checklist outlined by Page et al. (2021), ensuring rigorous reporting standards. By adhering to *PRISMA* guidelines, this research mitigates bias, improves transparency, and strengthens the credibility of the findings.

While systematic reviews provide a qualitative synthesis of research findings, bibliometric analysis offers a complementary quantitative perspective, mapping research trends, intellectual networks, and the evolution of scholarly contributions within a field. The origins of bibliometric analysis date back to the 1950s, with early discussions focusing on citation analysis and scientific mapping (Pritchard, 1969; Broadus, 1987). The methodology gained prominence with the advent of large-scale databases such as Scopus and Web of Science, enabling comprehensive data-driven insights into research trends. The primary objectives of bibliometric analysis include assessing research impact through citation analysis, mapping intellectual structures via co-citation and co-word analysis, and identifying knowledge gaps and emerging trends (Donthu et al., 2021). Unlike systematic reviews, which offer a qualitative synthesis of findings, bibliometric analysis provides a quantitative assessment of a research field, allowing for an objective evaluation of influential works, dominant research areas, and evolving scholarly discussions.

Note that bibliometric analysis complements systematic reviews by offering a data-driven approach to understanding the structure of academic literature. In this study, bibliometric analysis is used to identify the most influential journals and researchers in the field, analyze the evolution of research on digital transformation in the MI, and highlight research gaps that warrant further investigation. By integrating *PRISMA-based* systematic review and bibliometric analysis, this study presents a comprehensive perspective on the barriers to digital technology adoption in the MI. The integrated use of these methodologies strengthens the validity of the findings and contributes to a more holistic understanding of the existing research landscape.

3.1. Prısma

The *PRISMA* flowchart shown in *Figure 3.3.* illustrates the systematic review process undertaken in this study. Initially, studies were gathered from two major and one local databases: Web of Science and Scopus and DergiPark. After the initial collection, duplicate items were removed. The remaining studies were then screened, with some being excluded by automation tools and others manually excluded based on their titles and abstract irrelevances. Publications sought for retrieval were those for which full texts could be accessed. These publications were then assessed for eligibility, resulting in a final selection of forty-eight studies included in the review. This flowchart provides a clear and transparent overview of the research selection process, demonstrating the rigorous screening and evaluation employed.

Next, the search chain used in this review is presented in *Figure 3.4.*, providing a visual representation of the systematic process employed to identify relevant documents. This is followed by *Table 3.1.*, which details the specific search strategies and filtering methods applied across Scopus and the Web of Science. The inclusion and exclusion criteria, which guided the selection of the studies, are comprehensively demonstrated in *Table 3.2*. Lastly, *Figure 3.5.* illustrates the information resources, offering a graphical overview of the number of studies retrieved and processed from each source. These figures and tables collectively provide a structured and transparent overview of the methodology and data selection process, highlighting the rigorous approach employed in this study.

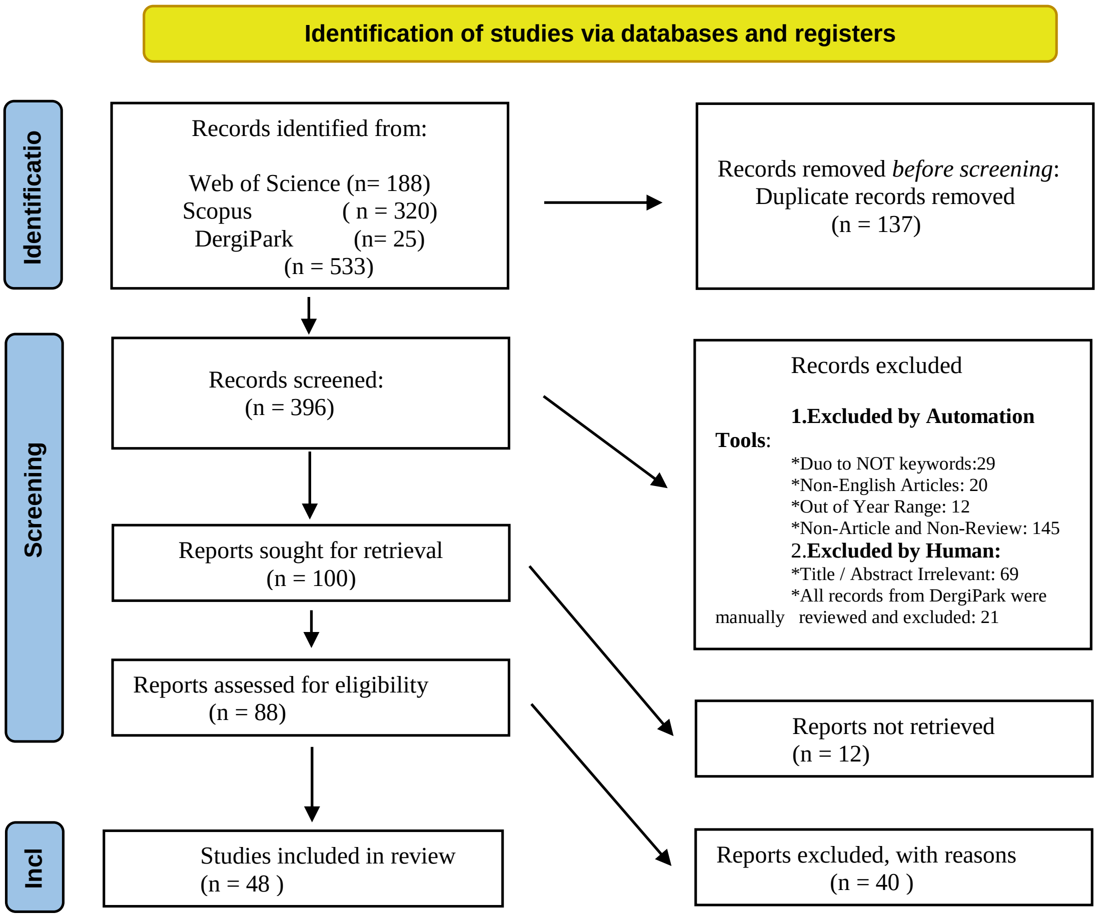

Figure 3.2. Scientific article selection process according to PRISMA methodology

*All records, excluded from Dergipark were manually processed.

("Industry 4.0" OR "mining 4.0" or "digital technolog*" OR "digitalization" OR "digital transformation" or "technology adoption " OR "digital transition" or "artificial intelligence" OR "AI" OR "Internet of Things" OR "IOT" OR "blockchain" OR "Robotics" OR "cloud mining" OR "Machine learning" OR "Neural networks" OR "Big Data" OR "Autonomous learning" OR "Digital Twin*" OR "Augmented reality" OR "Virtual reality" OR "Automatic Speech Recognition") AND ("mining industry" OR "mining sector" OR “mining supply chain”) AND ("challenges" OR "barriers" OR "obstacles")

Figure 3.3. Search STRING

Table 3.1. Search string and Filtering Criteria

	Search string	Filters
Web of Science	("Industry 4.0" OR "mining 4.0" or "digital technolog*" OR "digitalization" OR "digital transformation" OR "technology adoption " OR "digital transition" OR "artificial intelligence" OR "AI" OR "Internet of Things" OR "IOT" OR "blockchain" OR "Robotics" OR "cloud mining" OR "Machine learning" OR "Neural networks" OR "Big Data" OR "Autonomous learning" OR "Digital Twin*" OR "Augmented reality" OR "Virtual reality" OR "Automatic Speech Recognition") AND ("mining industry" OR "mining sector") AND ("challenges" OR "barriers" OR "obstacles"	("Industry 4.0" OR "mining 4.0" or "digital technolog*" OR "digitalization" OR "digital transformation" OR "technology adoption " OR "digital transition" OR "artificial intelligence" OR "AI" OR "Internet of Things" OR "IOT" OR "blockchain" OR "Robotics" OR "cloud mining" OR "Machine learning" OR "Neural networks" OR "Big Data" OR "Autonomous learning" OR "Digital Twin*" OR "Augmented reality" OR "Virtual reality" OR "Automatic Speech Recognition") AND ("mining industry" OR "mining sector") AND ("challenges" OR "barriers" OR "obstacles) (All Fields) NOT "data mining" or "text mining" or "process mining" (Topic) and 2011 or 2012 or 2013 or 2014 or 2015 or 2016 or 2017 or 2018 or 2019 or 2020 or 2021 or 2022 or 2023 or 2024 or 2025 (Publication Years) and Review Article or Article (Document Types) and English (Languages)
Scopus	("Industry 4.0" OR "mining 4.0" or "digital technolog*" OR "digitalization" OR "digital transformation" OR "technology adoption " OR "digital transition" OR "artificial intelligence" OR "AI" OR "Internet of Things" OR "IOT" OR "blockchain" OR "Robotics" OR "cloud mining" OR "Machine learning" OR "Neural networks" OR "Big Data" OR "Autonomous learning" OR "Digital Twin*" OR "Augmented reality" OR "Virtual reality" OR "Automatic Speech Recognition") AND ("mining industry" OR "mining sector") AND ("challenges" OR "barriers" OR "obstacles"	(TITLE-ABS-KEY (("Industry 4.0" OR "mining 4.0" OR "digital technolog*" OR "digitalization" OR "digital transformation" OR "technology adoption " OR "digital transition" OR "artificial intelli-gence " OR "AI" OR "Internet of Things" OR "IOT" OR "block-chain" OR "Robotics" OR "cloud mining" OR "Machine learning" OR "Neural networks" OR "Big Data" OR "Autonomous learnin"OR "Digital Twin*" OR "Augmented reality" OR "Virtual reality "OR "Automatic Speech Recognition") AND ("mining industry " OR"mining sector" OR "mining supply chain") AND ("challenges" OR "barriers" OR "obstacles")) AND NOT TITLE-ABS-KEY ("datamining" OR "text mining" OR "process minig")) AND PUBYEAR> 2010 AND PUBYEAR < 2026 AND (LIMIT-TO (LANGUAGE, "English")) AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE, "re"))
DergiPark	("Industry 4.0" OR "mining 4.0" or "digital technolog*" OR "digitalization" OR "digital transformation" OR "technology adoption " OR "digital transition" OR "artificial intelligence" OR "AI" OR "Internet of Things" OR "IOT" OR "blockchain" OR "Robotics" OR "cloud mining" OR "Machine learning" OR "Neural networks" OR "Big Data" OR "Autonomous learning" OR "Digital Twin*" OR "Augmented reality" OR "Virtual reality" OR "Automatic Speech Recognition") AND ("mining industry" OR "mining sector")	All records excluded from Dergipark were manually processed.

Table 3.2. Inclusıon and exclusıon crıterıa

Inclusion Criteria	*Exclusion Criteria*
• Studies related to the barriers, challenges and obstacles in the adoption and implementation of digital technologies in the MI. • Studies focusing on the operations of the MI where digital or emerging technologies are applied or can be applied. • Studies that analyze the impact of technologies such as, industry 4.0 and its components, or smart mining on operational efficiency, safety and environmental sustainability in the MI. • Peer-reviewed papers from 2011 to the present. • Full text Articles published in peer-reviewed journals or relevant databases. • Articles in English and Turkish for Local Database.	• Research unrelated to challenges, barriers and obstacles in adopting and implementation of digital technologies in the MI. • Articles focused on industries other than the MI. • Articles published before 2011. • Research not written in English or Turkish. • Books, theses, manuals, and reports were excluded. • Full-text articles without open access availability.
Justificatio	*Justification*
• Aligned with the research objective to explore factors influencing digital transformation • Provide specific and practical knowledge for improving operational efficiency and sustainable development. • To focus on studies directly relevant to the impact of modern technology on key aspects of the MI. • To provide essential information to assess the environmental sustainability of mining practices, facilitating responsible decision making and the promotion of greener approaches in the sector • To ensure relevance by capturing advancements since the introduction of Industry 4.0 in 2011. • Ensure credibility and reliability of the research.	• Such studies do not align with the research objective. • The scope of this study is limited to the MI. • To focus on developments and advancements since the introduction of Industry 4.0 in 2011 • Limits the ability to assess the content comprehensively. • These sources may lack rigorous academic review or direct relevance to the study. • To ensure unrestricted access to all included materials.

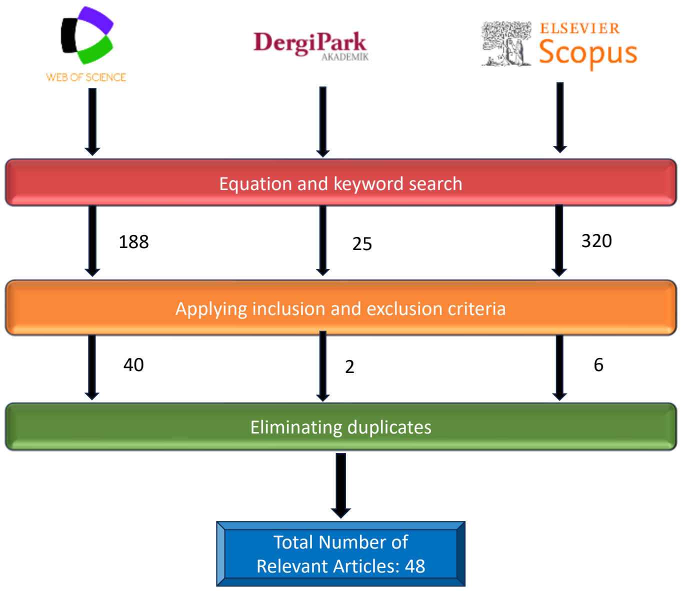

Figure 3.4. Information resources

A comprehensive summary of the forty-study included in this review is provided in *Appendix 1*. This table exhibits the key details of the publications such as the reference, title, methodology, findings, scope, and key themes for each study. By systematically organizing these elements, *Appendix 1* serves as a foundational resource that underpins the analysis conducted in this study. It also offers readers a clear and structured overview of the existing literature landscape, facilitating a deeper understanding of the diverse methodologies, findings, and thematic focuses within the domain.

3.2. Bibliometric Analysis

In this section, the details of the Bibliometric Analysis are demonstrated. For example, Figure 3.5. provides the distribution of where these forty-eight studies were published. This document count shows how many papers each journal has published, highlighting their contributions to the subject. In addition, the citation counts of these journals, reflecting the impact and recognition each paper has received within the academic community are presented in *Figure 3.6.* These figures collectively provide a thorough understanding of the amount of research published as well as its effect, assisting in the identification of the most influential journals in the subject. This analysis helps researchers target appropriate journals for future submissions and ensures that their work reaches well-established platforms with substantial academic reach. *Figure 3.7.* visualizes the co-citation relationships among journals, indicating thematic clusters and citation intensity based on network proximity.

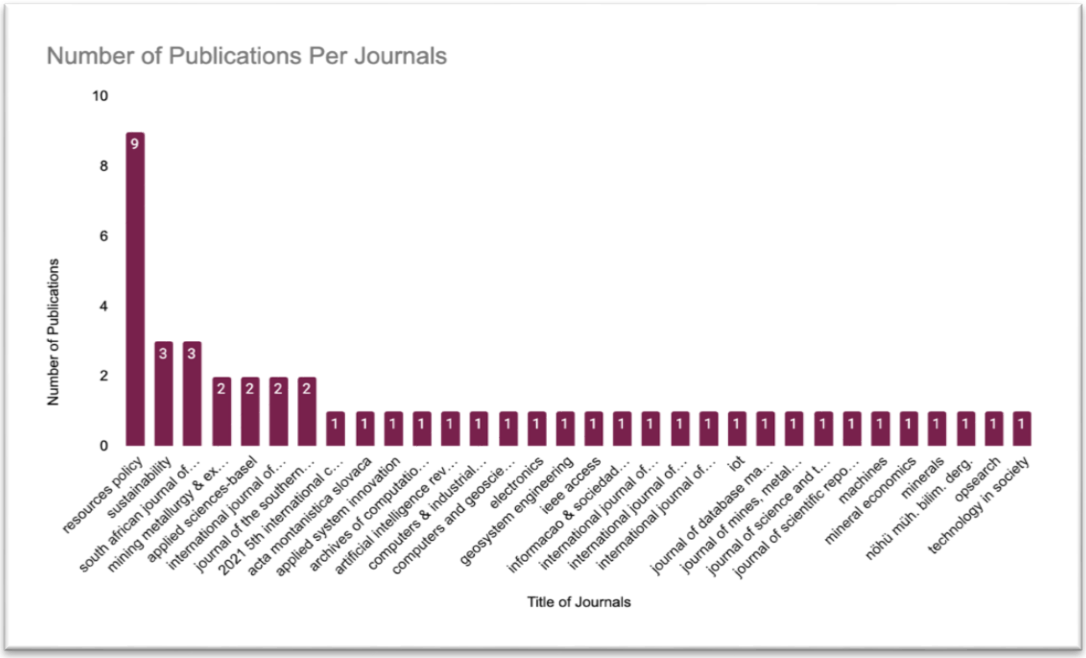

Figure 3.5. Number of Publıcatıons per Journal

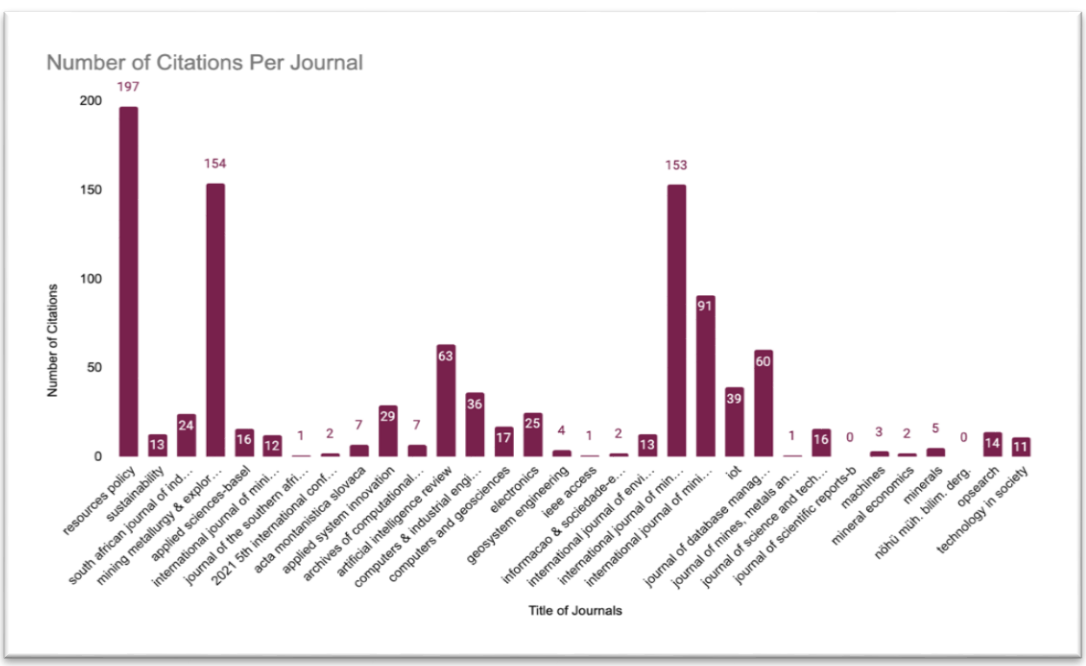

Figure 3.6. Number of Citations per Journal

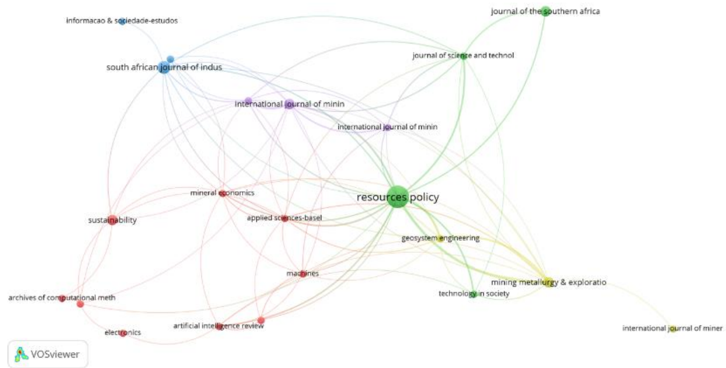

Figure 3.7. Journals Citation Network

A co-occurrence analysis of the keywords is also conducted in this study as shown in *Figure 3.8*. With a threshold set for a minimum occurrence of 1, a total of 386 keywords were identified. Of these, 376 are interconnected, forming a comprehensive network. This graphic effectively illustrates the primary themes and interrelations among the majority of the keywords, offering valuable insights into the core concepts and topics within the research.

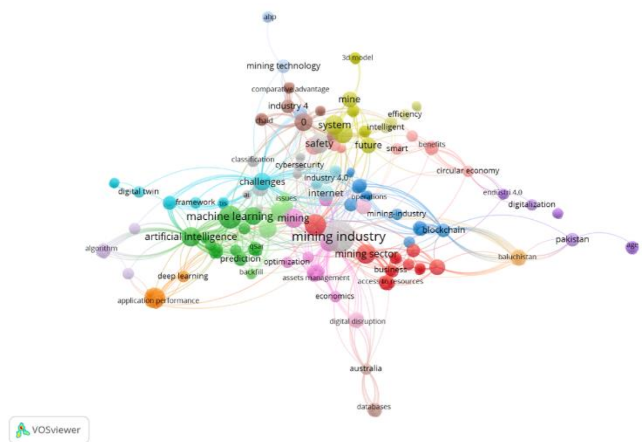

Figure 3.8. Keyword co-occurrence network

Moreover, an overview of the number of publications produced by each country, showing how many studies each nation has contributed to the field is provided in *Figure 3.9*. *Figure 3.10.* presents the citation counts received by these countries, reflecting the academic impact and recognition of their research output. These figures collectively offer valuable insights into both the volume of research produced by different countries and the influence that research has within the academic community. Understanding the number of publications and the corresponding citations is crucial for identifying key countries that are actively contributing to and shaping the research landscape.

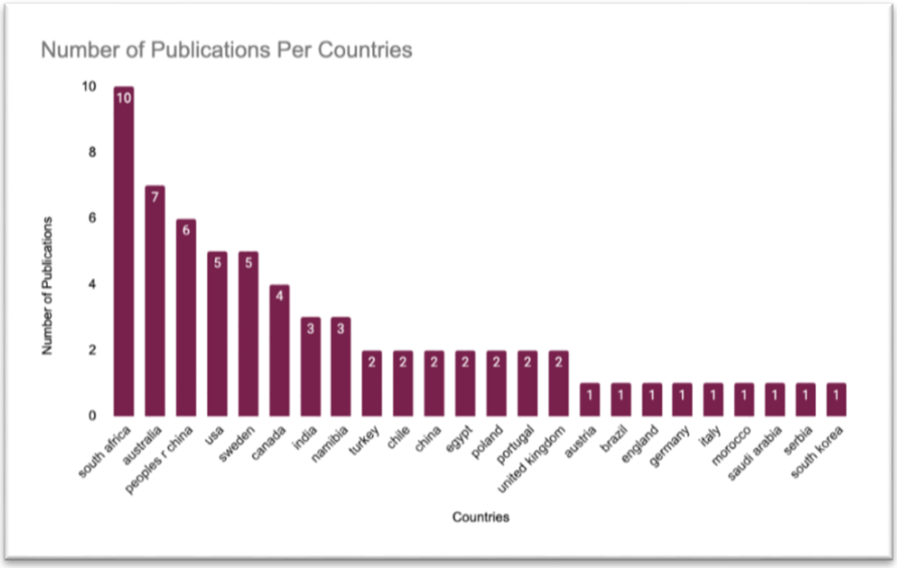

Figure 3.9. Number of Publication per Country

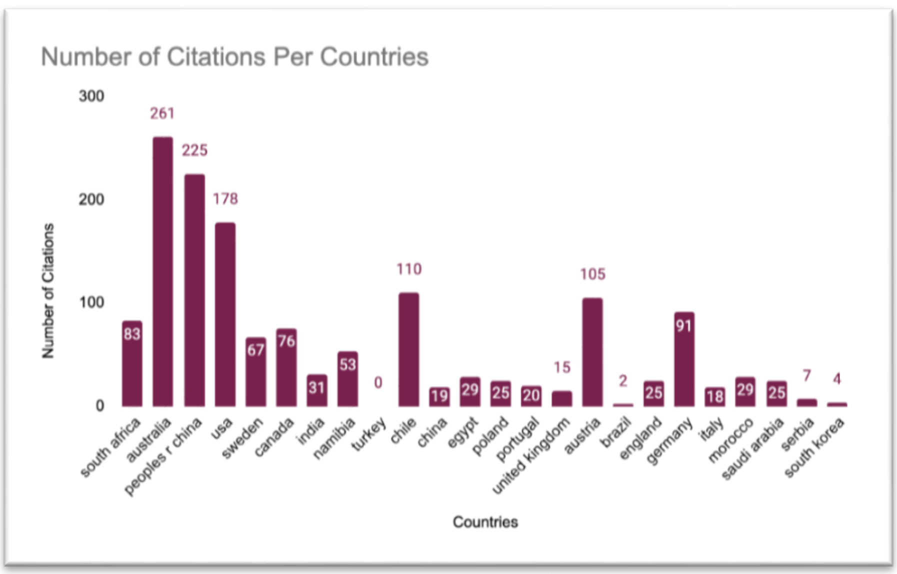

Figure 3.10. Number of Citations per Country

In this analysis, a total of twenty-four country was selected as shown in *Figure 3.9.* and *Figure 3.10*. Among these, eighteen countries are interconnected, indicating a significant level of collaboration or similarity in their contributions. This relationship is visualized in *Figure 3.11.*, which highlights the network and connections among these countries. This visualization provides a clear view of how these countries are related and emphasizes the collaborative efforts within the field.

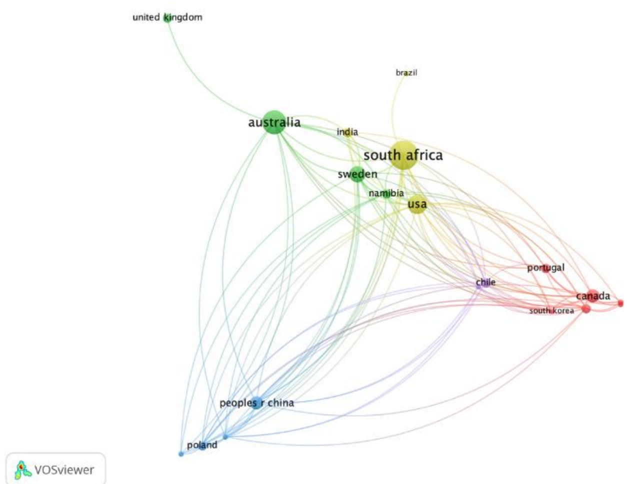

Figure 3.11. Country collaboration network

An overview of the number of articles published each year on the relevant topics, showing the temporal distribution of research in the field is provided in *Figure 3.12*. In addition, *Figure 3.13*. presents the citation counts for each individual article along with its publication year, reflecting the academic impact of research produced in different years. These figures collectively highlight the evolution of research over time and the influence of studies published in various periods. Understanding the annual publication trends and the corresponding citation counts is essential for recognizing how interest in the topic has developed and which periods have produced the most impactful research. Simply put, this analysis offers valuable insights into the temporal progression of the field and helps identify key years and studies that have significantly shaped academic discourse.

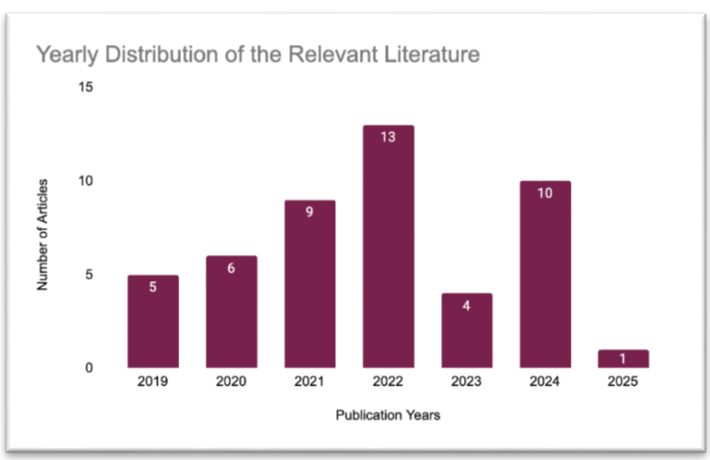

Figure 3.12. Yearly Distribution of the Relevant Literature

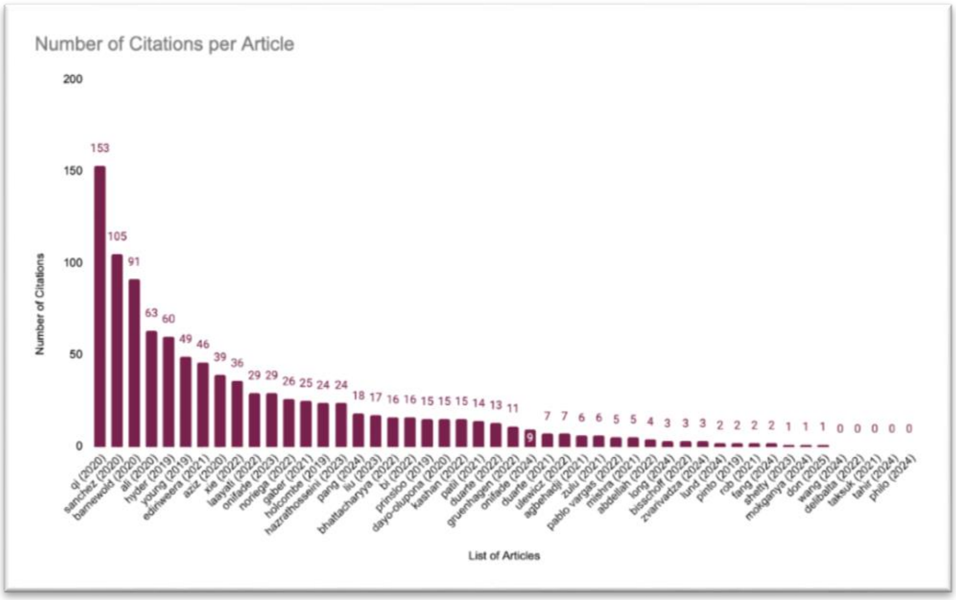

Figure 3.13. Number of Citations per Article

Finally, the data from *Figure 3.12. and Figure 3.13.*, illustrating the distribution of citations and total link strengths of the Forty-eight articles, are visually represented in *Figure 3.14.* This figure provides a graphical overview, enhancing the understanding of the impact and interconnectedness of these studies within the research landscape.

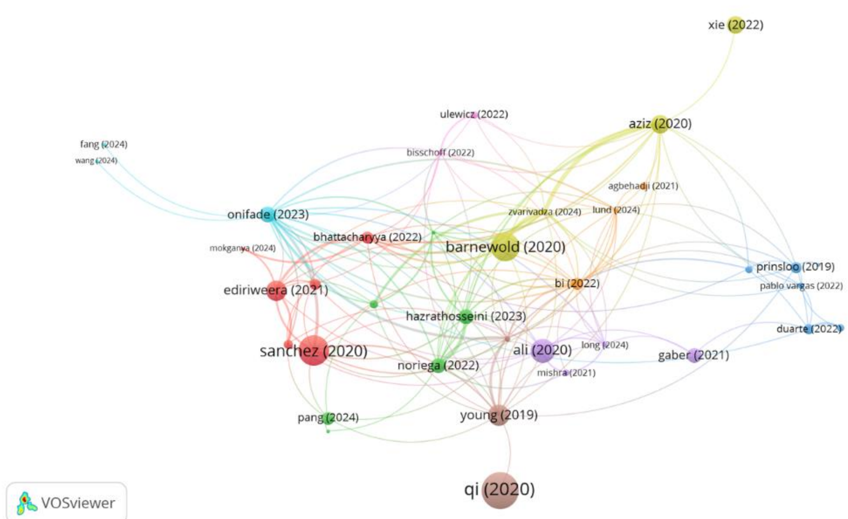

Figure 3.14. Article citation network

Although the MI's digital transformation has attracted increasing academic attention, the existing literature remains fragmented and lacks a comprehensive synthesis of alternative perspectives (Lund et al., 2024; Onifade et al., 2023). While numerous studies emphasize technological advancements and general implementation challenges, few have systematically examined the specific barriers that hinder digital adoption across diverse mining environments. Moreover, despite the availability of various review efforts, there is a notable absence of integrative analytical approaches that explore the underlying interdependencies among these barriers. This indicates a critical gap in the literature, highlighting the need for more structured and causally oriented methods to inform both theoretical development and practical decision-making in the MI.

3.3. Barriers to Digital Transformation in the MI

In this section, a comprehensive overview of the sixteen key barriers hindering the implementation of digital technologies in the MI is provided. Due to the distinct operational, cultural, and environmental challenges of the MI, the adoption of digital technologies in this sector is complicated. Interest in digital transformation is fueled by the promise of greater sustainability, safety, and efficiency, but the road to integration is fraught with difficulties that highlight the conflict between innovation and tradition. As a historically risk-averse and resource-intensive sector, mining has a conundrum: it needs to modernize to adapt to the changing global demands for cost competitiveness, environmental stewardship, and transparency, yet it also works in settings where change is intrinsically challenging. Adoption of digital technology is fraught with systemic issues rather than just technical or economical ones. Note that mining companies in general create an industry that is undergoing change, striking a balance between the need for modernization and the slowness of the workforce, economic, and physical ecosystems.

As demonstrated in *Table 5.1.,* each barrier is described using the supporting references, offering a robust foundation for understanding the obstacles to digital transformation in the MI. This includes critical challenges such as resistance to change, cultural barriers, lack of vision and top management commitment, integration issues, high initial costs, data complexity, uncertainty in Return on Investment (ROI), harsh environmental conditions and limited connectivity in remote locations and a lack of skilled workforce.

Table 3.3. The list of barriers and their descriptions

Code	*Barrier*	*Description*
B_1	Resistance to Change	Employees may resist change due to fear of job loss, reluctance to modify established workflows, and skepticism toward new technologies. Resistance can be exacerbated by a lack of clear communication and perceived threats to traditional work structures
B_2	Cultural Barriers	Traditional organizational cultures can slow down the adoption of technology. Companies with low digital maturity struggle to adapt to new technologies due to entrenched mindsets and reluctance to embrace innovation.
B_3	Lack of vision and top management commitment	Traditional leadership models and lack of top management commitment may fail to ensure strategic alignment in digital transformation, lack the vision to support innovation, and be resistant to disruptive technologies.
B_4	High Initial Investment	Implementing digital technologies (automation, IoT, AI, blockchain) requires significant capital investment that many companies, especially SMEs may lack.
B_5	Uncertainty in Return on Investment (ROI)	The cost-benefit balance of digital transformation projects is often unclear. Companies may hesitate to adopt technology due to uncertainty regarding financial returns, long payback periods, and difficulty quantifying benefits.
B_6	Integration Issues with Legacy Systems	Existing IT infrastructure in mining companies is often incompatible with new digital technologies, requiring expensive upgrades and complex system overhauls.
B_7	Harsh Environmental Conditions and Limited Connectivity in Remote Locations	Mining environments (underground, open-pit, or offshore) expose IoT sensors and hardware to extreme conditions (dust, moisture, vibrations, and temperature fluctuations), leading to frequent failures or data inaccuracies. In addition, poor internet infrastructure in remote mining areas hinders real-time monitoring and automation processes, making IoT and AI-driven analytics difficult to implement.
B_8	Cybersecurity Risks	Increased digitalization exposes mining operations to cyber threats, requiring robust security measures to mitigate risks such as data breaches and hacking attempts.
B_9	Lack of Skilled Workforce	A shortage of professionals trained in digital technologies such as AI, IoT, and blockchain slows down adoption and reduces efficiency in implementation
B_{10}	Insufficient Training and Awareness	Employees require extensive training to understand and operate new technologies effectively. Lack of training hinders the efficient implementation of digital systems.
B_{11}	Lack of effective regulatory framework	Varying and frequently changing regulations create confusion for businesses trying to implement digital solutions. The lack of clear legal frameworks for emerging technologies like AI and blockchain further complicates compliance efforts.
B_{12}	Compliance Costs and Administrative Burdens	High compliance costs, including legal fees and regulatory audits, create financial burdens, especially for SMEs. Complex approval processes and documentation requirements slow down digital adoption.
B_{13}	Limited External Stakeholder Engagement	Lack of collaboration with supply chain members including technology providers, research institutions, and regulators restricts knowledge sharing and innovation adoption, further slowing digital transformation
B_{14}	Loss of Routine Jobs through Automation	The adoption of automation reduces the demand for routine and semi-skilled jobs, leading to workforce displacement and resistance to technological change. This challenge is particularly significant for vulnerable worker groups, including those with limited access to reskilling opportunities
B_{15}	Data Complexity and overload	Mining operations generate vast data from diverse systems (drill sensors, haul trucks, geological surveys, weather stations, safety monitors). Integrating these into a unified digital twin is technically challenging. Managing and processing terabytes of real-time data (e.g., ore quality, equipment health) requires advanced analytics and high computing power.
B_{16}	Dynamic and Unpredictable Conditions in mining fields	Geological uncertainty including variability in ore composition, rock stability, or groundwater levels complicates accurate modeling in digital twins. In addition, operational volatility, unplanned events (equipment failures, weather disruptions) require real-time adaptability, which many digital technology tools such as digital twins lack.

These barriers span organizational, technological, financial, regulatory, and human resource dimensions, each presenting unique challenges to effective digitalization. The categorization of these barriers allows for a clearer understanding of the different aspects affecting digital transformation, highlighting the need for comprehensive, interdisciplinary strategies to overcome them. A detailed analysis of each barrier is provided in the following subsections.

Resistance to Change

Resistance to change is widely recognized as a fundamental barrier to digital technology adoption in the MI. Employees, accustomed to traditional operational methods, often view new digital tools such as automation, IoT applications, and analytics systems with skepticism and fear of job displacement (Mokganya et al., 2024; Kashan et al., 2022; Zulu et al., 2021). Such organizational inertia manifests in reluctance to abandon familiar practices, even when digital alternatives promise significant efficiency and safety gains (Bischoff & Grobbelaar, 2022; Agbehadji et al., 2021). Moreover, mining organizations often feature rigid hierarchical structures that amplify resistance, limiting open communication and participatory engagement in digital initiatives (Ediriweera & Wiewiora, 2021; Holcombe & Kemp, 2019). A risk-averse culture, deeply ingrained within many mining companies, further exacerbates this hesitation, as employees and middle management alike prefer to avoid the uncertainties associated with disruptive change (Pinto et al., 2019; Tahir et al., 2024; Lund et al., 2024). Consequently, without targeted change management strategies and strong leadership commitment to fostering a culture of innovation, digital transformation efforts frequently stall or fail to scale within mining operations.

Cultural Barriers

Cultural barriers, deeply rooted in traditional mining organizations, represent a persistent challenge to digital transformation. Rigid hierarchical structures often discourage open communication, cross-departmental collaboration, and experimentation with innovative practices (Zulu et al., 2021; Gruenhagen et al., 2022; Mokganya et al., 2024). Organizations with low digital maturity typically exhibit risk-averse attitudes, viewing technological disruption not as an opportunity but as a threat to established norms and routines (Jianing et al., 2024; Vargas et al., 2022).

This reluctance is further reinforced by isolated decision-making processes and siloed departments that limit knowledge exchange and slow the development of integrated digital strategies (Ali & Frimpong, 2020; Lund et al., 2024). Without a deliberate and sustained shift in organizational culture—supported by leadership that embraces innovation and empowers bottom-up change—efforts to digitize mining operations are likely to underperform or fail (Philo & Webber-Youngman, 2024; Young & Rogers, 2019).

Lack of Vision and Top Management Commitment

Strategic leadership is a critical enabler of digital transformation in the MI. Without a clear and unified digital vision articulated by top management, transformation efforts often face fragmented implementation, underutilized resources, and limited internal support (Mokganya et al., 2024; Kashan et al., 2022). Senior leaders play a pivotal role in aligning technological initiatives with broader organizational goals and in fostering a culture that values experimentation and innovation (Abdellah et al., 2022; Bhattacharyya & Shah, 2022). However, in many mining companies, leadership remains anchored in traditional management paradigms, showing limited engagement with emerging digital strategies (Young & Rogers, 2019; Pinto et al., 2019). This detachment creates uncertainty and skepticism among employees, especially when digital initiatives are not integrated into long-term strategic roadmaps (Bi et al., 2022). Moreover, the lack of executive-level ownership can lead to the perception of digital projects as isolated technical upgrades rather than organizational change drivers. To overcome these issues, leadership must actively promote cross-functional collaboration, allocate dedicated resources, and continuously communicate the strategic value of digitalization. Visionary and committed leadership are indispensable for sustaining momentum and embedding transformation deep into mining operations.

High Initial Investment

High initial investment remains a significant barrier to digital transformation in the MI, particularly for capital-intensive technologies such as automation systems, AI platforms, IoT-enabled machinery, and blockchain-based traceability tools (Long et al., 2024; Jianing et al., 2024; Philo & Webber-Youngman, 2024). The required upfront expenditures encompass not only equipment and software costs but also cybersecurity infrastructure, personnel training, systems integration, and long-term maintenance (Aziz et al., 2020; Bi et al., 2022). Small and medium-sized enterprises (SMEs), which often operate under tight financial constraints, are especially vulnerable to these capital barriers, resulting in delayed adoption or complete abandonment of digital initiatives (Noriega & Pourrahimian, 2022; Onifade et al., 2023; Dayo-Olupona et al., 2020).

In addition, the MI's traditionally cautious investment mindset further complicates technology deployment, as firms are reluctant to commit resources without clear return-on-investment timelines (Mishra, 2021; Young & Rogers, 2019; Pinto et al., 2019). Even when long-term efficiency and safety gains are evident, the formidable initial costs—both real and perceived—continue to act as a powerful deterrent to digital progress, particularly in volatile economic contexts (Tahir et al., 2024; Bischoff & Grobbelaar, 2022).

Uncertainty in Return on Investment (ROI)

Uncertainty in return on investment (ROI) constitutes a persistent obstacle to digital transformation in the MI. Despite the theoretical benefits of improved efficiency, safety, and productivity, many mining companies remain hesitant to invest due to concerns over long payback periods, unpredictable financial outcomes, and intangible short-term returns (Kashan et al., 2022; Pinto et al., 2019; Sánchez & Hartlieb, 2020). This hesitancy is further aggravated by market volatility, fluctuating commodity prices, and regulatory instability—factors that complicate cost-benefit analyses and increase perceived investment risk (Mishra, 2021; Zulu et al., 2021).

Additionally, the lack of industry-specific benchmarks and standardized evaluation frameworks makes it difficult for decision-makers to justify large-scale expenditures on emerging technologies such as IoT or AI (Bhattacharyya & Shah, 2022; Jianing et al., 2024). In many cases, mining firms—especially those with conservative financial cultures—delay transformation projects until clear, proven value can be demonstrated through pilot studies or quantifiable KPIs (Philo & Webber-Youngman, 2024). Thus, addressing ROI-related concerns requires more than technical viability; it demands strategic financial planning, transparency in performance outcomes, and trust-building mechanisms within and across organizations.

Integration Issues with Legacy Systems

Legacy systems remain a major obstacle to digital transformation in the MI, as outdated IT infrastructure is often incompatible with modern digital tools such as IoT platforms, AI-based analytics, and cloud computing architectures (Bischoff & Grobbelaar, 2022; Mokganya et al., 2024). Integrating new technologies into entrenched operational systems frequently necessitates expensive software rewrites, complex interface bridging, and prolonged implementation timelines, which can severely disrupt production continuity (Bi et al., 2022; Noriega & Pourrahimian, 2022; Don et al., 2025). These technical misalignments also hinder system interoperability, real-time data exchange, and the scalability of digital solutions across different mining operations.

Moreover, many legacy platforms lack modular design, limiting upgrade paths and forcing mining companies to either accept fragmented IT environments or undertake full-scale modernization—both of which strain financial and technical resources (Abdellah et al., 2022; Philo & Webber-Youngman, 2024). Without a coordinated integration roadmap and strategic system renewal initiatives, legacy infrastructure will continue to act as a structural bottleneck, delaying or derailing digital transformation efforts in the MI.

Harsh Environmental Conditions and Limited Connectivity in Remote Locations

The remote and environmentally harsh locations of many mining sites present persistent barriers to digital transformation. Factors such as high humidity, dust, extreme temperatures, and seismic instability severely affect the durability and performance of IoT sensors, autonomous machinery, and communication infrastructure (Mokganya et al., 2024; Jianing et al., 2024; Ali & Frimpong, 2020). These physical stressors increase the frequency of technical failures and reduce the lifespan of critical digital components, resulting in higher operational costs and system unreliability (Young & Rogers, 2019; Onifade et al., 2023). In addition, limited internet access in remote locations restricts the functionality of real-time monitoring, predictive maintenance systems, and centralized analytics platforms that depend on constant data flow (Noriega & Pourrahimian, 2022; Zulu et al., 2021). Mining firms operating in regions with underdeveloped digital infrastructure often struggle to establish stable networks, forcing them to delay or scale down automation projects despite their strategic importance. Ultimately, without robust connectivity investments and the deployment of resilient digital hardware adapted to extreme environments, mining companies risk ongoing system disruptions that compromise both operational efficiency and long-term digital scalability.

Cybersecurity Risks

As mining operations become increasingly digitalized, they are exposed to a growing spectrum of cybersecurity threats that can compromise operational continuity, safety, and data integrity. Cyber risks in the MI include unauthorized data access, ransomware attacks, phishing, and industrial sabotage targeting automated and IoT-based systems (Aziz et al., 2020; Bi et al., 2022; Onifade et al., 2023). These threats are particularly concerning given that many mining companies lack comprehensive cybersecurity frameworks and often rely on outdated protection systems (Qi, 2020; Zulu et al., 2021). The limited awareness among staff, combined with underinvestment in cybersecurity infrastructure, exacerbates the vulnerability of critical assets, including SCADA systems and remote monitoring platforms (Philo & Webber-Youngman, 2024; Tahir et al., 2024).

Barriers to effective cybersecurity also stem from the absence of sector-specific standards and real-time incident response strategies, especially in decentralized and globally distributed mining networks (Ali & Frimpong, 2020; Don et al., 2025). Unless robust, proactive, and well-resourced security protocols are integrated into digital transformation strategies, mining firms will remain exposed to attacks that threaten both operational resilience and stakeholder trust.

Lack of Skilled Workforce

A persistent shortage of professionals with expertise in digital technologies poses a significant barrier to transformation in the MI. While mining traditionally relies on mechanical, geological, and field-based competencies, the adoption of AI, IoT, blockchain, and data-driven automation demands a new generation of skills (Long et al., 2024; Bi et al., 2022; Mishra, 2021). However, the MI struggles to attract and retain digitally skilled professionals due to perceptions of mining as a conventional and low-tech industry (Philo & Webber-Youngman, 2024; Ulewicz et al., 2022). Many mining companies lack internal training programs that can bridge this competency gap, and education systems in some regions have yet to integrate industry-specific digital curricula (Ediriweera & Wiewiora, 2021; Young & Rogers, 2019). This leads to operational inefficiencies, slow adoption rates, and dependence on external consultants, which can be costly and unsustainable in the long term (Barnewold & Lottermoser, 2020; Dayo-Olupona et al., 2020). Unless proactive workforce development strategies are implemented—such as partnerships with technical institutions and on-site upskilling programs—the sector's digital transformation will continue to face a critical human capital constraint that limits innovation and scalability.

Insufficient Training and Awareness

Even when digital technologies are introduced into mining operations, the lack of structured training and awareness programs prevents employees from using these systems effectively. Many workers are unfamiliar with advanced digital tools such as AI interfaces, sensor-based monitoring platforms, and cloud-based control systems, leading to poor system utilization and low ROI (Mokganya et al., 2024; Young & Rogers, 2019). Training initiatives, when available, are often sporadic, generic, or fail to address the specific digital workflows relevant to mining tasks (Bischoff & Grobbelaar, 2022). This results in operational inefficiencies, safety risks due to improper handling of automated systems, and increased reliance on external consultants for routine digital tasks (Jianing et al., 2024).

Furthermore, the absence of continuous learning programs and digital awareness campaigns reinforces resistance to change, especially among older or less tech-oriented personnel. To overcome these limitations, mining firms must embed digital skill development into their organizational strategies, ensuring that training is contextual, regular, and aligned with the specific technologies being deployed.

Lack of Effective Regulatory Framework

The absence of a cohesive and up-to-date regulatory framework significantly impedes digital transformation in the MI. Many regulations governing mining operations have not evolved in parallel with advances in AI, IoT, and blockchain technologies, resulting in legal ambiguities that discourage innovation (Tahir et al., 2024; Kashan et al., 2022; Vargas et al., 2022). Frequent changes and inconsistencies in digital compliance requirements—especially regarding data privacy, cybersecurity, and environmental responsibilities—create confusion for companies attempting to implement new technologies (Jianing et al., 2024; Zulu et al., 2021). This lack of clarity is particularly problematic for cross-border mining firms, which must navigate a patchwork of national and regional laws, often with conflicting standards (Rob & Sharifuzzaman, 2021; Duarte et al., 2021). In emerging economies, regulatory bodies may also lack the technical expertise to assess and approve digital mining systems, further delaying adoption (Philo & Webber-Youngman, 2024; Sánchez & Hartlieb, 2020; Onifade et al., 2023). Unless governments and industry stakeholders collaborate to modernize and harmonize regulatory policies, uncertainty will continue to restrict investment in digital innovation and undermine the scalability of transformation efforts.

Compliance Costs and Administrative Burdens

The adoption of digital technologies in mining often entails navigating extensive regulatory procedures and incurring substantial compliance-related costs. Companies must address complex licensing requirements, legal documentation, and sector-specific audits, all of which require significant administrative effort and specialized knowledge (Kashan et al., 2022; Mokganya et al., 2024; Bi et al., 2022). For small and medium-sized mining enterprises (SMEs), these processes are especially burdensome, as they frequently lack dedicated compliance teams and legal resources (Ediriweera & Wiewiora, 2021; Ali & Frimpong, 2020).

Additionally, documentation demands, and approval timelines vary considerably across jurisdictions, adding further uncertainty and delays to digital transformation initiatives (Tahir et al., 2024; Lund et al., 2024). In some cases, companies are forced to abandon or postpone digital investments due to the overwhelming effort and cost associated with meeting regulatory obligations (Philo & Webber-Youngman, 2024). To enable smoother digital adoption, mining authorities and policymakers must simplify regulatory frameworks and streamline administrative processes, particularly for resource-constrained operators.

Limited External Stakeholder Engagement

Effective digital transformation in mining requires close collaboration between internal teams and external stakeholders such as technology providers, research institutions, government regulators, and supply chain partners. However, many mining firms operate in isolation, with limited participation in cross-sectoral initiatives or innovation networks (Ediriweera & Wiewiora, 2021; Gruenhagen et al., 2022). This lack of engagement hampers the flow of technical knowledge, delays the co-creation of industry-specific digital solutions, and reduces opportunities for shared learning (Bhattacharyya & Shah, 2022; Zulu et al., 2021). Regulatory agencies, too, are often left out of early-stage technology discussions, resulting in misaligned standards and delayed approvals that further complicate deployment. Moreover, the absence of collaborative ecosystems discourages small and medium-sized enterprises from adopting new technologies, as they lack access to collective resources, pilot programs, or public–private partnerships (Laayati et al., 2022). To fully realize the benefits of digitalization, the MI must foster multi-stakeholder platforms that promote trust, transparency, and innovation through continuous dialogue and joint problem-solving.

Loss of Routine Jobs through Automation

The integration of automation into mining operations significantly improves efficiency, safety, and consistency, yet it also brings social challenges—most notably the displacement of routine and semi-skilled labor. Workers engaged in repetitive manual tasks are often the first to be impacted by automated machinery, leading to fears of unemployment and job insecurity (Holcombe & Kemp, 2019; Agbehadji et al., 2021). This fear contributes to resistance against digital initiatives, as employees perceive automation as a threat rather than a tool for operational improvement (Onifade et al., 2023; Lund et al., 2024). The challenge is particularly acute in communities where mining serves as a primary employment source and where access to reskilling or alternative job opportunities is limited (Long et al., 2024). Without structured workforce transition strategies, automation risks eroding trust between labor and management, thereby undermining the broader digital transformation agenda. To mitigate these effects, companies must integrate inclusive labor policies, reskilling programs, and open communication channels into their automation strategies to ensure a just and socially responsible transformation process.

Data Complexity and Overload

Modern mining operations generate massive volumes of data from a wide array of sources, including geological surveys, drill sensors, weather stations, haul trucks, safety systems, and production monitoring tools. Integrating these diverse datasets into cohesive, real-time decision-making platforms presents a significant technical and organizational challenge (Pinto et al., 2019; Qi, 2020; Laayati et al., 2022). The heterogeneity of data formats, inconsistencies in data quality, and lack of standardized protocols often result in fragmented analytics systems and limited insight generation (Liu et al., 2023; Shetty et al., 2023). In particular, studies have shown that only a small fraction of collected data—sometimes less than 1%—is effectively utilized, with the remainder underexploited due to computational limitations and integration gaps (Don et al., 2025).

Additionally, the need to process and interpret terabytes of real-time data demands high-performance computing infrastructure and advanced data analytics capabilities, which are not always accessible to mining firms, particularly smaller operations. Without robust data governance strategies and interoperable digital architectures, data overload can overwhelm existing systems and inhibit the development of tools like digital twins or AI-driven automation. Therefore, addressing data complexity through standardized integration frameworks and scalable analytics solutions is essential for enabling accurate, efficient, and sustainable digital transformation in mining.

Dynamic and Unpredictable Conditions in Mining Fields

Mining environments are inherently volatile, marked by geological variability, rock instability, groundwater fluctuations, and extreme weather conditions. These dynamic factors significantly challenge the stability and adaptability of digital technologies used in real-time operations (Duarte et al., 2022; Hyder et al., 2019; Ali and Frimpong, 2020). Digital twins, automation systems, and predictive maintenance tools often lack the responsiveness required to function effectively in the face of such unpredictability (Liu et al., 2023). Sudden equipment failures, landslides, or weather-induced disruptions can render data models obsolete, requiring continuous recalibration and rapid system adaptation (Duarte et al., 2021).

Moreover, most existing digital platforms are designed for controlled industrial environments and struggle to accommodate the geological and environmental complexity of mining sites. Unless digital solutions are specifically tailored to operate in fluctuating and high-risk field conditions, their utility remains limited, hindering both operational reliability and long-term digital transformation success. The barriers identified above illustrate the intricate interplay between organizational inertia, financial constraints, technological incompatibilities, regulatory uncertainties, and human capital limitations—factors that collectively hinder the digital transformation of the MI. Systematically understanding these interrelated challenges is essential for designing targeted and effective strategies to address them. The following section presents a broader discussion of the findings, offering critical reflections on their implications for both managerial practice and future academic research.

4. METHODOLOGY

This methodology used in this research comprises two interrelated components—qualitative and quantitative methods—each offering distinct but complementary insight into the overarching research inquiry. The qualitative dimension aims to construct a robust conceptual foundation by systematically identifying and synthesizing the key challenges associated with digital transformation in MI, while the quantitative phase focuses on exploring the structural interdependencies among these challenges. As outlined in *Figure 4.1.*, this study applies an integrated methodological framework comprising qualitative and quantitative methods.

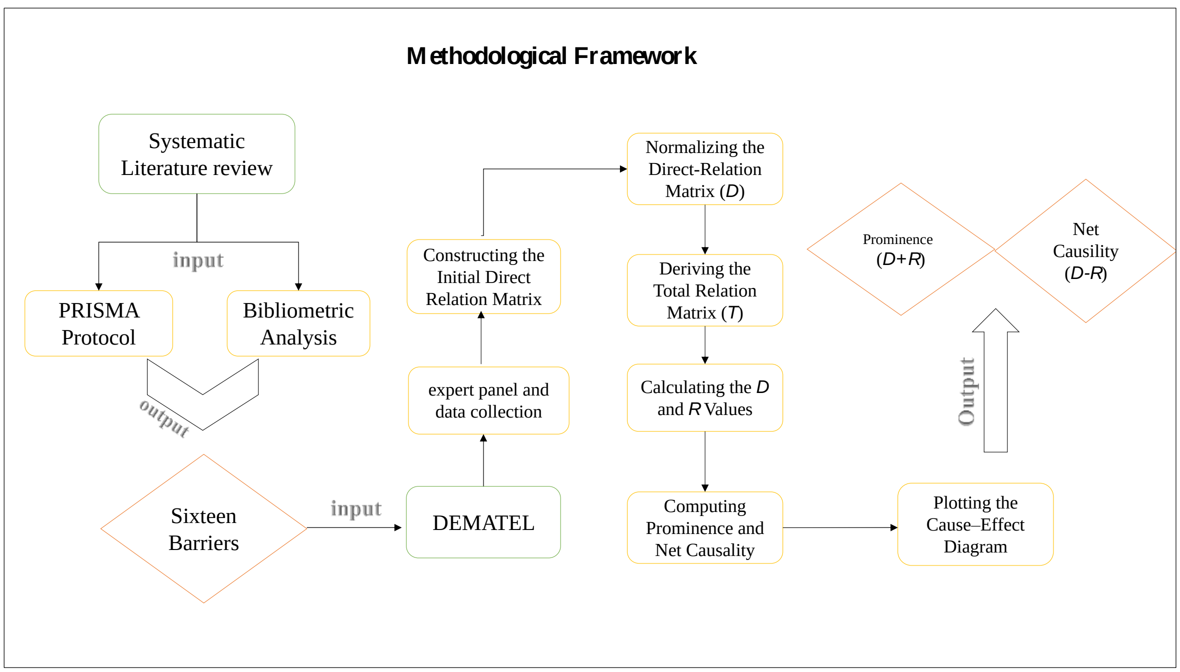

Figure 4.1. Methodological Framework

Qualitative methods used in this research include systematic literature review and bibliometric analysis to support the qualitative investigation. This framework ensures transparency, analytical depth, and reproducibility in capturing both the breadth and depth of scholarly contributions. The full procedural details—including search strategy, inclusion criteria, and screening stages—are documented in Section 3 of this thesis. This systematic review was conducted in accordance with the *PRISMA* protocol to ensure methodological rigor, while bibliometric techniques were employed to visualize thematic clusters and identify influential trends, authors, and publication sources. This dual-method approach enabled a comprehensive understanding of the field, highlighting not only content-based findings but also the underlying intellectual structure of the research landscape. This output serves as the empirical basis for the second phase of the methodology, in which the interrelationships among these barriers are quantitatively assessed using a causal-analytical approach.

Following the completion of the qualitative exploration, the second phase of the methodology—namely the quantitative component—was designed to investigate the causal interrelationships and prominence of barriers identified during the literature review. This study's methodological design comprises a quantitative phase aimed at revealing the systemic structure of interrelated barriers to digital transformation in the MI. This segment relies on the classical *DEMATEL* technique to model complex causal relationships and evaluate the prominence of each barrier. A structured process was followed to ensure the analytical robustness of this approach.

Originally developed by the Battelle Memorial Institute in Geneva during the 1970s under the sponsorship of the Science and Human Affairs Program of Japan, the *DEMATEL* method was intended to visualize the structure of complex causal relationships in large-scale systems (Gabus & Fontela, 1973). Its analytical framework facilitates the conversion of expert judgment into a causal diagram, making it particularly valuable for studies addressing interdependent barriers or factors in managerial and technological domains. The *DEMATEL* method is particularly well-suited for this research due to its capacity to analyze complex and interdependent systems, where each factor can simultaneously influence and be influenced by others. Given the systemic nature of digital transformation challenges—spanning organizational, technological, and regulatory domains—*DEMATEL* provides a structured framework to unravel both the intensity and direction of inter-barrier relationships. One of its key strengths lies in converting expert judgments into causal diagrams, allowing for the classification of factors into influencing (*cause*) and influenced (*effect*) groups based on the $D - R$ values. Furthermore, the method quantifies the overall prominence of each barrier within the system by computing the $D + R$ values. This dual analytical lens enables a comprehensive understanding of both the structural role and criticality of each barrier within the broader transformation ecosystem.

Numerous studies have successfully utilized *DEMATEL* in similar domains, underscoring its applicability and reliability. For instance, Paul and Mahapatra (2025) applied a fuzzy-DEMATEL approach to analyze sustainable supply chain drivers and barriers in the Indian MI, effectively classifying factors based on their causality and dominance. Katiyar et al. (2024) employed a hybrid ISM-DEMATEL framework to assess coal supply barriers in India's non-core sector, highlighting systemic constraints. Similarly, Chen et al. (2022) leveraged DEMATEL to evaluate the digital maturity of small- and medium-sized enterprises, demonstrating its effectiveness in capturing hierarchical dependencies. Li et al. (2022) integrated DEMATEL-ANP to identify key influences in the digital transformation of the construction industry, evidencing its value in infrastructure-heavy sectors. These empirical validations guided our selection of DEMATEL over other structural mapping techniques. Compared to other multi-criteria decision-making methods, such as Interpretive Structural Modeling (ISM) or MICMAC, DEMATEL offers superior granularity in mapping the direct and indirect effects among factors. ISM, although valuable for hierarchical structuring, lacks the capacity to quantify influence intensity. MICMAC, while categorizing factors, does not account for feedback loops. DEMATEL overcomes these limitations through a matrix-based computational framework, thus enabling not only classification but also the prioritization of barriers based on influence and prominence. Finally, while extended variants of the DEMATEL method exist (e.g., fuzzy, grey, or neutrosophic DEMATEL), the traditional form was deemed sufficiently robust for the scope of this research. The clarity and interpretability of its outputs further reinforced its suitability as a decision-support tool in the context of MI transformation analysis.

To enable the application of the DEMATEL method, a structured questionnaire was developed to evaluate the influence relationships among the identified barriers. A panel of domain experts was assembled to complete the assessment. The experts were selected based on their academic qualifications and practical experience in digital transformation, operations management, and mining technology. This diverse composition ensured the collection of informed and multidimensional judgments. The responses were consolidated into a direct-relation matrix, which subsequently served as the foundation for the DEMATEL computations.

Moreover, this process enhances the transparency and traceability of the findings. While the detailed procedure of expert engagement and matrix development is elaborated in the application section, this theoretical foundation provides the rationale and justification for the analytical choices made in the study.

The implementation of DEMATEL in this study follows a six-step analytical process, each of which is underpinned by distinct mathematical procedures. These are described below:

Step 1: Constructing the Initial Direct-Relation Matrix (A)

The *DEMATEL* procedure commences with the construction of the initial direct-relation matrix, which represents the perceived influence levels between each pair of barriers. This stage involves assembling a panel of domain experts with relevant academic and professional expertise in digital transformation and mining operations. Each expert independently assessed the degree to which one barrier influences another using a structured pairwise comparison scale. These individual judgments were then aggregated by computing their arithmetic mean, yielding a consensus-based initial matrix that quantifies the direct influence of each factor on the others. This aggregation process is formally expressed in Eq. (1).

$$A = [a_{ij}], \quad a_{ij} \in R, \quad a_{ii} = 0 \qquad [1]$$

In this matrix, a_{ij} represents the degree to which barrier i influences barrier $_j$, while the diagonal values are set to zero to reflect the absence of self-influence. Their assessments are averaged to form the initial direct-relation matrix.

Step 2: Normalizing the Direct-Relation Matrix (D)

After constructing the initial direct-relation matrix A, the next step is to normalize its values to facilitate meaningful comparisons and maintain numerical stability in subsequent stages. This normalization process is crucial to ensure that the maximum row sum does not exceed unity, thereby keeping all computations within defined mathematical bounds.

To achieve this, a normalization coefficient s is first determined using Eq. (2), which calculates the maximum sum of any row in the matrix:

$$\boldsymbol{s = \max_{i}\left(\sum_{j=1}^{n} a_{ij}\right)} \qquad [2]$$

Once this coefficient is obtained, each element of the matrix *A* is divided by s, producing the normalized direct-relation matrix D. This is expressed in Eq. (3):

$$\boldsymbol{D = \frac{1}{s} \cdot A} \qquad [3]$$

The resulting matrix $D = [d_{ij}]$ contains proportionally scaled values, where each entry represents the normalized degree of influence that barrier *i* exerts on barrier *j*. This step ensures that the influence weights remain bounded, enabling reliable matrix-based modeling in subsequent phases of the *DEMATEL* methodology.

Step 3: Deriving the Total Relation Matrix (T)

After normalization, the next step involves calculating the total relation matrix, which captures not only the direct influence of one barrier on another but also the indirect effects mediated through intermediate barriers. This is essential for understanding the full scope of interrelationships within the system. The total relation matrix *T* is derived using Eq. (4) based on the convergent infinite geometric series:

$$\boldsymbol{T = D(\mathbf{I} - D)^{-1}} \qquad [4]$$

Here:

- *D* is the normalized direct-relation matrix,
- I is the identity matrix of the same dimensions as D,
- $(I - D)^{-1}$ is the inverse matrix that accounts for cumulative indirect effects.

The resulting matrix $T = [t_{ij}]$ provides a complete picture of the interaction dynamics among barriers, with each element t_{ij} representing the total (direct + indirect) influence that barrier $_i$ has on barrier $_j$.

Step 4: Calculating the D and R Values

Once the total relation matrix *T* is derived, the next stage involves quantifying the influence dynamics of each barrier by computing two fundamental metrics: the dispatching power D_i and the receiving power R_i. These indices provide essential insight into the structural behavior of each element within the system.

• Dispatching value D_i indicates the total amount of influence that barrier *i* exerts on the other elements in the system. It is obtained by summing all the entries in the *i-th* row of matrix *T*, as defined in Eq. (5):

$$\boldsymbol{D_i} = \sum_{j=1}^{n} \boldsymbol{t_{ij}} \tag{5}$$

Receiving value R_i represents the total amount of influence that barrier i receives from the rest of the system. It is calculated as the sum of the i-th column of matrix *T*, following Eq. (6):

$$\boldsymbol{R_i} = \sum_{j=1} \boldsymbol{t_{ji}} \tag{6}$$

Together, D_i and R_i reveal the interactive positioning of each barrier—those with high dispatching values are considered as dominant or causal factors, whereas those with high receiving values tend to be more reactive or effect-driven within the transformation network.

Step 5: Computing Prominence and Net Causality

Following the calculation of dispatching D_i and receiving R_i values in the previous step, two composite metrics are introduced to further interpret the structural roles of barriers in the system: prominence and net causality.

• *Prominence* P_i quantifies the overall level of interaction a barrier maintains within the network. It captures how much a barrier both exerts and receives influence, thereby reflecting its systemic visibility. This metric is computed by summing the respective D_i and R_i values for each barrier, as defined in Eq. (7):

$$\boldsymbol{P_i} = \boldsymbol{D_i} + \boldsymbol{R_i} \tag{7}$$

• *Net Causality* N_i evaluates the directional orientation of a barrier's influence—whether it behaves predominantly as a source or a recipient of influence. A positive N_i indicates a causetype barrier that drives change, whereas a negative value points to an effect-type barrier that is predominantly influenced by others. The metric is computed using Eq. (8):

$$\boldsymbol{N_i = D_i - R_i} \quad [8]$$

Together, these metrics support the classification and strategic prioritization of barriers. Prominent barriers with high P_i values are those deeply embedded in the transformation network, while net causality values N_i help identify leverage points for targeted intervention—distinguishing drivers from consequences within the system.

Step 6: Determining the Threshold Value for Causal Mapping

In the DEMATEL methodology, identifying a threshold value \theta is an essential step for refining the causal representation derived from the total relation matrix. This threshold serves to filter out negligible interactions and focus on the most significant causal links within the system.

The value of \theta is generally computed as the arithmetic mean of all off-diagonal elements in the total relation matrix $T = [t_{ij}]$, as shown in Eq. (9):

$$\boldsymbol{\theta = \frac{1}{n(n-1)} \sum_{i \neq j} t_{ij}} \quad [9]$$

In this equation, t_{ij} represents the influence of barrier i on barrier j, and *n(n-1)* denotes the number of off-diagonal elements in an n times n matrix—excluding the diagonal values, which are zero by definition.

Applying this threshold value enhances the interpretability of the network structure by retaining only those relationships whose strength exceeds \theta. This filtering step helps eliminate low-impact connections that may obscure key dynamics, thus yielding a more concise and policy-relevant visualization of the inter-barrier influences.

Step 7: Plotting the Cause–Effect Diagram

The final analytical step in the *DEMATEL* procedure entails the graphical visualization of systemic interactions using a two-dimensional *cause–effect* diagram. This scatter plot enables a structured interpretation of each barrier's functional role by positioning it within a Cartesian coordinate space according to its net causality and prominence values, calculated in Eq. (7) and Eq. (8).

Formally, each barrier i is represented by coordinates:

$$\boldsymbol{x_i = D_i - R_i, \quad y_i = D_i + R_i} \qquad [10]$$

The horizontal axis x_i reflects the net causal influence of the barrier. A positive value ($x_i > 0$) designates a causal or driving factor, while a negative value ($x_i < 0$) denotes an effect-type or reactive barrier.

• The vertical axis y_i denotes overall prominence, indicating how extensively the barrier interacts within the system as both an influencer and a recipient of influence.

In sum, the *DEMATEL* methodology furnishes a theoretically grounded and methodologically rigorous framework for elucidating the intricate web of interrelationships among digital transformation barriers. The sequential analytical procedures delineated above lay the conceptual and computational groundwork for the forthcoming empirical application, wherein the derived model is operationalized and interpreted through domain-specific data.

5. APPLICATION AND FINDINGS

This chapter applies the methodology displayed in *Figure 4.1.* to investigate the interrelationships among barriers hindering digital transformation in the MI. Based on insights derived from the preceding systematic literature review and bibliometric analysis, a consolidated list of Sixteen critical barriers was developed. As a result of this qualitative phase, a total of sixteen critical barriers to digital transformation were identified, encompassing technological, organizational, regulatory, and financial dimensions. These barriers were extracted through iterative analysis and synthesis of the literature and are presented with their respective codes in Table 5.2. below. These barriers encompass a combination of technical, organizational, and policy-related challenges that have been frequently cited in both academic and industry-focused studies. The results of the *DEMATEL* analysis are presented in the following section. This part includes both the detailed application process of the method and the findings derived from the analysis.

Table 5.1. Barriers and their codes

Code	***Barrier***
B_1	Resistance to Change
B_2	Cultural Barriers
B_3	Lack of vision and top management commitment
B_4	High Initial Investment
B_5	Uncertainty in Return on Investment (ROI)
B_6	Integration Issues with Legacy Systems
B_7	Harsh Environmental Conditions and Limited Connectivity in Remote Locations
B_8	Cybersecurity Risks
B_9	Lack of Skilled Workforce
B_{10}	Insufficient Training and Awareness
B_{11}	Lack of effective regulatory framework
B_{12}	Compliance Costs and Administrative Burdens
B_{13}	Limited External Stakeholder Engagement
B_{14}	Loss of Routine Jobs through Automation
B_{15}	Data Complexity and overload
B_{16}	Dynamic and Unpredictable Conditions in mining fields

To ensure the practical relevance and conceptual robustness of the sixteen identified barriers, an expert validation process was carried out prior to the application of the DEMATEL method. A diverse panel of Eleven Turkish professionals was assembled, comprising four academic scholars specializing in mining engineering, mineral processing, mineral economics, and data science; four senior policymakers from national ministries and public agencies including the Ministry of Energy and Natural Resources, Ministry of Industry and Technology, and the General Directorate of Mineral Research and Exploration (MTA) ; two industry experts from leading state-owned and private mining companies; and one representative from a non-governmental organization focusing on social impact in mining communities. These experts possess between five and eighteen years of domain experience, including leading roles in national digital mining initiatives, technology policy design, ESG and labor compliance, and the integration of AI, automation, and predictive analytics into mining operations. The panel was purposefully selected to reflect a balanced perspective across academia, industry, government, and civil society, with a shared emphasis on expertise in digital transformation and operational efficiency in the MI.

Table 5.2. Expert Group

Role	Affiliation	Experience Duration	Experience	Expertise
Professor of Mining Engineering	University in Ankara, Mining Engineering	Fourteen years	Conducts research on mining innovation with a focus on digitalization and sustainability in Türkiye. Led a 2020 project in coal mines, published in Minerals Engineering. Collaborated with TÜBİTAK on borate mining automation.	Mining technology adoption, data analytics,
Professor of Mineral Processing	University in Istanbul, Mining Engineering	Six years	Specializes in workforce development and digital transformation in Türkiye's mining sector. Published a 2022 study on AI skills gaps in chromite mines.	Workforce reskilling, AI and automation, socio-economic impacts of digitalization in Türkiye.
Associate Professor of Mineral Economics	University in Ankara, Mining Engineering	Fifteen years	Experienced in analyzing mineral markets and investment policy, with advisory roles in public–private partnership development for the mining sector.	Mining economics, investment policy,regulatory impact studies.
Professor of Data Science in Mining	University in Istanbul, Faculty of Engineering	Twelve years	Specialized in integrating AI and machine learning into extractive operations; contributed to national smart mining initiatives.	AI in mining, data analytics, intelligent maintenance systems.
Senior Policy Advisor	Ministry of Energy and Natural Resources, General Directorate of Mining and Petroleum Affairs	Twelfe years	Focused on shaping Türkiye's mining policies, with an emphasis on environmental regulations and digitalization incentives.	Mining regulations, environmental compliance, government-industry collaboration for technology adoption.
Regional Development Coordinator	Aegean Region Development	Nine years	Oversaw mining innovation in Türkiye's Aegean region, a hub for marble and feldspar. Led initiatives to improve connectivity for digital tools in remote mines.	Regional infrastructure development, digital connectivity, public-private partnerships.
Chief Technology Officer	State-Owned Borate Mining Company	Eighteen years	Led digital initiatives at a major borate producer in Türkiye, including the implementation of predictive maintenance technologies in Kütahya's borate mines.	Digital strategy, predictive analytics, automation, operational efficiency in Türkiye's state-owned mining.
Director of Mineral Resource Strategy	General Directorate of Mineral Research and Exploration (MTA), Ankara	Eighteen years	Oversaw national mineral resource planning with a focus on long-term digital infrastructure investments.	Resource strategy, national policy, digital infrastructure funding.
Social Impact Coordinator	Human Rights NGO, Ankara	Eight years	Addressed labor and human rights in Türkiye's mining sector, particularly in Zonguldak coal mines. Collaborated on a 2023 report promoting safer conditions through digital monitoring.	Labor rights, community welfare, ethical technology adoption in Türkiye's mining communities.
Director of Technology Policy	Ministry of Industry and Technology, Ankara	Eleven years	Developed technology adoption policies for Türkiye's industrial sectors, including mining. Led a 2024 initiative to fund 5G infrastructure for remote mining operations in Eastern Türkiye.	Technology policy, industrial digitalization, funding mechanisms for innovation.
Director of Operations	Private Gold Mining Company	Five years	Worked in gold and base metal mining, with a focus on digital transformation initiatives.	Operational optimization, ESG compliance, technology integration in Turkish mining.

The data collection process was conducted through direct visits to the participants. A structured questionnaire was physically delivered in Microsoft Word format, and completed forms were subsequently returned via email. The survey was designed as a pairwise comparison instrument aligned with the traditional DEMATEL method. Each of the sixteen barriers was compared against the remaining Fifteen, and respondents were asked to evaluate the relative influence using a *0–4 scale*, where a higher value indicated stronger causal influence. The comparison format followed a symmetric structure, such as:

0: No influence **1:** Veery little influence **2:** low influence **3:** high influence **4:** Very high influence

Barrier A	4	3	2	1	0	1	2	3	4	**Barrier B**

The total number of pairwise comparisons in the survey was 120 questions, ensuring full coverage of all unique barrier relationships. Although the survey was distributed to over 20 potential respondents, only 11 completed responses met the criteria for inclusion in the analysis. After collecting the data, the pairwise judgments were transferred from Word documents into Excel format. The subsequent stages of the DEMATEL analysis, including matrix construction, normalization, and total relation calculation, were performed in accordance with the standard DEMATEL procedure as outlined in the Methodology section. A sample of the DEMATEL questionnaire used in the expert survey is provided in appendix 2.

5.1. The results of DEMATEL Analysis

Following the completion of the expert survey, the collected pairwise comparison data were systematically compiled to construct the direct-relation matrix required by the DEMATEL method. Each of the eleven experts provided judgments on the influence of one barrier over another using a 0–4 scale, where 0 indicated no influence and 4 indicated very strong influence. The survey structure required the evaluation of 120 unique barrier pairs, covering all possible directed relationships among the 16 identified barriers.

Initially, individual 16 × 16 matrices were created for each expert, with diagonal elements set to zero to reflect the principle that a barrier cannot influence itself. These matrices were then aggregated by computing the arithmetic mean of corresponding cells, yielding a single average direct-relation matrix that reflects the collective judgment of the expert panel. This matrix served as the foundation for the subsequent stages of normalization and total-relation matrix calculation within the DEMATEL process. A detailed analysis of the resulting values is presented in the next chapter.

The *DEMATEL* analysis commenced with the establishment of the average direct-relation matrix, which captures the collective judgments of the expert panel regarding the intensity of influence among the identified barriers. The expert panel consisted of eleven individuals with demonstrated expertise in fields such as digital transformation, mining operations, and organizational systems. The evaluations provided by the experts were aggregated through arithmetic averaging to construct a consolidated 16×16 matrix. Each element $a_{\{ij]}$ in this matrix represents the mean perceived influence that barrier $_i$ exerts on barrier $_j$ across all expert inputs, with diagonal entries set to zero to exclude self-influence. This matrix—referred to as the initial direct-relation matrix—serves as the foundational input for the DEMATEL procedure. It reflects the structural assumptions embedded in expert consensus and forms the basis for all subsequent steps in the causal analysis. The full matrix is presented in *Table 5.4.*

Table 5.3. Average direct-relation matrix constructed from expert panel consensus (16 × 16)

Barriers	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12	B13	B14	B15	B16
B1		0,0247	0,0185	0,0000	0,0000	0,0432	0,0185	0,0247	0,0247	0,0185	0,0000	0,0000	0,0185	0,0247	0,0062	0,0062
B2	0,1049		0,1049	0,0185	0,0000	0,0617	0,0309	0,0185	0,0617	0,0802	0,0556	0,0185	0,0432	0,0432	0,0062	0,0185
B3	0,0988	0,0062		0,0185	0,0123	0,0247	0,0432	0,0432	0,0494	0,0617	0,0432	0,0432	0,0432	0,0802	0,0617	0,0556
B4	0,1296	0,0370	0,0494		0,1049	0,0494	0,0617	0,0679	0,0679	0,0617	0,0556	0,0617	0,0741	0,0617	0,0556	0,0617
B5	0,0802	0,0247	0,0309	0,0185		0,0185	0,0309	0,0432	0,0247	0,0247	0,0185	0,0185	0,0185	0,0185	0,0185	0,0185
B6	0,0370	0,0062	0,0247	0,0370	0,0370		0,0309	0,0494	0,0370	0,0556	0,0247	0,0617	0,0247	0,0679	0,0617	0,0247
B7	0,0494	0,0185	0,0309	0,0556	0,0617	0,0000		0,0370	0,0494	0,0309	0,0247	0,0185	0,0494	0,0309	0,0247	0,0370
B8	0,0309	0,0062	0,0247	0,0494	0,0494	0,0000	0,0185		0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
B9	0,0556	0,0185	0,0432	0,0123	0,0617	0,0247	0,0370	0,0432		0,0679	0,0679	0,0185	0,0309	0,0988	0,0519	0,0556
B10	0,0679	0,0062	0,0494	0,0123	0,0556	0,0000	0,0370	0,0494	0,0185		0,0000	0,0247	0,0062	0,0802	0,0432	0,0370
B11	0,0617	0,0000	0,0432	0,0370	0,0432	0,0556	0,0370	0,0296	0,0000	0,0617		0,0679	0,0494	0,0556	0,0556	0,0556
B12	0,0802	0,0185	0,0494	0,0123	0,0679	0,0000	0,0432	0,0247	0,0247	0,0494	0,0309		0,0370	0,0494	0,0370	0,0494
B13	0,0309	0,0000	0,0247	0,0123	0,0309	0,0000	0,0185	0,0556	0,0000	0,0432	0,0062	0,0185		0,0185	0,0185	0,0185
B14	0,0309	0,0062	0,0000	0,0247	0,0432	0,0000	0,0185	0,0741	0,0000	0,0185	0,0000	0,0000	0,0062		0,0679	0,0370
B15	0,0741	0,0185	0,0247	0,0370	0,0802	0,0000	0,0185	0,0741	0,0000	0,0370	0,0123	0,0000	0,0185	0,0000		0,0185
B16	0,0926	0,0370	0,0123	0,0556	0,0864	0,0370	0,0556	0,0741	0,0185	0,0432	0,0247	0,0494	0,0617	0,0494	0,0802	

Following the construction of the average direct-relation matrix, the next critical step involved normalizing the matrix to ensure computational stability and comparability across all influence scores. This procedure is essential for bounding the values of the matrix and preparing it for further matrix operations, particularly for deriving the total relation matrix in subsequent stages. The normalization process was performed by identifying the maximum row sum in the 16×16 average direct-relation matrix $A = [a_{ij}]$. This scalar value, denoted as s, represents the greatest total outgoing influence from any single barrier within the system. Each element of matrix A was then divided by s, resulting in the normalized direct-relation matrix $D = [d_{ij}]$, where all values lie within the interval [0,1].

This transformation preserves the relative structure of influence among the barriers while ensuring that the matrix remains within the convergence requirements necessary for DEMATEL's recursive computations. The normalized matrix is shown in *Table 5.5.*, derived directly from the "*Average–D matrix*" using the maximum row sum normalization procedure.

Following the construction of the average direct-relation matrix, the next critical step involved normalizing the matrix to ensure computational stability and comparability across all influence scores. This procedure is essential for bounding the values of the matrix and preparing it for further matrix operations, particularly for deriving the total relation matrix in subsequent stages. The normalization process was performed by identifying the maximum row sum in the 16×16 average direct-relation matrix $A = [a_{ij}]$. This scalar value, denoted as s, represents the greatest total outgoing influence from any single barrier within the system. Each element of matrix A was then divided by s, resulting in the normalized direct-relation matrix $D = [d_{ij}]$, where all values lie within the interval [0,1].

This transformation preserves the relative structure of influence among the barriers while ensuring that the matrix remains within the convergence requirements necessary for DEMATEL's recursive computations. The normalized matrix is shown in *Table 5.5.*, derived directly from the "*Average–D matrix*" using the maximum row sum normalization procedure.

Table 5.4. Normalized direct-relation matrix

Barriers	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12	B13	B14	B15	B16
B1		0,0247	0,0185	0,0000	0,0000	0,0432	0,0185	0,0247	0,0247	0,0185	0,0000	0,0000	0,0185	0,0247	0,0062	0,0062
B2	0,1049		0,1049	0,0185	0,0000	0,0617	0,0309	0,0185	0,0617	0,0802	0,0556	0,0185	0,0432	0,0432	0,0062	0,0185
B3	0,0988	0,0062		0,0185	0,0123	0,0247	0,0432	0,0432	0,0494	0,0617	0,0432	0,0432	0,0432	0,0802	0,0617	0,0556
B4	0,1296	0,0370	0,0494		0,1049	0,0494	0,0617	0,0679	0,0679	0,0617	0,0556	0,0617	0,0741	0,0617	0,0556	0,0617
B5	0,0802	0,0247	0,0309	0,0185		0,0185	0,0309	0,0432	0,0247	0,0247	0,0185	0,0185	0,0185	0,0185	0,0185	0,0185
B6	0,0370	0,0062	0,0247	0,0370	0,0370		0,0309	0,0494	0,0370	0,0556	0,0247	0,0617	0,0247	0,0679	0,0617	0,0247
B7	0,0494	0,0185	0,0309	0,0556	0,0617	0,0000		0,0370	0,0494	0,0309	0,0247	0,0185	0,0494	0,0309	0,0247	0,0370
B8	0,0309	0,0062	0,0247	0,0494	0,0494	0,0000	0,0185		0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
B9	0,0556	0,0185	0,0432	0,0123	0,0617	0,0247	0,0370	0,0432		0,0679	0,0679	0,0185	0,0309	0,0988	0,0519	0,0556
B10	0,0679	0,0062	0,0494	0,0123	0,0556	0,0000	0,0370	0,0494	0,0185		0,0000	0,0247	0,0062	0,0802	0,0432	0,0370
B11	0,0617	0,0000	0,0432	0,0370	0,0432	0,0556	0,0370	0,0296	0,0000	0,0617		0,0679	0,0494	0,0556	0,0556	0,0556
B12	0,0802	0,0185	0,0494	0,0123	0,0679	0,0000	0,0432	0,0247	0,0247	0,0494	0,0309		0,0370	0,0494	0,0370	0,0494
B13	0,0309	0,0000	0,0247	0,0123	0,0309	0,0000	0,0185	0,0556	0,0000	0,0432	0,0062	0,0185		0,0185	0,0185	0,0185
B14	0,0309	0,0062	0,0000	0,0247	0,0432	0,0000	0,0185	0,0741	0,0000	0,0185	0,0000	0,0000	0,0062		0,0679	0,0370
B15	0,0741	0,0185	0,0247	0,0370	0,0802	0,0000	0,0185	0,0741	0,0000	0,0370	0,0123	0,0000	0,0185	0,0000		0,0185
B16	0,0926	0,0370	0,0123	0,0556	0,0864	0,0370	0,0556	0,0741	0,0185	0,0432	0,0247	0,0494	0,0617	0,0494	0,0802	

After completing the normalization step, the analysis proceeded with deriving the total relation matrix. To derive the total relation matrix, the procedure began by generating the 16×16 identity matrix *I*, in which all diagonal elements are equal to 1 and all off-diagonal elements are 0. This matrix serves as the baseline for isolating the system's residual influence structure. The identity matrix used in this computation is provided in *Table 5.6.*. In the next sub-step, the matrix $(I - D)$ was constructed by subtracting the normalized direct-relation matrix *D* from the identity matrix. This operation isolates the non-redundant structure of inter-barrier influences, setting the stage for recursive interaction analysis. The resulting matrix is displayed in *Table 5.7.* Thereafter, the inverse of this matrix, $(I - D)^{-1}$, was computed. This inverse matrix enables the propagation of influence across all direct and indirect paths within the network. It functions as a scaling mechanism that reveals the depth and reach of influence flows embedded in the normalized matrix. The full inverse matrix is shown in *Table 5.8.* The final step in this sequence involved multiplying the normalized matrix *D* by the inverse matrix $(I - D)^{-1}$, resulting in the total relation matrix *T*. This matrix encapsulates the complete interaction dynamics among the 16 barriers, accounting for both immediate and recursive causal linkages. As expected, the values in matrix *T* are consistently greater than those in the normalized matrix, capturing the compounded systemic effects. The final matrix is provided in *Table 5.9.* and serves as the primary input for the subsequent interpretive analysis.

After completing the normalization step, the analysis proceeded with deriving the total relation matrix. To derive the total relation matrix, the procedure began by generating the 16×16 identity matrix *I*, in which all diagonal elements are equal to 1 and all off-diagonal elements are 0. This matrix serves as the baseline for isolating the system's residual influence structure. The identity matrix used in this computation is provided in *Table 5.6.* In the next sub-step, the matrix $(I - D)$ was constructed by subtracting the normalized direct-relation matrix *D* from the identity matrix. This operation isolates the non-redundant structure of inter-barrier influences, setting the stage for recursive interaction analysis. The resulting matrix is displayed in *Table 5.7.* Thereafter, the inverse of this matrix, $(I - D)^{-1}$, was computed. This inverse matrix enables the propagation of influence across all direct and indirect paths within the network. It functions as a scaling mechanism that reveals the depth and reach of influence flows embedded in the normalized matrix. The full inverse matrix is shown in *Table 5.8.* The final step in this sequence

involved multiplying the normalized matrix D by the inverse matrix $(I - D)^{-1}$, resulting in the total relation matrix T. This matrix encapsulates the complete interaction dynamics among the 16 barriers, accounting for both immediate and recursive causal linkages. As expected, the values in matrix T are consistently greater than those in the normalized matrix, capturing the compounded systemic effects. The final matrix is provided in *Table 5.9*. and serves as the primary input for the subsequent interpretive analysis.

Table 5.5. Identity matrix

Barriers	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12	B13	B14	B15	B16
B1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B2	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B3	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
B4	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
B5	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
B6	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
B7	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
B8	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
B9	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
B10	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
B11	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
B12	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
B13	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
B14	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
B15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
B16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

Table 5.6. Matrix $(I - D)$, obtained by subtracting the normalized direct-relation matrix from the identity matrix

Barriers	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12	B13	B14	B15	B16
B1	1,0000	0,0247	0,0185	0,0000	0,0000	0,0432	0,0185	0,0247	0,0247	0,0185	0,0000	0,0000	0,0185	0,0247	0,0062	0,0062
B2	0,1049	1,0000	0,1049	0,0185	0,0000	0,0617	0,0309	0,0185	0,0617	0,0802	0,0556	0,0185	0,0432	0,0432	0,0062	0,0185
B3	0,0988	0,0062	1,0000	0,0185	0,0123	0,0247	0,0432	0,0432	0,0494	0,0617	0,0432	0,0432	0,0432	0,0802	0,0617	0,0556
B4	0,1296	0,0370	0,0494	1,0000	0,1049	0,0494	0,0617	0,0679	0,0679	0,0617	0,0556	0,0617	0,0741	0,0617	0,0556	0,0617
B5	0,0802	0,0247	0,0309	0,0185	1,0000	0,0185	0,0309	0,0432	0,0247	0,0247	0,0185	0,0185	0,0185	0,0185	0,0185	0,0185
B6	0,0370	0,0062	0,0247	0,0370	0,0370	1,0000	0,0309	0,0494	0,0370	0,0556	0,0247	0,0617	0,0247	0,0679	0,0617	0,0247
B7	0,0494	0,0185	0,0309	0,0556	0,0617	0,0000	1,0000	0,0370	0,0494	0,0309	0,0247	0,0185	0,0494	0,0309	0,0247	0,0370
B8	0,0309	0,0062	0,0247	0,0494	0,0494	0,0000	0,0185	1,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
B9	0,0556	0,0185	0,0432	0,0123	0,0617	0,0247	0,0370	0,0432	1,0000	0,0679	0,0679	0,0185	0,0309	0,0988	0,0519	0,0556
B10	0,0679	0,0062	0,0494	0,0123	0,0556	0,0000	0,0370	0,0494	0,0185	1,0000	0,0000	0,0247	0,0062	0,0802	0,0432	0,0370
B11	0,0617	0,0000	0,0432	0,0370	0,0432	0,0556	0,0370	0,0296	0,0000	0,0617	1,0000	0,0679	0,0494	0,0556	0,0556	0,0556
B12	0,0802	0,0185	0,0494	0,0123	0,0679	0,0000	0,0432	0,0247	0,0247	0,0494	0,0309	1,0000	0,0370	0,0494	0,0370	0,0494
B13	0,0309	0,0000	0,0247	0,0123	0,0309	0,0000	0,0185	0,0556	0,0000	0,0432	0,0062	0,0185	1,0000	0,0185	0,0185	0,0185
B14	0,0309	0,0062	0,0000	0,0247	0,0432	0,0000	0,0185	0,0741	0,0000	0,0185	0,0000	0,0000	0,0062	1,0000	0,0679	0,0370
B15	0,0741	0,0185	0,0247	0,0370	0,0802	0,0000	0,0185	0,0741	0,0000	0,0370	0,0123	0,0000	0,0185	0,0000	1,0000	0,0185
B16	0,0926	0,0370	0,0123	0,0556	0,0864	0,0370	0,0556	0,0741	0,0185	0,0432	0,0247	0,0494	0,0617	0,0494	0,0802	1,0000

Table 5.7. Inverse matrix $(I-D)^{-1}$

Barriers	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12	B13	B14	B15	B16
B1	0,0257	0,0301	0,0323	0,0120	0,0191	0,0500	0,0313	0,0443	0,0347	0,0356	0,0097	0,0104	0,0297	0,0435	0,0227	0,0191
B2	0,1784	0,0180	0,1407	0,0485	0,0543	0,0863	0,0705	0,0763	0,0902	0,1285	0,0805	0,0503	0,0784	0,1023	0,0566	0,0595
B3	0,1695	0,0260	0,0369	0,0507	0,0718	0,0471	0,0802	0,1015	0,0732	0,1051	0,0646	0,0684	0,0763	0,1272	0,1060	0,0907
B4	0,2351	0,0651	0,1049	0,0463	0,1818	0,0836	0,1160	0,1487	0,1063	0,1281	0,0899	0,1001	0,1226	0,1328	0,1179	0,1128
B5	0,1235	0,0363	0,0543	0,0371	0,0325	0,0342	0,0533	0,0752	0,0424	0,0525	0,0334	0,0346	0,0397	0,0490	0,0438	0,0399
B6	0,1045	0,0235	0,0577	0,0642	0,0898	0,0183	0,0641	0,0997	0,0592	0,0936	0,0453	0,0829	0,0540	0,1088	0,0997	0,0577
B7	0,1130	0,0350	0,0621	0,0786	0,1068	0,0213	0,0325	0,0832	0,0713	0,0688	0,0460	0,0415	0,0777	0,0713	0,0603	0,0667
B8	0,0568	0,0135	0,0365	0,0569	0,0646	0,0095	0,0309	0,0169	0,0121	0,0147	0,0093	0,0097	0,0127	0,0154	0,0128	0,0120
B9	0,1320	0,0374	0,0795	0,0464	0,1180	0,0481	0,0752	0,1029	0,0260	0,1117	0,0883	0,0470	0,0649	0,1451	0,0986	0,0917
B10	0,1194	0,0209	0,0720	0,0353	0,0932	0,0158	0,0623	0,0896	0,0373	0,0298	0,0163	0,0403	0,0296	0,1093	0,0732	0,0608
B11	0,1368	0,0200	0,0783	0,0679	0,1008	0,0752	0,0750	0,0879	0,0280	0,1049	0,0226	0,0944	0,0828	0,1027	0,1000	0,0904
B12	0,1437	0,0354	0,0799	0,0391	0,1122	0,0213	0,0748	0,0737	0,0479	0,0866	0,0501	0,0228	0,0660	0,0898	0,0740	0,0789
B13	0,0632	0,0086	0,0401	0,0264	0,0549	0,0089	0,0346	0,0781	0,0117	0,0593	0,0150	0,0288	0,0136	0,0380	0,0359	0,0329
B14	0,0674	0,0168	0,0176	0,0416	0,0717	0,0105	0,0357	0,0999	0,0122	0,0367	0,0100	0,0110	0,0216	0,0176	0,0835	0,0500
B15	0,1190	0,0310	0,0481	0,0547	0,1090	0,0162	0,0412	0,1040	0,0185	0,0612	0,0258	0,0160	0,0384	0,0274	0,0222	0,0375
B16	0,1767	0,0591	0,0575	0,0899	0,1480	0,0625	0,0964	0,1363	0,0506	0,0932	0,0510	0,0774	0,0986	0,0993	0,1233	0,0395

Table 5.8. Total relation matrix $T = D \cdot (I - D)^{-1}$

Barriers	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12	B13	B14	B15	B16	D(Rox)
B1	0,0257	0,0301	0,0323	0,0120	0,0191	0,0500	0,0313	0,0443	0,0347	0,0356	0,0097	0,0104	0,0297	0,0435	0,0227	0,0191	0,4502
B2	0,1784	0,0180	0,1407	0,0485	0,0543	0,0863	0,0705	0,0763	0,0902	0,1285	0,0805	0,0503	0,0784	0,1023	0,0566	0,0595	1,3193
B3	0,1695	0,0260	0,0369	0,0507	0,0718	0,0471	0,0802	0,1015	0,0732	0,1051	0,0646	0,0684	0,0763	0,1272	0,1060	0,0907	1,2953
B4	0,2351	0,0651	0,1049	0,0463	0,1818	0,0836	0,1160	0,1487	0,1063	0,1281	0,0899	0,1001	0,1226	0,1328	0,1179	0,1128	1,8927
B5	0,1235	0,0363	0,0543	0,0371	0,0325	0,0342	0,0533	0,0752	0,0424	0,0525	0,0334	0,0346	0,0397	0,0490	0,0438	0,0399	0,7817
B6	0,1045	0,0235	0,0577	0,0642	0,0898	0,0183	0,0641	0,0997	0,0592	0,0936	0,0453	0,0829	0,0540	0,1088	0,0997	0,0577	1,1231
B7	0,1130	0,0350	0,0621	0,0786	0,1068	0,0213	0,0325	0,0832	0,0713	0,0688	0,0460	0,0415	0,0777	0,0713	0,0603	0,0667	1,0360
B8	0,0568	0,0135	0,0365	0,0569	0,0646	0,0095	0,0309	0,0169	0,0121	0,0147	0,0093	0,0097	0,0127	0,0154	0,0128	0,0120	0,3843
B9	0,1320	0,0374	0,0795	0,0464	0,1180	0,0481	0,0752	0,1029	0,0260	0,1117	0,0883	0,0470	0,0649	0,1451	0,0986	0,0917	1,3128
B10	0,1194	0,0209	0,0720	0,0353	0,0932	0,0158	0,0623	0,0896	0,0373	0,0298	0,0163	0,0403	0,0296	0,1093	0,0732	0,0608	0,9050
B11	0,1368	0,0200	0,0783	0,0679	0,1008	0,0752	0,0750	0,0879	0,0280	0,1049	0,0226	0,0944	0,0828	0,1027	0,1000	0,0904	1,2677
B12	0,1437	0,0354	0,0799	0,0391	0,1122	0,0213	0,0748	0,0737	0,0479	0,0866	0,0501	0,0228	0,0660	0,0898	0,0740	0,0789	1,0963
B13	0,0632	0,0086	0,0401	0,0264	0,0549	0,0089	0,0346	0,0781	0,0117	0,0593	0,0150	0,0288	0,0136	0,0380	0,0359	0,0329	0,5499
B14	0,0674	0,0168	0,0176	0,0416	0,0717	0,0105	0,0357	0,0999	0,0122	0,0367	0,0100	0,0110	0,0216	0,0176	0,0835	0,0500	0,6039
B15	0,1190	0,0310	0,0481	0,0547	0,1090	0,0162	0,0412	0,1040	0,0185	0,0612	0,0258	0,0160	0,0384	0,0274	0,0222	0,0375	0,7702
B16	0,1767	0,0591	0,0575	0,0899	0,1480	0,0625	0,0964	0,1363	0,0506	0,0932	0,0510	0,0774	0,0986	0,0993	0,1233	0,0395	1,4591
	1,9656	0,4765	0,9984	0,7959	1,4285	0,6088	0,9738	1,4181	0,7217	1,2102	0,6580	0,7355	0,9065	1,27978	1,1305	0,9398	

The subsequent stage of the analysis involved the computation of dispatching *(D)* and receiving *(R)* values, which quantify the extent to which each barrier exerts influence on, and is influenced by, the remaining elements within the system. These indices, derived from the total relation matrix, offer critical insights into the directional dynamics among the barriers. Building upon this, two higher-order metrics—*prominence (D + R)* and *net causality (D - R)*—were calculated to further elucidate each barrier's systemic role. Prominence reflects the overall degree of interaction a barrier maintains within the network, while net causality distinguishes whether the barrier primarily functions as a driver *(cause)* or as a responder *(effect).* The results of these calculations are collectively presented in *Table 6.1.*, which includes all four values *(D, R, D + R, D - R)* for the 16 identified barriers. The tabulated data illustrate notable asymmetries in influence distribution. For instance, *High Initial Investment* (B_4) and *Lack of Effective Regulatory Framework* (B_{11}) display elevated dispatching values, indicating their structural influence as initiating factors. In contrast, *Resistance to Change* (B_1) and *Cybersecurity Risks* (B_8) exhibit negative net causality scores, thereby functioning as effect-type barriers that accumulate rather than transmit influence. Simultaneously, barriers such as *Lack of Skilled Workforce* (B_9) and *Uncertainty in ROI* (B_5) attain high prominence values, underscoring their centrality within the transformation ecosystem regardless of their causal orientation.

Table 5.9. Summary of dispatching (*D*), receiving (*R*), prominence (*D* + *R*), and net causality (*D* - *R*) values for the Sixteen barriers

Code	*Barrier*	*D*	*R*	*D + R*	*D - R*
B_1	Resistance to Change	0,4502	1,9656	2,4158	-1,5154
B_2	Cultural Barriers	1,3193	0,4765	1,7958	0,8428
B_3	Lack of vision and top management commitment	1,2953	0,9984	2,2937	0,2969
B_4	High Initial Investment	1,8927	0,7959	2,6886	1,0968
B_5	Uncertainty in Return on Investment (ROI)	0,7817	1,4285	2,2102	-0,6468
B_6	Integration Issues with Legacy Systems	1,1231	0,6088	1,7319	0,5143
B_7	Harsh Environmental Conditions and Limited Connectivity in Remote Locations	1,0360	0,9738	2,0098	0,0622
B_8	Cybersecurity Risks	0,3843	1,4181	1,8024	-1,0338
B_9	Lack of Skilled Workforce	1,3128	0,7217	2,0345	0,5911
B_{10}	Insufficient Training and Awareness	0,9050	1,2102	2,1152	-0,3052
B_{11}	Lack of effective regulatory framework	1,2677	0,6580	1,9257	0,6097
B_{12}	Compliance Costs and Administrative Burdens	1,0963	0,7355	1,8318	0,3608
B_{13}	Limited External Stakeholder Engagement	0,5499	0,9065	1,4564	-0,3566
B_{14}	Loss of Routine Jobs through Automation	0,6039	1,2797	1,8836	-0,6758
B_{15}	Data Complexity and overload	0,7702	1,1305	1,9007	-0,3603
B_{16}	Dynamic and Unpredictable Conditions in mining fields	1,4591	0,9398	2,3989	0,5193

To enhance the clarity of the causal mapping process, a threshold value was calculated and applied to the total relation matrix. This threshold was determined by computing the arithmetic mean of all off-diagonal elements in the 16×16 total relation matrix derived in the previous step. The calculation excluded diagonal elements, as these represent self-influence and are not meaningful in assessing inter-barrier relationships. The resulting threshold value was **θ = 0.0659**, representing the minimum intensity required for a relationship to be considered significant within the system. All values below this threshold were omitted from the causal diagram to filter out weak or negligible interactions. This step ensures that the final visualization highlights only those barriers with a substantial influence on others, thereby improving interpretability and analytical focus.

Figure 5.1. illustrates the outcome of this process: a directed causal relationship diagram in which only the strongest links—those equal to or exceeding the calculated threshold—are retained. The diagram offers a condensed yet comprehensive representation of the system's most impactful interdependencies, serving as a bridge to the subsequent analysis of cause-effect groupings and prominence rankings.

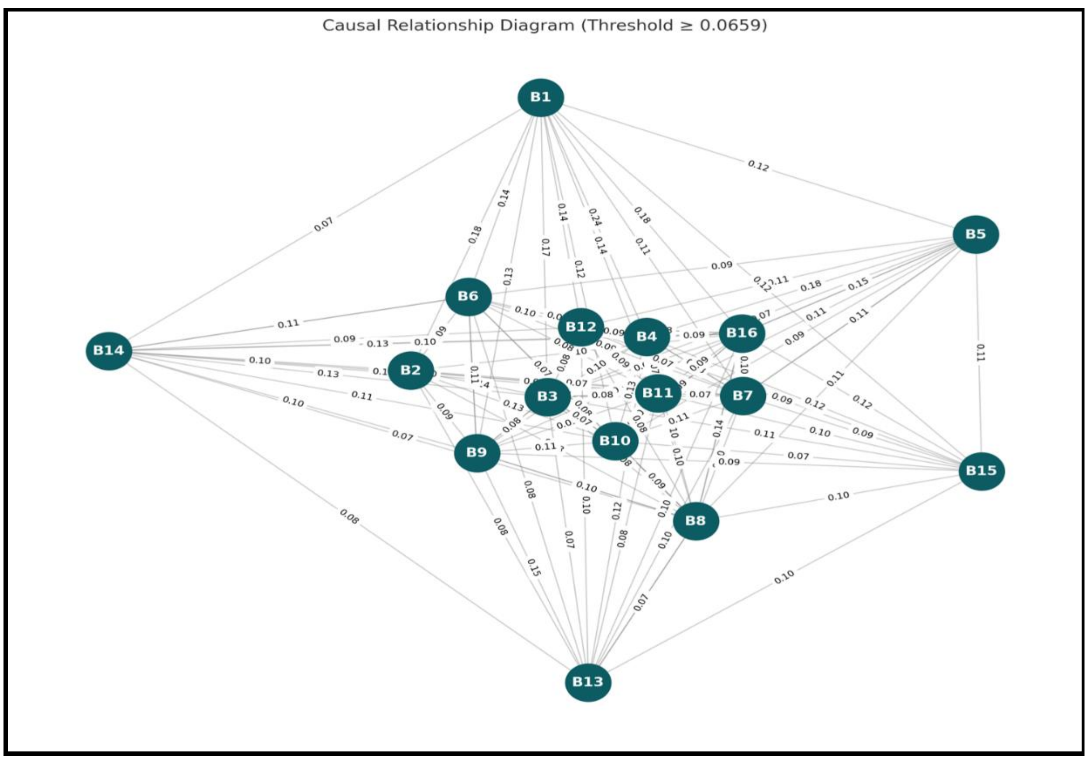

Figure 5.1. Causal relationship diagram

Based on the computed $D - R$ values, the Sixteen identified barriers were classified into two categories: cause group and effect group. Barriers with a positive $D - R$ score are considered net influencers within the system, forming the cause group. Conversely, those with a negative $D - R$ score are categorized into the effect group, indicating that they are primarily influenced by other elements rather than driving the system themselves. This classification is first illustrated in *Figure 5.2.*, which plots the barriers according to their $D - R$ (horizontal axis) and $D + R$ (vertical axis) values. This scatter plot provides an analytical perspective on both the net influence and prominence of each barrier within the system. Barriers positioned in the upper-right quadrant tend to be highly influential and prominent, while those in the lower-left reflect passive and dependent elements in the transformation process. To complement this, *Figure 5.3.* presents a visually structured classification that clearly separates the cause-and-effect groups. The cause group includes barriers such as *High Initial Investment (B_4)*, *Cultural Barriers (B_2)*, and *Lack of Effective Regulatory Framework (B_{11})*—barriers that exert a strong driving force over others. Meanwhile, the effect group features elements like *Resistance to Change (B_1)*, *Cybersecurity Risks (B_8)*, and *Loss of Routine Jobs through Automation (B_{14})*, which are more reactive in nature and influenced by systemic drivers.

In addition, *Figure 5.4.* offers a comparative visualization of each barrier's prominence score, calculated as the sum of its dispatching and receiving values *($D + R$)*. This figure ranks the barriers in descending order of systemic centrality, thereby highlighting those with the highest levels of interaction and involvement. Barriers such as High Initial Investment, Resistance to Change, and Dynamic and Unpredictable Conditions exhibit the highest prominence scores, indicating that they are deeply embedded within the system's interdependencies and should therefore be prioritized in strategic planning. To differentiate between highly influential and peripheral barriers, a threshold value of $D + R \geq 2.0$ was set. Barriers exceeding this threshold are considered prominent, indicating their structural significance within the system of interrelated challenges. This classification aids in prioritizing managerial focus and policy interventions. Notably, the arithmetic mean of the $D + R$ scores across all sixteen barriers was calculated as *2.031*, which further supports the selection of the 2.0 threshold as a rational and analytically grounded cutoff. This approach ensures that barriers meaningfully above average prominence are effectively flagged for strategic consideration.

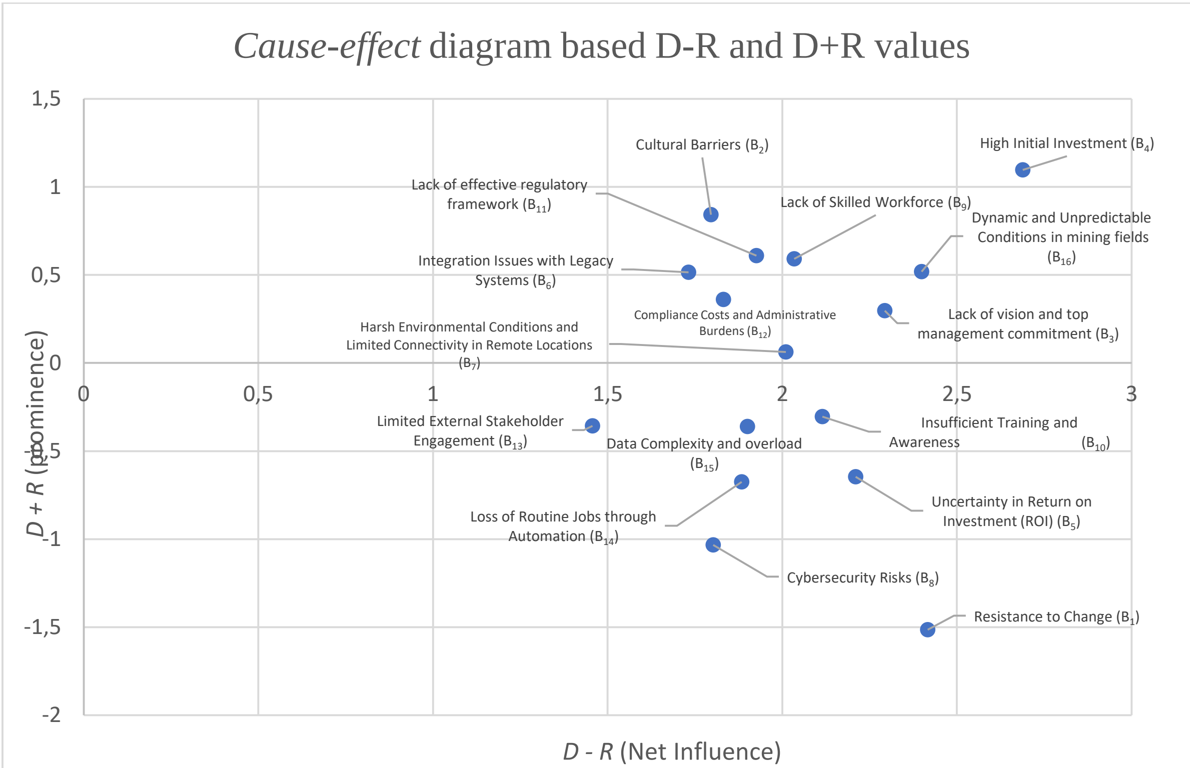

Figure 5.2. Scatter Plot Based on D – R and D + R Values

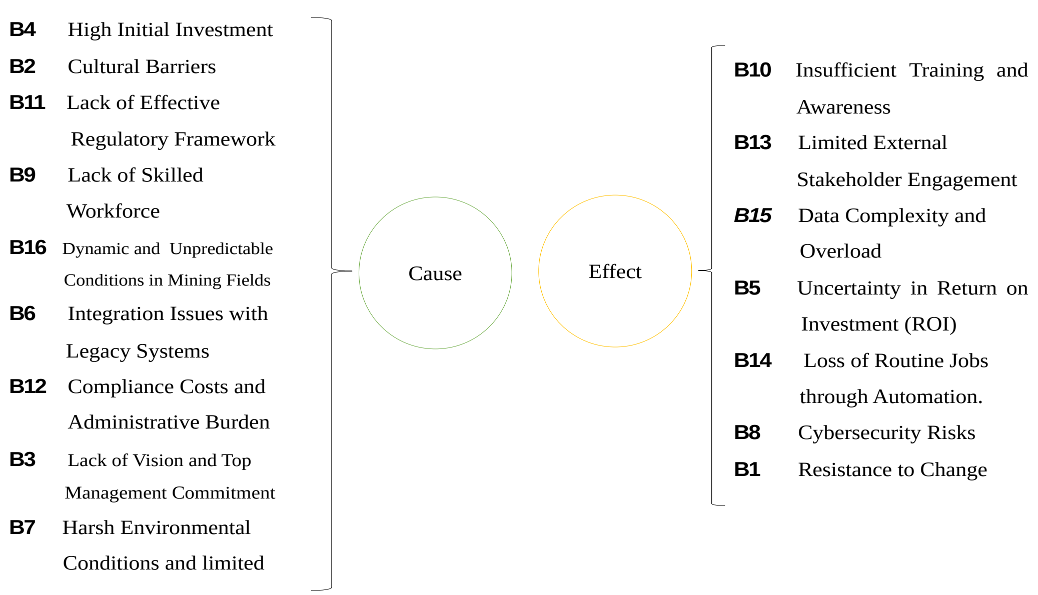

Figure 5.3. Classification of the Identified Barriers into Cause-and-Effect Group

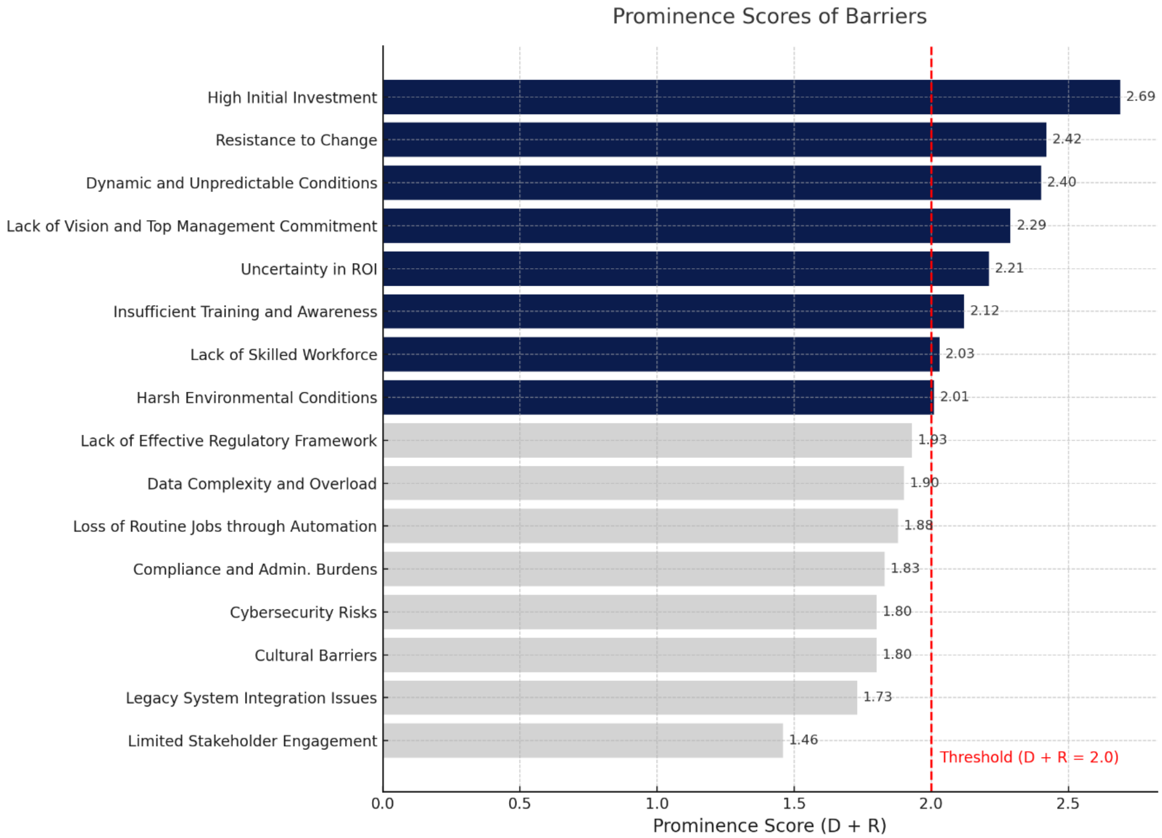

Figure 5.4. Prominence Scores of Barriers with Threshold Highlight (D + R ≥ 2.0)

This integrated set of visualizations offers a multidimensional understanding of the structural dynamics underlying the barriers to digital transformation in the MI. While the scatter plot (Figure 5.2.) captures the interplay between influence and prominence, the categorical classification (Figure 5.3.) clarifies systemic roles, and the prominence ranking (Figure 5.4.) provides a practical basis for prioritization. Together, these analytical outputs enable a more targeted and effective decision-making process. In the subsequent section, these findings are further interpreted to formulate strategic insights and actionable recommendations for industry stakeholders and policymakers aiming to accelerate digital transformation in mining operations.

The *DEMATEL*-based evaluation offers a comprehensive and data-driven lens through which to analyze the systemic complexity of digital transformation barriers in the MI. Through the integration of causal analysis, group classification, and prominence mapping, the study enables not only an identification of the most problematic barriers but also an understanding of their structural roles and relative importance. The three figures—scatter plot (Figure 5.2.), cause–effect classification (Figure 5.3.), and prominence ranking (Figure 5.4.)—collectively form the analytical foundation upon which targeted strategic interventions can be designed.

The scatter plot in *Figure 5.2.* provides a two-dimensional representation of each barrier's systemic position based on its net causality $(D - R)$ and prominence $(D + R)$ scores. Barriers located in the upper-right quadrant (e.g., *High Initial Investment (B_4)*, *Dynamic and Unpredictable Conditions (B_{16})*, and *Lack of Skilled Workforce (B_9)*) are not only net influencers but also highly engaged with the broader system. These are considered "strategic levers," whose modification can create significant ripple effects. In contrast, barriers found in the lower-left quadrant—such as *Cybersecurity Risks (B_8)* and *Resistance to Change (B_1)*—are more passive, typically resulting from upstream deficiencies. Interestingly, *Resistance to Change (B_1)*, although highly prominent, holds the lowest $D - R$ score, indicating that it is shaped by the influence of multiple other barriers rather than acting independently. This plot thus serves as an analytical compass, differentiating between drivers, mediators, and outcomes in the systemic landscape.

Complementing this visual, Figure 5.3. organizes the Sixteen barriers into *cause-and-effect* groups based on the sign of their $D - R$ values. Barriers in the cause group are those with positive net influence and include foundational challenges such as *High Initial Investment (B_4)*, *Cultural Barriers (B_2)*, and *Lack of Vision and Top Management Commitment (B_3)*. These barriers act as initiators in the system, meaning that efforts to mitigate them are likely to reduce several secondary barriers simultaneously. On the other hand, effect group barriers, including *Insufficient Training and Awareness (B_{10})*, *Loss of Routine Jobs through Automation (B_{14})*, and *Resistance to Change (B_1)*, are largely symptomatic—they do not generate systemic dysfunction but rather reflect it. This classification provides decision-makers with a causality-based roadmap: interventions should start with root causes before addressing outcomes, ensuring that solutions are both efficient and sustainable.

Further refinement is provided through *Figure 5.4.*, which ranks the barriers by their prominence scores $(D + R)$. This metric reflects the total degree of interaction a barrier has with all others, irrespective of direction. *High Initial Investment (B_4)* again emerges as the most systemically significant barrier, confirming its dual role as both a strong influencer and a highly embedded component of the network. Other prominent barriers include *Resistance to Change (B_1)*, *Dynamic and Unpredictable Conditions (B_{16})*, and *Lack of Vision and Top Management Commitment (B_3)*—all of which are tightly interconnected with various system elements. These high-prominence barriers deserve strategic prioritization, not only because of their influence but also due to their widespread connectivity, which makes them ideal leverage points for transformation. Conversely, barriers like *Limited External Stakeholder Engagement (B_{13})* and *Legacy System Integration Issues (B_6)* fall below the prominence threshold, indicating that while they may pose local challenges, they are less central to systemic inertia.

Taken together, these figures provide a multilayered framework for decision-making. The scatter plot reveals how influence and prominence intersect, identifying both pivotal and passive barriers. The cause–effect classification clarifies which barriers are systemic origins versus dependent symptoms. The prominence ranking highlights where the most system-wide traction can be achieved. Integrating these insights, a coherent intervention strategy emerges: rather than treating all barriers as equal, efforts should concentrate on cause group barriers with high prominence, such as *High Initial Investment*, *Lack of Vision*, and *Cultural Barriers*. These are not only the sources of multiple downstream effects but also the most embedded within the system, making their resolution a critical step toward holistic digital transformation. From a policy and managerial standpoint, this implies the need for a phased and influence-aware strategy—beginning with structural enablers such as financial accessibility and leadership alignment, and only later expanding to operational and behavioral issues. Addressing high-leverage causes may, over time, neutralize several effect group barriers without direct intervention. In this sense, the DEMATEL framework is not merely a tool for mapping complexity; it is a strategic guide for sequencing change, optimizing resource allocation, and maximizing impact.

6. DISCUSSION AND IMPLICTIONS

This study provides a causality-based, system-level understanding of the interdependent barriers hindering digital transformation in the MI. By applying the classical DEMATEL method, the analysis goes beyond conventional thematic clustering and exposes both the directional influence *$(D - R)$* and the systemic prominence *$(D + R)$* of each barrier. These findings contribute not only to theoretical modeling of transformation barriers, but also to practical prioritization for decision-makers operating in capital-intensive and institutionally constrained sectors.

The analysis was preceded by a systematic literature review, conducted using the PRISMA protocol and supported by bibliometric mapping techniques. This stage identified, categorized, and refined an initial pool of digital transformation barriers in the MI, ultimately synthesizing them into sixteen core challenges. The review encompassed diverse disciplinary perspectives—from engineering and policy to organizational behavior—and ensured that the selected barriers reflected both academic consensus and emerging real-world concerns. Bibliometric indicators highlighted the growing scholarly focus on workforce skill gaps, regulatory fragmentation, and digital infrastructure, while keyword co-occurrence analysis revealed thematic convergence around investment, automation, and cultural inertia. By systematically filtering and validating these barriers through peer-reviewed evidence, the study enhanced both the methodological rigor and contextual relevance of its findings. This approach not only strengthens the theoretical foundation of the DEMATEL model but also ensures that the Sixteen selected barriers represent the most recurrent and influential challenges identified in contemporary literature. In contrast to studies that rely solely on expert intuition or isolated case examples, the integration of a structured review process guarantees that the subsequent causal analysis is grounded in a transparent, comprehensive, and academically validated base. This combination of systematic review and causal mapping increases the robustness and generalizability of the study's conclusions, offering stakeholders a more reliable basis for strategic planning and intervention.

One of the most critical findings is the identification of *High Initial Investment (B_4)* as the most influential and prominent barrier. This aligns with existing studies that emphasize financial constraints as a primary limitation to digital adoption in MI (Long et al., 2024; Philo & Webber-Youngman, 2024). While previous literature treats capital intensity as a static challenge, this study demonstrates its systemic leverage—(B_4) drives other constraints such as uncertainty in ROI (B_5), lack of skilled workforce (B_9), and organizational resistance (B_1). This corroborates the view that without financial intervention, other digital initiatives remain vulnerable to underperformance (Sánchez & Hartlieb, 2020; Kashan et al., 2022). At the opposite end, *Resistance to Change* (B_1) appears as the most affected barrier with the lowest $D - R$ score. However, its high $D + R$ value suggests deep systemic entanglement. These results echo Mokganya et al. (2024) and Bi et al. (2022), who argue that resistance often stems from fear of job loss, poor communication, and lack of training, rather than being an independent barrier. Furthermore, Bisschoff & Grobbelaar (2022) highlight that resistance is amplified when leadership fails to communicate a compelling digital vision—findings consistent with our identification of B_3 (lack of top management commitment) as a major causal factor.

Figures 4.1. and 5.1. visually reinforce the classification of *Cultural Barriers* (B_2), *Lack of Vision* (B_3), and Lack of effective regulatory framework (B_{11}) as upstream drivers. This pattern supports insights from Gruenhagen et al. (2022) and Sánchez & Hartlieb (2020), who emphasize that digital transformation is as much an institutional and managerial challenge as a technological one. Cultural inertia, particularly in safety-oriented industries like mining, creates an organizational atmosphere that is resistant to risk and skeptical of technological change (Jianing et al., 2024). Our study strengthens this argument by empirically situating B_2 (*Cultural Barriers*) within the cause group, and showing its propagation effect toward B_1 (resistance to change) and B_{10} (Insufficient Training and Awareness), in line with Mokganya et al. (2024).

The prominence analysis (*Figure 5.2.*) introduces additional depth by evaluating barriers' systemic centrality. *Dynamic and Unpredictable Conditions* (B_{16}) and *Lack of Skilled Workforce* (B_9)—though not dominant causes—rank high in $D + R$, indicating their entanglement across multiple subsystems. This confirms previous conclusions by Duarte et al. (2022) and Liu et al. (2023), who highlight the MI's vulnerability to geological uncertainty and operational disruptions that compromise technological consistency. Similarly, the role of workforce-related barriers reflects patterns observed by Noriega & Pourrahimian (2022) and Young & Rogers (2019), who document digital literacy gaps and infrastructure limitations in remote mining areas. Cybersecurity risks (B_8), often framed in isolation in broader technology studies, are interpreted in this study as a secondary, effect-type barrier, influenced by upstream challenges in data integration and training. This supports Don et al. (2025), who emphasize that cybersecurity challenges in mining are exacerbated by fragmented IT systems and lack of data governance frameworks.

Overall, this research confirms that digital transformation in MI cannot be tackled through fragmented or one-dimensional approaches. Prior studies (Zulu et al., 2021; Vargas et al, 2022) have already stressed the need for policy clarity, infrastructure investments, and regulatory reform. What this study adds is a structured causal and prominence-based framework to operationalize those recommendations. For example, rather than broadly "supporting innovation," stakeholders can now target specific high-leverage barriers like B_4, B_2, and B_3, which function as both systemic bottlenecks and network amplifiers. In conclusion, the findings underscore that successful digital transformation in MI must begin with a reconfiguration of financial models, leadership engagement, and institutional frameworks. These elements form the backbone of the digital ecosystem, upon which workforce readiness, technology adoption, and operational resilience are built. By presenting a causal and prominence-based map of the digital transformation landscape, this study offers a novel contribution to both theory and practice, paving the way for targeted, sequenced, and system-sensitive strategies.

6.1. Managerial and Policy Implications

The findings of this study offer comprehensive and actionable insights for a wide array of stakeholders—including managers, policymakers, non-governmental organizations (NGOs), labor representatives, educational institutions, and regional development agencies—who are collectively responsible for enabling digital transformation in the MI. The DEMATEL-based analysis reveals that the barriers are not isolated challenges but part of a deeply interconnected system. Addressing one barrier in isolation is unlikely to lead to sustainable progress; instead, coordinated, targeted interventions are needed that account for both the causal influence and systemic prominence of each barrier.

A core implication emerges around *High Initial Investment* (B_4), which was identified as the most influential and prominent barrier in the system. This finding underscores that financial limitations are not merely passive constraints but active inhibitors that suppress other transformation enablers such as workforce development, automation, and digital infrastructure deployment. Managers in mining firms should adopt scalable and modular investment approaches, such as piloting technologies in high-value or less volatile sites before broader implementation. Beyond firm-level adaptation, addressing the systemic implications of high initial investment (B_4) requires a coordinated, multi-stakeholder response. Policymakers must establish fiscal incentives, such as tax credits, accelerated depreciation schemes, and low-interest green bonds, specifically targeted at digital infrastructure investments in capital-intensive sectors like mining. These instruments can reduce perceived risk and unlock latent private capital. Public–private partnerships (PPPs), particularly in developing economies, offer a viable mechanism to share upfront costs and align strategic objectives across sectors. Non-governmental organizations (NGOs) and international development agencies can play a catalytic role by offering grant-backed pilot programs and acting as intermediaries to broker trust between mining firms and communities. Their involvement is particularly critical in contexts where financial risks intersect with environmental and social sensitivities. Academia, meanwhile, can support cost-efficient innovation by developing open-source digital mining tools, simulation environments, and modular training platforms tailored for low-resource settings. Collaborative research funded by public agencies can explore adaptive investment models—such as outcome-based financing or shared data ecosystems—to mitigate sunk costs and improve ROI transparency. In sum, mitigating B_4's barrier effect demands more than firm-level agility; it calls for structural alignment of financial, regulatory, and innovation systems to collectively de-risk and democratize access to transformative digital technologies.

From a policy standpoint, government agencies can support digital initiatives through targeted grants, tax incentives, and shared digital platforms—particularly for SMEs that operate in geologically complex or remote regions. Public–private partnerships (PPPs) may also be leveraged to mitigate upfront costs and share innovation risks.

The causal prominence of *Lack of Top Management Commitment* (B_3) and *Cultural Barriers* (B_2) suggests that digital transformation is not solely a technological upgrade but a deep organizational change process. Mining executives must champion digital agendas by clearly articulating long-term digital visions, allocating sufficient resources, and setting measurable transformation goals. Leadership development programs focused on digital competencies and change management can build internal capacity for sustained transformation. Culturally, mining organizations—often characterized by rigid hierarchies and safety-conservative mindsets—must cultivate an innovation-friendly climate that rewards experimentation, cross-functional collaboration, and open communication. Appointing digital transformation "champions" within departments can bridge the gap between vision and implementation, turning strategy into day-to-day operations.

From a regulatory and institutional standpoint, *Lack of Effective Regulatory Framework* (B_{11}) emerges as a bottleneck for sector-wide alignment. The absence of updated, digital-ready regulations—particularly in areas such as cybersecurity, data ownership, interoperability, and environmental monitoring—creates uncertainty for investors and operational managers alike. Regulators should embrace co-creation approaches, collaborating with industry experts, academics, and civil society actors to design agile, adaptive regulatory frameworks that promote innovation while safeguarding ethical and environmental standards. Legal instruments should encourage responsible data usage, promote open standards for interoperability, and embed accountability mechanisms in digital transformation strategies.

Barriers categorized as "effect-type" such as *Resistance to Change* (B_1) and *Lack of Skilled Workforce* (B_9) still exhibit high prominence scores, meaning they are not peripheral but systemically embedded. Workforce-related interventions must therefore begin early, not as a reactive measure but as a foundational strategy. Companies should design holistic training programs that go beyond technical skill-building to include digital literacy, cross-role understanding, and employee empowerment. These programs should also emphasize the purpose and long-term benefits of digital transformation to reduce fear, mistrust, and job insecurity. Moreover, integrating employee representatives and trade unions into planning processes can build legitimacy and foster bottom-up support for transformation agendas.

The study also highlights *Dynamic and Unpredictable Conditions* (B_{16})—stemming from geological uncertainty and harsh environments—as major environmental constraints. Managers must select technologies that are robust, adaptive, and compatible with volatile field conditions. Investment in ruggedized IoT devices, decentralized data architectures, and hybrid (terrestrial–

satellite) communication systems is critical to ensuring real-time responsiveness. Regional infrastructure development—especially in Eastern Türkiye and Anatolia's remote mining regions—should accompany such technological efforts, coordinated by regional development agencies and supported by state infrastructure funding.

In this broader context, non-governmental organizations (NGOs) and civil society groups can play critical bridging roles. These actors can conduct impact assessments to monitor the social and ethical implications of digitalization, particularly regarding labor displacement, community well-being, and data privacy. They can facilitate community engagement workshops, represent vulnerable groups in policymaking discussions, and ensure inclusive digital capacity-building. NGOs can also collaborate with industry actors to design social responsibility programs that pair digital rollouts with socio-economic development objectives in mining-affected communities.

Academic and educational institutions also have a central role in addressing knowledge gaps and future-proofing the workforce. University–industry partnerships can align curricula with real-world digital competencies required in the MI, while technical schools can integrate field-ready training modules in predictive maintenance, data analytics, and automation. Collaborative research programs should be funded to test and localize digital technologies under realistic mining conditions, generating local knowledge and reducing dependency on imported solutions.

Lastly, successful digital transformation in the MI cannot be achieved through fragmented, actor-specific initiatives. The systemic structure of barriers identified in this study underscores the need for an integrated, ecosystem-wide strategy. A central coordinating platform—perhaps under the auspices of a national mining innovation council—could harmonize efforts across stakeholders, align resources, and monitor progress. Strategic sequencing is also crucial: causal barriers like B_4 (*financial constraints*), B_3 (*management commitment*), and B_{11} (*regulatory gaps*) must be addressed first to enable meaningful action on downstream challenges like skills shortages or technological failures. By prioritizing systemic leverage points and fostering cross-sectoral collaboration, the MI can transition toward a digitally mature, sustainable, and socially inclusive future. A summary of these stakeholder-specific recommendations is provided in *Table 7.1*.

Table 6.1. Summarizes stakeholder-specific strategies for addressing key barriers

Stakeholder	*Barrier Addressed*	*Strategic Action*	*Implementation Level*	*Time Horizon*
Managers	*B_4 – High Initial Investment*	Launch modular digital pilots in high-value operations	Company-Level	Short-Term
Policymakers	*B_{11} – Lack of Effective Regulatory Framework*	Develop adaptive legal frameworks for data governance, cybersecurity, and interoperability	National / Regulatory Level	Mid-Term
NGOs / Civil Society	*B_1 – Resistance to Change*	Conduct digital awareness and community-based trust-building campaigns	Community-Level	Short-Term
Academic Institutions	*B_9 – Lack of Skilled Workforce*	Align technical curricula with industry needs via university-industry partnerships	Regional / Educational Level	Long-Term
Development Agencies	*B_{16} – Dynamic and Unpredictable Conditions*	Fund deployment of ruggedized IoT/5G/satellite connectivity solutions in remote sites	Regional Level	Mid-Term
Managers	*B_2 – Cultural Barriers*	Promote innovation-oriented leadership and internal communication strategies	Organizational Level	Mid-Term
Trade Unions	*B_1 – Resistance to Change*	Participate in strategic planning and workforce engagement processes	Workforce-Level	Short-Term
Policymakers	*B_3 – Lack of Top Management Commitment*	Incentivize executive digital leadership through policy tools and KPIs	Government / Industry Interface	Mid-Term
Mining Firms	*B_3 – Lack of Vision / Top Management Commitment*	Appoint internal digital champions and establish cross-functional innovation teams	Company-Level	Short-Term
Regional Authorities	*B_{16} – Dynamic and Unpredictable Conditions*	Coordinate funding and technical assistance for regional digital infrastructure	Regional Development Policy	Mid-Term

6.2. Research and Theoretical Implications

This study articulates a substantive theoretical and methodological contribution to the domain of industrial digital transformation by embedding the analysis of barriers within a causally interdependent and systemically integrated framework. Eschewing reductionist taxonomies that treat transformation constraints as isolated or thematically grouped phenomena, the present research advances a multidimensional perspective wherein each barrier is positioned within a dynamic matrix of influence, entanglement, and reciprocal causation. From a theoretical standpoint, the findings underscore that digital transformation in the MI is governed not by additive accumulations of discrete challenges, but by intricate hierarchies of structural initiation and behavioral propagation. For instance, the barrier identified as *Lack of Vision and Top Management Commitment* operates not merely as a managerial deficiency but as a systemic initiator, triggering a cascade of contingent constraints such as inadequate workforce development, diminished interdepartmental coherence, and organizational inertia. This conceptual stratification facilitates a more rigorous understanding of prioritization, wherein interventions can be sequenced according to structural centrality rather than thematic prevalence.

The research also deepens conceptual clarity regarding organizational and cultural inertia by illustrating how entrenched values, risk aversion, and hierarchical rigidity actively mediate the system's adaptive capacity. *Cultural Barriers*, for example, are not simply passive residuals of resistance but function as recursive agents that perpetuate disengagement, training deficits, and non-adoption. This reinforces calls in the literature for theorizing culture not as an exogenous backdrop, but as an endogenous mechanism of systemic constraint. Methodologically, the study exemplifies the utility of causal network modeling in operationalizing abstract interdependencies that are typically overlooked in conventional analyses. The relational configuration uncovered—such as the latent linkage between *Cybersecurity Concerns* and *Job Loss Anxiety*—reveals how behavioral apprehensions can retroactively compromise infrastructural adoption, thereby suggesting a circularity of influence often unrecognized in linear or checklist-based approaches.

Furthermore, the empirical identification of feedback loops within the transformation barrier ecosystem provides an important extension to prior theoretical assertions. The recursive nature of these loops—where upstream deficiencies magnify downstream dysfunctions, which in turn reinforce the initial structural barriers—corroborates emerging systems-thinking paradigms in organizational theory and digital innovation scholarship. In sum, this research transcends descriptive diagnosis by advancing a causally layered, theoretically nuanced, and analytically reproducible model of digital transformation barriers. The framework developed herein offers not only an interpretive tool for academic theorists but also a prescriptive basis for scholars and practitioners seeking to formulate structurally informed and strategically sequenced interventions in complex industrial environments.

7. CONCLUSIONS

The MI plays a foundational role in enabling economic growth and global industrialization by supplying essential raw materials. Despite its importance, the sector faces persistent challenges such as workforce limitations, safety risks, regulatory pressure, and increasing demand for environmental accountability. In response, digital technologies—including automation, artificial intelligence, and the Internet of Things—offer transformative potential to enhance operational performance, sustainability, and resilience. However, the implementation of these technologies is often hindered by a complex set of interdependent barriers.

To systematically address these challenges, this study employed an integrated methodological framework combining both qualitative and quantitative approaches. The process began with a systematic literature review guided by the *PRISMA* protocol, supported by bibliometric analysis to identify and validate key themes and trends. This phase led to the identification of sixteen core barriers to digital transformation in the MI. These barriers were then examined through the classical *DEMATEL* method using expert panel input to construct, normalize, and analyze the direct-relation matrices. The final output included the calculation of D and R values, determination of barrier prominence $(D+R)$ and net causality $(D-R)$, and the visualization of cause–effect relationships.

The findings of this study indicate that several upstream barriers—especially *High Initial Investment* (B_4), *Lack of Top Management Commitment* (B_3), and *Ineffective Regulatory Frameworks* (B_{11})—exert significant influence over a range of downstream challenges such as *Resistance to Change* (B_1), *Skill Shortages* (B_9), and *Cybersecurity Risks* (B_8). These insights provide a structured understanding of systemic dynamics and inform the prioritization of interventions across multiple stakeholder groups. The study thus contributes both methodologically and practically to advancing digital transformation in complex industrial settings such as mining.

7.1. Research Contributions

This research provides several contributions across three key dimensions: theoretical, methodological, and industrial. Theoretically, it enhances the conceptual understanding of digital transformation by framing barriers not as isolated themes but as elements of an interdependent system. By establishing a structured classification of influence among challenges, the study shifts the analytical focus from surface-level categorization to a deeper exploration of structural dynamics. Methodologically, the adoption of the *DEMATEL* technique in conjunction with expert evaluation introduces a replicable approach for identifying and analyzing causal patterns within complex decision environments. This research addresses a notable gap in digital transformation literature by concentrating on the MI —a context where the urgency for modernization is matched by deep-seated institutional and operational constraints. By grounding its findings in the real-world conditions of mining operations, the study offers not only theoretical insight but also practical guidance for stakeholders navigating digital change in similarly complex industries.

7.2. Limitations of the Study

While this study provides a robust analytical framework and yields valuable insights into the digital transformation challenges in the MI, several limitations must be acknowledged. First, during the systematic literature review phase, not all potentially relevant studies were accessible in full-text form due to institutional access limitations or paywall restrictions. Although a comprehensive database search was conducted and inclusion criteria were rigorously applied, this constraint may have excluded certain perspectives, niche studies, or region-specific insights from the final synthesis. Second, the focus on the MI enhances the contextual specificity and depth of the findings; however, it also limits the direct transferability of the conclusions to other sectors. Industries with different regulatory structures, workforce profiles, or technological maturity may face distinct configurations of digital transformation barriers. Third, the study focused exclusively on barriers to digital transformation. Enablers, success factors, or performance outcomes were beyond the scope of this analysis, despite their potential interaction with barriers. Future studies may benefit from examining the co-evolution of drivers and constraints within integrated transformation models. Fourth, the causal structure was derived solely from expert judgment using the *DEMATEL* technique. While this method provides a valuable mapping of interrelationships, it relies on perceived influence scores without triangulation from empirical field data or organizational records. This may introduce subjective bias or overlook real-world variations in barrier behavior. Fifth, the *DEMATEL* approach models directional influence among barriers but does not capture temporal sequencing, underlying causal mechanisms, or empirical validation of influence pathways. As a result, the method may simplify or overstate the complexity of certain feedback loops—especially in socio-organizational domains such as culture and resistance to change.

7.3. Future Research Opportunities

While this study provides a structured and insightful analysis of digital transformation barriers in the MI, several opportunities exist for extending and enriching future research. First, the current analysis is context-specific and static, relying on expert perceptions at a particular time and place. Future research could explore comparative studies across different countries and regions to capture how digital transformation challenges vary in different regulatory, economic, and cultural contexts. Such cross-national investigations would allow for the identification of universal versus localized barriers and help adapt intervention strategies accordingly. Second, longitudinal studies could track how the influence and prominence of specific barriers evolve over time. As digital maturity increases and external factors such as regulation or technology availability change, the barrier landscape may shift. A dynamic modeling approach would offer policymakers and practitioners better foresight into emerging priorities. Third, integrating qualitative methods—such as interviews, case studies, or ethnographic analysis—could enrich the quantitative findings derived from *DEMATEL*. These approaches would provide deeper insight into how different stakeholder groups perceive, interpret, and respond to the barriers. Mixed-method designs would also help uncover context-specific dynamics that may not be visible through expert scoring alone.

There is also an opportunity to apply or develop hybrid methodologies that combine *DEMATEL* with other decision-making techniques. Future studies could adopt advanced approaches such as fuzzy-DEMATEL, ANP-DEMATEL, or grey system models to better handle uncertainty and incorporate more nuanced expert judgments, especially in high-risk or data-scarce environments. Moreover, future research could investigate the broader ethical and social implications of digital transformation in mining. Topics such as job displacement, workforce reskilling, and stakeholder trust are crucial dimensions that merit greater scholarly attention, particularly in regions where mining plays a dominant socio-economic role. Finally, the development of practical frameworks for assessing the return on investment (ROI) of digital technologies remains an open challenge. Further research could design integrated models that measure both tangible and intangible outcomes—such as efficiency gains, safety improvements, and environmental performance—thereby supporting more informed and confident decision-making in technology adoption. In summary, future research should move toward more adaptive, interdisciplinary, and context-aware approaches to fully capture the evolving complexity of digital transformation in the MI. *Table* provides the key future research opportunities to advance scholarly understanding and the MI practice.

Table 7.1. Future Research Opportunities

	Future Research Opportunities
New studies on data policy and cybersecurity	• Industry-specific Challenges: Conduct research to examine mining operational technology systems for weaknesses. • Data Ownership: Do research on examining the moral and legal ramifications of sharing data throughout mining supply chains.
Innovative approaches to policy development and governance	• Responsive Governance: Provide flexible legal frameworks that keep up with new developments in technology. • International Standards of Conduct: Research the unification of labor, environmental, and safety regulations for international digital mining operations.
New studies on Novel quantitative Methodologies to address challenges	• Mixed-Methods Methods: For more in-depth understanding, combine qualitative stakeholder interviews with quantitative big data analytics including novel multi-criteria methods. • Longitudinal Studies: Monitor the changes in obstacles to digital adoption over time to spot trends and turning points.
New research on evaluating Return on investments and economic effectiveness	• Cost-benefit analysis: Conduct research on creating measures for assessing the long-term return on investment of digital initiatives, considering indirect advantages such as social sustainability, increased safety or a better reputation. • Novel Funding Methods: New studies that investigate new partnerships needed for funding new start-ups.
New studies on supply chain resilience in the mining industry	• Agility: Conduct research on examining new technologies for the mining industry to quickly adapt its new environment. • Supply Chain Resilience: Research new technology-based business models to improve traceability, visibility and resilience in mining supply chains.
The association between sustainability and digitalization in the MI	• Addressing Trade-offs: Explore how efficiency benefits, energy use, and e-waste are balanced by digital technologies in the MI. • Circular mining supply chains: Investigate digital ways to recycle important minerals or lessen the environmental impact of resource exploitation.
Studies focused on human resources in the MI	• Skill Gaps: Examine practical methods for retraining or improving employees on digital technologies. • Cultural Resistance: To reduce resistance and promote innovation-driven attitudes, conduct research on novel corporate change management strategies.
Research on implementing new technologies	• Next-Gen Technologies: Conduct research on developing new implementation frameworks for emerging technologies in mining operations. • Interoperability: Create novel frameworks to integrate new technologies with existing systems
Investigations on contextual barriers in various countries	• Regional Barriers: Examine how adoption problems are specifically shaped by socioeconomic, infrastructure, and regulatory environments (such as developing vs developed countries). • Case Studies: To pinpoint regional barriers, compare the digital revolution in overlooked areas (such as Southeast Asia and Africa).

REFERENCE

Abdellah, W.R., Kim, J.G., Hassan, M.M.A. & Ali, M.A.M., 2022. The key challenges towards the effective implementation of digital transformation in the mining industry. *Geosystem Engineering*, 25(1–2), pp.44–52. https://doi.org/10.1080/12269328.2022.2120093

Agbehadji, I.E., Awuzie, B.O. & Ngowi, A.B., 2021. COVID-19 pandemic waves: 4IR technology utilisation in multi-sector economy. *Sustainability*, 13(10168). https://doi.org/10.3390/su131810168

Ali, D., & Frimpong, S. (2020). Artificial intelligence, machine learning and process automation: Existing knowledge frontier and way forward for mining sector. *Artificial Intelligence Review, 53*(8), 6025–6042. https://doi.org/10.1007/s10462-020-09841-6

Axios. (2025, June 11). *U.S. races to break China's hold on rare earth magnets*. Axios. https://www.axios.com/2025/06/11/trump-us-china-trade-talks-minerals

Aziz, A., Schelén, O., & Bodin, U. (2020). A study on Industrial IoT for the mining industry: Synthesized architecture and open research directions. *IoT, 1*(2), 529–550. https://doi.org/10.3390/iot1020029

Barnewold, L. & Lottermoser, B.G., 2020. Identification of digital technologies and digitalisation trends in the mining industry. *International Journal of Mining Science and Technology*, 30(5), pp.747–757. https://doi.org/10.1016/j.ijmst.2020.07.003

Bhattacharyya, S.S. & Shah, Y., 2022. Emerging technologies in Indian mining industry: An exploratory empirical investigation regarding the adoption challenges. *Journal of Science and Technology Policy Management*, 13(2), pp.358–381. https://doi.org/10.1108/JSTPM-03-2021-0048

Bi, L., Wang, Z., Wu, Z. & Zhang, Y., 2022. A new reform of mining production and management modes under Industry 4.0: Cloud mining mode. *Applied Sciences*, 12(2781). https://doi.org/10.3390/app12062781

Bisschoff, R.A.D.P. & Grobbelaar, S., 2022. Evaluation of data-driven decision-making implementation in the mining industry. *South African Journal of Industrial Engineering*, 33(3), pp.218–232. https://doi.org/10.7166/33-3-2799

Broadus, R.N., 1987. Toward a definition of bibliometrics. *Scientometrics*, vol. 12, nos. 5–6, pp. 373–379. https://doi.org/10.1007/BF02016680

Chalmers, I., Hedges, L.V. & Cooper, H., 2002. A brief history of research synthesis. *Evaluation & the Health Professions*, 25(1), pp.12–37. https://doi.org/10.1177/0163278702025001003

Chen, Q., Zhang, W., Jin, N., Wang, X., & Dai, P. (2022). Digital transformation evaluation for small- and medium-sized manufacturing enterprises using the fuzzy synthetic method DEMATEL-ANP. *Sustainability*, *14*(20), 13038. https://doi.org/10.3390/su142013038

Dayo-Olupona, O., Genc, B. & Onifade, M., 2020. Technology adoption in mining: A multi-criteria method to select emerging technology in surface mines. *Resources Policy*, 69, p.101879. https://doi.org/10.1016/j.resourpol.2020.101879

Delibalta, M. S. (2022). Türkiye madencilik sektöründe döngüsel ekonomi ve dijitalleşme uygulamaları. *Niğde Ömer Halisdemir Üniversitesi Mühendislik Bilimleri Dergisi, 11*(4), 1121–1126. https://doi.org/10.28948/ngmuh.1141644

Donthu, N., Kumar, S., Mukherjee, D., Pandey, N. & Lim, W.M., 2021. How to conduct a bibliometric analysis: An overview and guidelines. *Journal of Business Research*, 133, pp.285–296. https://doi.org/10.1016/j.jbusres.2021.04.070

Duarte, J., Rodrigues, F. & Castelo Branco, J., 2022. Sensing technology applications in the mining industry—a systematic review. *International Journal of Environmental Research and Public Health*, 19(2334). https://doi.org/10.3390/ijerph19042334

Duarte, J., Rodrigues, M.F. & Baptista, J.S., 2021. Data digitalisation in the open-pit mining industry: A scoping review. *Archives of Computational Methods in Engineering*, 28, pp.3167–3181. https://doi.org/10.1007/s11831-020-09493-3

Ediriweera, A. & Wiewiora, A., 2021. Barriers and enablers of technology adoption in the mining industry. *Resources Policy*, 73, p.102188. https://doi.org/10.1016/j.resourpol.2021.102188

Fang, C., Yuan, Y., Chen, J., Gao, D., & Peng, J. (2024). Examination of green productivity in China's mining industry: An in-depth exploration of the role and impact of digital economy. *Sustainability*, *16*(1), 463. https://doi.org/10.3390/su16010463

Fontela, E., & Gabus, A. (1976). The DEMATEL Observer. Geneva: Battelle Geneva Research Center.

Gaber, T., El Jazouli, Y., Eldesouky, E. & Ali, A., 2021. Autonomous haulage systems in the mining industry: Cybersecurity, communication and safety issues and challenges. *Electronics*, 10(1357). https://doi.org/10.3390/electronics10111357

Don, M. G., Wanasinghe, T. R., Gosine, R. G., & Warrian, P. J. (2025). *Digital twins and enabling technology applications in mining: Research trends, opportunities, and challenges*. IEEE Access, 13, 6945–6959. https://doi.org/10.1109/ACCESS.2025.3526881

Gruenhagen, J.H., Cox, S. & Parker, R., 2022. An actor-oriented perspective on innovation systems: Functional analysis of drivers and barriers to innovation and technology adoption in the mining sector. *Technology in Society*, 68, p.101920. https://doi.org/10.1016/j.techsoc.2022.101920

Hazrathosseini, A. & Moradi Afrapoli, A., 2023. The advent of digital twins in surface mining: Its time has finally arrived. *Resources Policy*, 80, p.103155. https://doi.org/10.1016/j.resourpol.2022.103155

Holcombe, S. & Kemp, D., 2019. Indigenous peoples and mine automation: An issues paper. *Resources Policy*, 63, p.101420. https://doi.org/10.1016/j.resourpol.2019.101420

Hong, Q.N. & Pluye, P., 2018.

Systematic reviews: A brief historical overview. *Education for Information*, 34(3), pp.261–276. https://doi.org/10.3233/EFI-180219

Hyder, Z., Siau, K. & Nah, F., 2019. Artificial intelligence, machine learning, and autonomous technologies in mining industry. *Journal of Database Management*, 30(2), pp.67–79. https://doi.org/10.4018/JDM.2019040104

Jianing, P., Bai, K., Solangi, Y. A., Magazzino, C., & Ayaz, K. (2024). Examining the role of digitalization and technological innovation in promoting sustainable natural resource exploitation. Resources Policy, 92, 105036. https://doi.org/10.1016/j.resourpol.2024.105036

Kashan, A.J., Lay, J., Wiewiora, A. & Bradley, L., 2022. The innovation process in mining: Integrating insights from innovation and change management. *Resources Policy*, 76, p.102575. https://doi.org/10.1016/j.resourpol.2022.102575

Katiyar, R., Panigrahi, S. S., Ghatak, R. R., & Singh, R. (2024). Exploring barriers towards effective coal supply—A non-core perspective using ISM-DEMATEL. *Resources Policy*, *92*, 105010. https://doi.org/10.1016/j.resourpol.2024.105010

Koç, Ö., Taksuk, M., & Toraman, S. (2022). Madencilikte yeni eğilim "dijitalleşme". *Journal of Scientific Reports-B*, *4*(1), 1–7.

Laayati, O., Bouzi, M., & Chebak, A. (2022). Smart energy management system: Design of a monitoring and peak load forecasting system for an experimental open-pit mine. *Applied System Innovation*, *5*(1), 18. https://doi.org/10.3390/asi5010018

Li, H., Han, Z., Zhang, J., Philbin, S. P., Liu, D., & Ke, Y. (2022). Systematic identification of the influencing factors for the digital transformation of the construction industry based on LDA-DEMATEL-ANP. *Buildings*, *12*(9), 1409. https://doi.org/10.3390/buildings12091409

Liu, Y., Wang, X., Zhang, Z. & Deng, F., 2023. Deep learning in image segmentation for mineral production: A review. *Computers & Geosciences*, 180, p.105455. https://doi.org/10.1016/j.cageo.2023.105455

Long, M., Schafrik, S., Kolapo, P., Agioutantis, Z. & Sottile, J., 2024. Equipment and operations automation in mining: a review. *Machines*, 12(713). https://doi.org/10.3390/machines12100713

Lund, E., Pekkari, A., Johansson, J. & Lööw, J., 2024. Mining 4.0 and its effects on work environment, competence, organisation and society – a scoping review. *Mineral Economics*. https://doi.org/10.1007/s13563-024-00427-0

Mishra, A.K., 2021. AI4R2R (AI for Rock to Revenue): A review of the applications of AI in mineral processing. *Minerals*, 11(1118). https://doi.org/10.3390/min11101118

Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., & The PRISMA Group. (2009). Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. *PLoS Medicine, 6*(7), e1000097. https://doi.org/10.1371/journal.pmed.1000097

Mokganya, P.J., Webber-Youngman, R.C.W., Uys, J. & Olwagen, J., 2024. The role of leadership in technology adoption in the South African mining industry. *Journal of the Southern African Institute of Mining and Metallurgy*, 124(11), pp.617–630. https://doi.org/10.17159/2411-9717/2220/2024

Noriega, R. & Pourrahimian, Y., 2022. A systematic review of artificial intelligence and data-driven approaches in strategic open-pit mine planning. *Resources Policy*, 77, p.102727. https://doi.org/10.1016/j.resourpol.2022.102727

Onifade, M., Adebisi, J.A. & Zvarivadza, T., 2024. Recent advances in blockchain technology: prospects, applications and constraints in the minerals industry. *International Journal of Mining, Reclamation and Environment*, 38(7), pp.497–533. https://doi.org/10.1080/17480930.2024.2319453

Onifade, M., Adebisi, J.A., Shivute, A.P. & Genc, B., 2023. Challenges and applications of digital technology in the mineral industry. *Resources Policy*, 85, p.103978. https://doi.org/10.1016/j.resourpol.2023.103978

Page, M.J. et al., 2021. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ*, 372, n71. https://doi.org/10.1136/bmj.n71

Patil, S. D., Mitra, A., Katarikonda, K. T., & others. (2021). Predictive asset availability optimization for underground trucks and loaders in the mining industry. *OPSEARCH*, *58*(3), 751–772. https://doi.org/10.1007/s12597-020-00502-4

Paul, A., & Mahapatra, S. S. (2025). An integrated fuzzy-AHP and fuzzy-DEMATEL approach for analyzing sustainable supply chain factors in the mining industry. *Supply Chain Analytics*, *10*, 100113. https://doi.org/10.1016/j.sca.2025.100113

Pritchard, A. (1969). Statistical bibliography or bibliometrics? *Journal of Documentation*, *25*(4), 348–349.

Pinto, V.A., Cardoso, A.M.P., Pinheiro, M.M.K. & Parreiras, F.S., 2019. Interdisciplinarity in data science over big data: Findings for mining industry. *Informação & Sociedade: Estudos*, 29(4), pp.61–74. https://doi.org/10.22478/ufpb.1809-4783.2019v29n4.49543

Philo, K.G. & Webber-Youngman, R.C.W., 2024. A critical investigation into identifying key focus areas for the implementation of blockchain applications in the mining industry. *Journal of the Southern African Institute of Mining and Metallurgy*, 124(6), pp.319–330. https://doi.org/10.17159/2411-9717/2597/2024

Prinsloo, J., Vosloo, J. C., & Mathews, E. H. (2019). Towards Industry 4.0: A roadmap for the South African heavy industry sector. *South African Journal of Industrial Engineering, 30*(3), 174–186. https://doi.org/10.7166/30-3-2237

Qi, C.C., 2020. Big data management in the mining industry. *International Journal of Minerals, Metallurgy and Materials*, 27(2), pp.131–139. https://doi.org/10.1007/s12613-019-1937-z,

Reuters. (2025, June 10). *US, China reach deal to ease export curbs, keep tariff truce alive*. Reuters. https://www.reuters.com/world/china/us-china-trade-talks-resume-second-day-2025-06-10/?

Rob, M.A. & Sharifuzzaman, S.A.S.M., 2021. The role of IoT in digitalizing mining sector of Bangladesh. *5th International Conference on Electrical Engineering and Information & Communication Technology (ICEEICT)*, pp.1–6. https://doi.org/10.1109/ICEEICT53905.2021.9667893

Sánchez, F. & Hartlieb, P., 2020. Innovation in the mining industry: Technological trends and a case study of the challenges of disruptive innovation. *Mining, Metallurgy & Exploration*, 37, pp.1385–1399. https://doi.org/10.1007/s42461-020-00262-1

Shetty, V., Shedthi, B.S. & Shashishekar, C., 2023. Application and challenges of machine learning techniques in mining engineering and material science. *Journal of Mines, Metals and Fuels*, 71(11), pp.1989–2000. https://doi.org/10.18311/jmmf/2023/36099

Tahir, I., Shahzad, K. & Ensari, M.S., 2024. Utilising blockchain technology for managing natural resources: A case study of Reko Diq copper-gold project, Pakistan. *Resources Policy*, 98, p.105341. https://doi.org/10.1016/j.resourpol.2024.105341

The Verge. (2025, May 23). *A new cold war is brewing over rare earth minerals*. The Verge. https://www.theverge.com/electric-cars/665198/rare-earth-magnet-ev-motor-china-tariff

Ulewicz, R., Krstić, B. & Ingaldi, M., 2022. Mining Industry 4.0 – Opportunities and Barriers. *Acta Montanistica Slovaca*, 27(2), pp.291–305. https://doi.org/10.46544/AMS.v27i2.02

Vargas, J.P., Muñoz Lagos, A.P., Feriz Torres, J.G., Kinney, I.S., Pérez Cortés, S. & Hurtado, J.P., 2022. Achieving circularity through novel product-service systems in the mining industry: An opportunity for circularity. *Sustainability*, 14(3614). https://doi.org/10.3390/su14063614

Wang, J., Zheng, X., Shahani, N. M., Guo, X., Xin, W., Yue, W., Liu, L., & Yan, K. (2024). Review of major influencing factors contributing to persisting safety problems in coal mines: Addressing systemic challenges. *Applied Sciences, 14*(21), 9665. https://doi.org/10.3390/app14219665

Xie, J., Liu, S., & Wang, X. (2022). Framework for a closed-loop cooperative human cyber-physical system for the mining industry driven by VR and AR: MHCPS. *Computers & Industrial Engineering, 168*, 108050. https://doi.org/10.1016/j.cie.2022.108050

Young, A., & Rogers, P. (2019). A review of digital transformation in mining. *Mining, Metallurgy & Exploration, 36*(4), 683–699. https://doi.org/10.1007/s42461-019-00103-w

Zulu, M.S., Pretorius, M.W. & van der Lingen, E., 2021. The strategic competitiveness of the South African mining industry in the age of the Fourth Industrial Revolution. *South African Journal of Industrial Engineering*, 32(3), pp.185–200. https://doi.org/10.7166/32-3-2627

Zvarivadza, T., Onifade, M., Dayo-Olupona, O., Said, K.O., Githiria, J.M., Genc, B. & Celik, T., 2024. On the impact of Industrial Internet of Things (IIoT) – mining sector perspectives. *International Journal of Mining, Reclamation and Environment*, 38(10), pp.771–809. https://doi.org/10.1080/17480930.2024.2347131

APPENDICES

Appendix 1: Relevant Research

Reference	Title	Methodology	Findings	Scope	Key Themes
(Don et al. 2025)	"Digital Twins and Enabling Technology Applications in Mining: Research Trends, Opportunities, and Challenges"	Systematic Literature Review, Bibliometric & Time-Series Analysis	DT and enabling technologies improve safety, productivity, and efficiency in mining, but adoption is limited due to policy, technical, and data-related barriers	Global mining industry	Digital twins, enabling technologies, Industry 4.0, safety, VR/AR, automation, data challenges
(Mokganya et al. 2024)	"The role of leadership in technology adoption in the South African mining industry"	Qualitative research	Leadership styles significantly influence technology adoption	Mining industry (South Africa)	Leadership, Organizational resistance
(Wang et al. 2024)	"Review of Major Influencing Factors Contributing to Persisting Safety Problems in Coal Mines"	Systematic Review, Bibliometric Analysis	Persistent safety issues due to lack of data, outdated practices, weak regulation	Coal Mining industry Pakistan (with global comparison)	Safety, Regulation, Technology, Risk, Policy
(Long et al. 2024)	"Equipment and Operations Automation in Mining: A Review"	Literature review	Automation improves safety and efficiency in mining but faces challenges like high cost, workforce adaptation, and	Global (Focus on underground and surface mining)	Mining automation. AI, Safety, workforce challenges

			underground limitations.		
(Philo and Webber youngman 2024)	"A critical investigation into identifying key focus areas for the implementation of blockchain applications in the mining industry"	Literature review	Blockchain can improve data security, transparency, and compliance in mining. Key benefits include enhanced process automation, traceability, and trust.	Mining industry (Global)	Blockchain, digital transformation, traceability, compliance
(Zvarivadza et al. 2024)	"On the impact of Industrial Internet of Things (IIoT) - mining sector perspectives"	Literature review	IIoT enhances mining operations by improving safety, productivity, and sustainability, but faces challenges like integration issues and workforce upskilling.	Mining industry (Global)	IIoT, safety, automation, environmental sustainability, workforce training
(Jianing et al. 2024)	"Examining the role of digitalization and technological innovation in promoting sustainable natural resource exploitation"	Fuzzy AHP and Fuzzy VIKOR	Digitalization and innovation improve sustainability in natural resource exploitation, but face challenges like policy, infrastructure, and human capital gaps.	Mining industry (Pakistan)	Sustainability, digitalization, MCDM methods, challenges in resource exploitation
(Lund et al. 2024)	"Mining 4.0 and its effects on work environment, competence,	scoping review	Mining 4.0 technologies affect work environment, competences, and organizational	Mining industry (Global)	Mining 4.0, work environment, competence, Industry 5.0, human factors

	organization and society – a scoping review”		structures. Highlights the need for human-centric approaches and sustainability.		
(Onifade et al. 2024)	“Recent advances in blockchain technology: prospects, applications and constraints in the minerals industry”	Literature review	Blockchain improves transparency, traceability, and ethical practices in mining but faces challenges like scalability, energy consumption, and regulatory compliance.	Mining industry (Global)	Blockchain, transparency, supply chain, scalability, environmental impact
Fang et al. (2024)	“Examination of Green Productivity in China’s Mining Industry: An In-Depth Exploration of the Role and Impact of Digital Economy”	Meta-frontier Malmquist–Luenberger Index, Spatial Durbin Model, Panel Data (2008–2021)	Digital economy improves green productivity directly and indirectly; spatial spillover and industrial upgrading effects confirmed	mining industry (China)	Digital economy, green total factor productivity (GTFP), sustainability, spatial spillover, industrial transformation
(Onifade et al.2023)	“Challenges and applications of digital technology in the mineral industry”	Literature review	Digital technology enhances safety, productivity, and sustainability in mining but faces challenges like cybersecurity, skills gaps, and infrastructure limitations.	Mining industry (Global)	Digital transformation, safety, automation, sustainability

(Hazrathosseini and Moradi Afrapoli, 2023)	"The advent of digital twins in surface mining: Its time has finally arrived"	Literature review	Digital twins can transform surface mining by enabling real-time data exchange, cognitive decision-making, and predictive maintenance.	Surface mining (Global)	Digital twin, Mining 4.0, real-time data, predictive maintenance, Industry 4.0
(Bisschoff and Grobbelaar. 2022)	"Evaluation of Data-Driven Decision-Making Implementation in the Mining Industry"	scoping review	DDDM enhances decision-making in mining by integrating ERP, IoT, and analytics tools. Challenges include data integration issues, limited expertise, and technology gaps.	Mining industry (South Africa)	DDDM tools, Industry 4.0, data integration, decision-making
(Abdellah et al. 2022)	"The key challenges towards the effective implementation of digital transformation in the mining industry"	Literature review	Digital transformation in mining faces challenges like unclear strategies, skill gaps, cybersecurity issues, and difficulties integrating legacy systems.	Mining industry (Global)	Digital transformation, challenges, cybersecurity, skill gaps
(Noriega and Pourrahimian. 2022)	"A systematic review of artificial intelligence and data-driven approaches	Systematic Review	AI and data-driven methods enhance strategic planning in	Surface mining (Global)	Artificial intelligence, data-driven approaches, strategic

	in strategic open-pit mine planning”		surface mining, particularly in production scheduling, equipment management, and grade control.		planning, production scheduling
Xie et al. (2022)	“Framework for a Closed-Loop Cooperative Human Cyber-Physical System for the Mining Industry Driven by VR and AR”	System design, lab-based prototype testing, simulation & AR/VR integration	MHCPS enables human-machine collaboration in mining via VR/AR fusion, achieving stable closed-loop control and improved operator interaction	Mining industry (China, underground coal mining)	Cyber-Physical Systems, VR/AR, human–machine interaction, intelligent mining, real-time monitoring
(Bi et al. 2022)	“A New Reform of Mining Production and Management Modes under Industry 4.0: Cloud Mining Mode”	Literature review	Cloud mining mode enhances efficiency and collaboration in mining through cloud-based technologies but faces challenges in integration and adoption.	Mining industry (Global)	Cloud mining, Industry 4.0, collaboration, digital transformation
(Vargas et al. 2022)	“Achieving Circularity through Novel Product-Service Systems in the Mining Industry: An Opportunity for Circularity”	Systematic Literature Review	PSS models can improve circularity in mining by integrating digital technologies and lean approaches. Implementation faces barriers like lack of clear design for	Mining industry (Global)	Circular economy, PSS, sustainability, servitization, barriers

			circularity.		
(Gruenhagen et al. 2022)	"An actor-oriented perspective on innovation systems: Functional analysis of drivers and barriers to innovation and technology adoption in the mining sector"	Case Study Analysis	Barriers and drivers of innovation in mining innovation systems include market demand, actor networks, regulations, and organizational culture dynamics.	Mining industry (Australia)	Technological Innovation Systems (TIS), barriers, enablers, actor networks
(Duarte et al. 2022)	"Sensing Technology Applications in the Mining Industry—A Systematic Review"	Systematic Review (Prisma)	Sensing technologies improve safety, monitoring, and management in mining. Challenges include environmental hazards and integration difficulties.	Mining industry (Global)	Sensors, Industry 4.0, safety, monitoring, underground mining
(Laayati et al. 2022)	"Smart Energy Management System: Design of a Monitoring and Peak Load Forecasting System for an Experimental Open-Pit Mine"	Experimental Design	The proposed system integrates SCADA, predictive algorithms, and energy sensors to monitor, forecast, and optimize energy use in mining.	Open-Pit Mining (Experimental, Morocco)	Smart grids, SCADA, energy 4.0, load forecasting, optimization
(Ulewicz et al. 2022)	"Mining Industry 4.0 – Opportunities and Barriers"	Multi-Criteria Analysis (NAIADE)	It identifies digital transformation scenarios in mining, emphasizing automation, AI, and	Mining industry (Global)	Industry 4.0, Mining 4.0, automation, digitization, stakeholder analysis

			IoT. Highlights barriers such as skill deficits and social resistance.		
(Zulu et al. 2021)	"The Strategic Competitiveness of The South African Mining Industry in The Age of The Fourth Industrial Revolution"	Integrative Literature review	4IR technologies can improve cost-effectiveness and competitiveness in mining. Barriers include high failure rates in implementation, skill gaps, and technological constraints.	Mining industry (South Africa)	4IR, digital transformation, competitiveness, implementation challenges
(Mishra. 2021)	"AI4R2R (AI for Rock to Revenue): A Review of the Applications of AI in Mineral Processing"	Systematic Literature Review	AI and ML offer solutions for challenges in mineral processing, such as ore complexity, sustainability, and reducing human error. Sensor-based AI systems (SensAI) improve efficiency and accuracy.	Mineral Processing (Global)	Artificial intelligence, machine learning, ethical mining, sustainable processing, digital transformation
(Agbehadji et al. 2021)	"COVID-19 Pandemic Waves: 4IR Technology Utilization in Multi-Sector Economy"	Exploratory Literature review	4IR technologies were applied across sectors such as education and mining to manage COVID-19 impacts,	Multi-Sector Economy Including Mining (Global)	Fourth Industrial Revolution (4IR), pandemic management, digital transformation

			but challenges like data privacy and skill gaps persist.		
(Bhattacharyya and Shah. 2022)	“Emerging technologies in Indian mining industry: exploratory empirical investigation regarding the adoption challenges”	Exploratory Qualitative Research	Emerging technologies like IoT, blockchain, AI, and robotics are applied in Indian mining processes such as drilling and blasting. Adoption is hindered by managerial gaps, cultural inertia, and high costs.	Mining industry (India)	Emerging technologies, technology adoption, challenges, TOE and DOI frameworks
(Ediriweera and Wiewiora. 2021)	“Barriers and enablers of technology adoption in the mining industry”	Qualitative (TOE Framework)	It identified environmental and organizational barriers (e.g., market cycles, trust deficits) and enablers (e.g., learning culture) for technology adoption in mining.	Mining industry (Australia)	Technology adoption, barriers, enablers, innovation culture
(Gaber et al. 2021)	“Autonomous Haulage Systems in the Mining Industry: Cybersecurity, Communication and Safety Issues and Challenges”	Systematic Literature Review	Autonomous Haulage Systems (AHS) enhance mining operations through improved safety and efficiency but face challenges like cybersecurity threats	Mining industry (Global)	Autonomous systems, cybersecurity, communication, safety, Industry 4.0

			and communication failures.		
Patil et al. (2021)	“Predictive Asset Availability Optimization for Underground Trucks and Loaders in the Mining Industry”	Supervised Machine Learning (CHAID, C5.0, Cox Model), CRISP-DM Framework	Predictive models using engineered features improved OEE by reducing downtime; health scores and failure predictions integrated into dashboards	Underground mining (trucks & loaders)	Predictive maintenance, OEE, asset availability, machine learning, Industry 4.0
(Aziz et al. 2020)	“A Study on Industrial IoT for the Mining Industry: Synthesized Architecture and Open Research Directions”	Qualitative Synthesis	It developed a high-level IIoT architecture tailored for mining, addressing challenges like interoperability, scalability, and safety. Identified gaps in standards application and highlighted future research areas such as edge virtualization and digital twins.	Mining industry (Global)	IIoT architecture, interoperability, edge computing, digital transformation
(Duarte et al. 2021)	“Data Digitalization in the Open-Pit Mining Industry: A Scoping Review”	Scoping Review	It identified main digitalization tools and processes in open-pit mining, highlighting techniques such as UAV photogrammetry and LiDAR for detailed	Open-Pit Mining (Global)	Digitalization, UAV, LiDAR, Mining 4.0, digital modeling

			modeling. Agisoft PhotoScan was frequently used as a digitalization tool. Highlighted challenges in data integration and standards.		
(Sánchez and Hartlieb. 2020)	“Innovation in the Mining Industry: Technological Trends and a Case Study of the Challenges of Disruptive Innovation”	Review and Case Study	It identified key innovation drivers and technological trends shaping the mining industry. Highlighted the importance of digital transformation and disruptive technologies for improving productivity and sustainability.	Mining industry (Global)	Innovation, disruptive technologies, digital transformation, Industry 4.0
(Ali and Frimpong. 2020)	“Artificial intelligence, machine learning and process automation: existing knowledge frontier and way forward for mining sector”	Systematic Literature Review	Machine learning and AI are underutilized in mining but have the potential to enhance efficiency, safety, and sustainability. Key areas include mineral exploration, mine planning, equipment automation, and	Mining industry (Global)	Artificial intelligence, machine learning, automation, sustainability

			mineral processing.		
(Dayo-Olupona et al. 2020)	"Technology adoption in mining: A multi-criteria method to select emerging technology in surface mines"	Analytical hierarchy process (AHP) and PROMETHEE	AI identified as the most preferred technology; economic and operational barriers highlighted.	Mining industry, specifically surface mines (Global)	Barriers to digital transformation, decision-making frameworks
(Barnewold and Lottermoser. 2020)	"Identification of digital technologies and digitalization trends in the mining industry"	Text-mining and co-word analysis	It points out the high adoption of automation and IoT in large-scale operations and noted implementation barriers for smaller operations	Mining industry across various scales (Global)	Adoption trends, challenges for smaller mining operations
(Qi. 2020)	"Big data management in the mining industry"	Review	It highlights the potential of big data management (BDM) to improve efficiency, safety, and sustainability in mining. Identifies challenges in data integration and storage.	Mining industry (Global)	Big data, data integration, Industry 4.0, sustainability
(Prinsloo et al. 2019)	"Towards Industry 4.0: A Roadmap for The South African Heavy Industry Sector"	Review and Case Study	A digital framework and toolbox for Industry 4.0 adoption were proposed, identifying barriers like outdated	Mining industry (South Africa)	Industry 4.0, digital transformation, decentralization, wireless networks

			infrastructure and emphasizing the need for decentralization and wireless communication.		
(Pinto et al. 2019)	“Interdisciplinarity In Data Science Over Big Data: findings for mining industry”	Narrative Literature Review	Interdisciplinary approaches in data science and big data can enhance mining operations. Applications include reducing costs and improving decision-making in the iron ore industry	Mining industry (Global)	Interdisciplinary approaches, big data, data science, cost reduction, decision-making
(Young and Rogers. 2019)	“A Review of Digital Transformation in Mining”	Review	It explores digital transformation in mining, highlighting its components: ubiquitous data, connectivity, and decision-making. Identifies the industry’s challenges in adopting digital technologies.	Mining industry (Global)	Digital transformation, data-driven decision-making, Industry 4.0
(Hyder et al. 2019)	“Artificial Intelligence, Machine	Interviews and Literature Review	Explores the status of AI, machine learning, and autonomous	Mining industry (Global)	AI, machine learning, autonomous technologies, safety,

	Learning, and Autonomous Technologies in Mining Industry”		technologies in mining, highlighting economic, technological, and social challenges while identifying potential benefits for safety, efficiency, and cost reduction.		cost reduction
(Tahir et al. 2024)	“Utilizing blockchain technology for managing natural resources: A case study of Reko Diq copper-gold project, Pakistan”	Semi-structured interviews, Blockchain screening tool	Blockchain technology offers potential solutions for trust, transparency, and environmental sustainability issues in the Reko Diq project. Infrastructure limitations remain a key hurdle.	Reko Diq Project, Pakistan	Blockchain, trust, transparency, environmental and economic sustainability
(Shetty et al. 2023)	“Application and Challenges of Machine Learning Techniques in Mining Engineering and Material Science”	Systematic Review and Framework	It highlights the application of machine learning techniques in predicting mineral quality, equipment failures, and environmental impact. Challenges include data collection, preprocessing, and algorithm selection.	Mining and Material Science (Global)	Machine learning, prediction, environmental impact, data challenges

(Liu et al. 2023)	"Deep learning in image segmentation for mineral production: A review"	Literature Review and Experiments	It explores deep learning methods for mineral image segmentation, highlighting benefits in accuracy, efficiency, and edge detection while addressing challenges in real-world applications.	Mining industry (Global)	Deep learning, image segmentation, mineral exploration, efficiency, edge detection
(Kashan et al. 2022)	"The innovation process in mining: Integrating insights from innovation and change management"	Qualitative Exploratory Approach (Interviews)	It develops a three-phased process model for innovation adoption in mining, integrating change management and innovation frameworks. Emphasizes human roles and stakeholder engagement in innovation.	Mining industry (Global)	Innovation process, change management, human factors, stakeholder engagement
(Rob and Sharifuzzaman. 2021)	"The Role of IoT in Digitalizing Mining Sector of Bangladesh"	Qualitative Research	IoT enhances mining efficiency, safety, and sustainability. Challenges include cost, technical issues (e.g., interference), and regulatory hurdles. IoT adoption	Mining industry (Bangladesh)	IoT, digital transformation, automation, sustainability, challenges

			could transform the Bangladeshi mining industry.		
(Holcombe and Kemp. 2019)	“Indigenous peoples and mine automation: An issues paper”	Issues Paper (Conceptual Study)	It examines the impact of mine automation on Indigenous peoples, highlighting risks such as job losses in routine roles, and the need for industry to adapt employment strategies.	Mining industry (Australia, Canada)	Indigenous employment, mine automation, social impact
(Koç et al. 2022)	“Madencilikte Yeni Eğilim: Dijitalleşme”	Theoretical discussion, trend review, secondary data analysis	Digitalization is essential for transforming mining; challenges include organizational resistance, policy gaps, and lack of technical capacity	Turkish mining industry	Digital transformation, automation, smart mining, AI, big data, policy, Industry 4.0
(Delibalta 2022)	“Circular Economy and Digitalization Practices in the Mining Sector of Türkiye”	Literature review, secondary data analysis, national statistics	Integration of circular economy and digitalization is key to improving sustainability, productivity, and waste management in Turkish mining	Turkish mining industry	Circular economy, sustainability, digitalization, Industry 4.0, waste management, smart mining

Appendix 2: Expert Survey Questionnaire

QUESTIONNAIRE

Considering the examples above, please indicate the degree of influence between the following pairs of barriers using the scale provided below:

0: No influence 1: Very low influence 2: Low influence 3: High influence 4: Very high influence

Resistance to Change	4	3	2	1	0	1	2	3	4	Cultural Barriers
Resistance to Chang	4	3	2	1	0	1	2	3	4	Lack of vision and top management commitment
Resistance to Change	4	3	2	1	0	1	2	3	4	High Initial Investment
Resistance to Change	4	3	2	1	0	1	2	3	4	Uncertainty in Return on Investment (ROI)
Resistance to Change	4	3	2	1	0	1	2	3	4	Integration Issues with Legacy Systems
Resistance to Change	4	3	2	1	0	1	2	3	4	Harsh Environmental Conditions and Limited Connectivity in Remote Locations
Resistance to Change	4	3	2	1	0	1	2	3	4	Cybersecurity Risks
Resistance to Change	4	3	2	1	0	1	2	3	4	Lack of Skilled Workforce
Resistance to Change	4	3	2	1	0	1	2	3	4	Insufficient Training and Awareness
Resistance to Change	4	3	2	1	0	1	2	3	4	Lack of effective regulatory framework
Resistance to Change	4	3	2	1	0	1	2	3	4	Compliance Costs and Administrative Burdens
Resistance to Change	4	3	2	1	0	1	2	3	4	Limited External Stakeholder Engagement
Resistance to Change	4	3	2	1	0	1	2	3	4	Loss of Routine Jobs through Automation
Resistance to Change	4	3	2	1	0	1	2	3	4	Data Complexity and overload

Resistance to Change	4	3	2	1	0	1	2	3	4	Dynamic and Unpredictable Conditions in mining fields
Cultural Barriers	4	3	2	1	0	1	2	3	4	Lack of vision and top management commitment
Cultural Barriers	4	3	2	1	0	1	2	3	4	High Initial Investment
Cultural Barriers	4	3	2	1	0	1	2	3	4	Uncertainty in Return on Investment (ROI)
Cultural Barriers	4	3	2	1	0	1	2	3	4	Integration Issues with Legacy Systems
Cultural Barriers	4	3	2	1	0	1	2	3	4	Harsh Environmental Conditions and Limited Connectivity in Remote Locations
Cultural Barriers	4	3	2	1	0	1	2	3	4	Cybersecurity Risks
Cultural Barriers	4	3	2	1	0	1	2	3	4	Lack of Skilled Workforce
Cultural Barriers	4	3	2	1	0	1	2	3	4	Insufficient Training and Awareness
Cultural Barriers	4	3	2	1	0	1	2	3	4	Lack of effective regulatory framework
Cultural Barriers	4	3	2	1	0	1	2	3	4	Compliance Costs and Administrative Burdens
Cultural Barriers	4	3	2	1	0	1	2	3	4	Limited External Stakeholder Engagement
Cultural Barriers	4	3	2	1	0	1	2	3	4	Loss of Routine Jobs through Automation
Cultural Barriers	4	3	2	1	0	1	2	3	4	Data Complexity and overload
Cultural Barriers	4	3	2	1	0	1	2	3	4	Dynamic and Unpredictable Conditions in mining fields
Lack of vision and top management commitment	4	3	2	1	0	1	2	3	4	High Initial Investment
Lack of vision and top management commitment	4	3	2	1	0	1	2	3	4	Uncertainty in Return on Investment (ROI)
Lack of vision and top management commitment	4	3	2	1	0	1	2	3	4	Integration Issues with Legacy Systems

Lack of vision and top management commitment	4	3	2	1	0	1	2	3	4	Harsh Environmental Conditions and Limited Connectivity in Remote Locations
Lack of vision and top management commitment	4	3	2	1	0	1	2	3	4	Cybersecurity Risks
Lack of vision and top management commitment	4	3	2	1	0	1	2	3	4	Lack of Skilled Workforce
Lack of vision and top management commitment	4	3	2	1	0	1	2	3	4	Insufficient Training and Awareness
Lack of vision and top management commitment	4	3	2	1	0	1	2	3	4	Lack of effective regulatory framework
Lack of vision and top management commitment	4	3	2	1	0	1	2	3	4	Compliance Costs and Administrative Burdens
Lack of vision and top management commitment	4	3	2	1	0	1	2	3	4	Limited External Stakeholder Engagement
Lack of vision and top management commitment	4	3	2	1	0	1	2	3	4	Loss of Routine Jobs through Automation
Lack of vision and top management commitment	4	3	2	1	0	1	2	3	4	Data Complexity and overload
Lack of vision and top management commitment	4	3	2	1	0	1	2	3	4	Dynamic and Unpredictable Conditions in mining fields
High Initial Investment	4	3	2	1	0	1	2	3	4	Uncertainty in Return on Investment (ROI)
High Initial Investment	4	3	2	1	0	1	2	3	4	Integration Issues with Legacy Systems

High Initial Investment	4	3	2	1	0	1	2	3	4	Harsh Environmental Conditions and Limited Connectivity in Remote Locations
High Initial Investment	4	3	2	1	0	1	2	3	4	Cybersecurity Risks
High Initial Investment	4	3	2	1	0	1	2	3	4	Lack of Skilled Workforce
High Initial Investment	4	3	2	1	0	1	2	3	4	Insufficient Training and Awareness
High Initial Investment	4	3	2	1	0	1	2	3	4	Lack of effective regulatory framework
High Initial Investment	4	3	2	1	0	1	2	3	4	Compliance Costs and Administrative Burdens
High Initial Investment	4	3	2	1	0	1	2	3	4	Limited External Stakeholder Engagement
High Initial Investment	4	3	2	1	0	1	2	3	4	Loss of Routine Jobs through Automation
High Initial Investment	4	3	2	1	0	1	2	3	4	Data Complexity and overload
High Initial Investment	4	3	2	1	0	1	2	3	4	Dynamic and Unpredictable Conditions in mining fields
Uncertainty in Return on Investment (ROI)	4	3	2	1	0	1	2	3	4	Integration Issues with Legacy Systems
Uncertainty in Return on Investment (ROI)	4	3	2	1	0	1	2	3	4	Harsh Environmental Conditions and Limited Connectivity in Remote Locations
Uncertainty in Return on Investment (ROI)	4	3	2	1	0	1	2	3	4	Cybersecurity Risks
Uncertainty in Return on Investment (ROI)	4	3	2	1	0	1	2	3	4	Lack of Skilled Workforce
Uncertainty in Return on Investment (ROI)	4	3	2	1	0	1	2	3	4	Insufficient Training and Awareness
Uncertainty in Return on Investment (ROI)	4	3	2	1	0	1	2	3	4	Lack of effective regulatory framework

Uncertainty in Return on Investment (ROI)	4	3	2	1	0	1	2	3	4	Compliance Costs and Administrative Burdens
Uncertainty in Return on Investment (ROI)	4	3	2	1	0	1	2	3	4	Limited External Stakeholder Engagement
Uncertainty in Return on Investment (ROI)	4	3	2	1	0	1	2	3	4	Loss of Routine Jobs through Automation
Uncertainty in Return on Investment (ROI)	4	3	2	1	0	1	2	3	4	Data Complexity and overload
Uncertainty in Return on Investment (ROI)	4	3	2	1	0	1	2	3	4	Dynamic and Unpredictable Conditions in mining fields
Integration Issues with Legacy Systems	4	3	2	1	0	1	2	3	4	Harsh Environmental Conditions and Limited Connectivity in Remote Locations
Integration Issues with Legacy Systems	4	3	2	1	0	1	2	3	4	Cybersecurity Risks
Integration Issues with Legacy Systems	4	3	2	1	0	1	2	3	4	Lack of Skilled Workforce
Integration Issues with Legacy Systems	4	3	2	1	0	1	2	3	4	Insufficient Training and Awareness
Integration Issues with Legacy Systems	4	3	2	1	0	1	2	3	4	Lack of effective regulatory framework
Integration Issues with Legacy Systems	4	3	2	1	0	1	2	3	4	Compliance Costs and Administrative Burdens
Integration Issues with Legacy Systems	4	3	2	1	0	1	2	3	4	Limited External Stakeholder Engagement
Integration Issues with Legacy Systems	4	3	2	1	0	1	2	3	4	Loss of Routine Jobs through Automation
Integration Issues with Legacy Systems	4	3	2	1	0	1	2	3	4	Data Complexity and overload
Integration Issues with Legacy Systems	4	3	2	1	0	1	2	3	4	Dynamic and Unpredictable Conditions in mining fields
Harsh Environmental Conditions and	4	3	2	1	0	1	2	3	4	Cybersecurity Risks

Limited Connectivity in Remote Locations										
Harsh Environmental Conditions and Limited Connectivity in Remote Locations	4	3	2	1	0	1	2	3	4	Lack of Skilled Workforce
Harsh Environmental Conditions and Limited Connectivity in Remote Locations	4	3	2	1	0	1	2	3	4	Insufficient Training and Awareness
Harsh Environmental Conditions and Limited Connectivity in Remote Locations	4	3	2	1	0	1	2	3	4	Lack of effective regulatory framework
Harsh Environmental Conditions and Limited Connectivity in Remote Locations	4	3	2	1	0	1	2	3	4	Compliance Costs and Administrative Burdens
Harsh Environmental Conditions and Limited Connectivity in Remote Locations	4	3	2	1	0	1	2	3	4	Limited External Stakeholder Engagement
Harsh Environmental Conditions and Limited Connectivity in Remote Locations	4	3	2	1	0	1	2	3	4	Loss of Routine Jobs through Automation
Harsh Environmental Conditions and Limited Connectivity in Remote Locations	4	3	2	1	0	1	2	3	4	Data Complexity and overload
Harsh Environmental Conditions and Limited Connectivity in Remote Locations	4	3	2	1	0	1	2	3	4	Dynamic and Unpredictable Conditions in mining fields

Cybersecurity Risks	4	3	2	1	0	1	2	3	4	Lack of Skilled Workforce
Cybersecurity Risks	4	3	2	1	0	1	2	3	4	Insufficient Training and Awareness
Cybersecurity Risks	4	3	2	1	0	1	2	3	4	Lack of effective regulatory framework
Cybersecurity Risks	4	3	2	1	0	1	2	3	4	Compliance Costs and Administrative Burdens
Cybersecurity Risks	4	3	2	1	0	1	2	3	4	Limited External Stakeholder Engagement
Cybersecurity Risks	4	3	2	1	0	1	2	3	4	Loss of Routine Jobs through Automation
Cybersecurity Risks	4	3	2	1	0	1	2	3	4	Data Complexity and overload
Cybersecurity Risks	4	3	2	1	0	1	2	3	4	Dynamic and Unpredictable Conditions in mining fields
Lack of Skilled Workforce	4	3	2	1	0	1	2	3	4	Insufficient Training and Awareness
Lack of Skilled Workforce	4	3	2	1	0	1	2	3	4	Lack of effective regulatory framework
Lack of Skilled Workforce	4	3	2	1	0	1	2	3	4	Compliance Costs and Administrative Burdens
Lack of Skilled Workforce	4	3	2	1	0	1	2	3	4	Limited External Stakeholder Engagement
Lack of Skilled Workforce	4	3	2	1	0	1	2	3	4	Loss of Routine Jobs through Automation
Lack of Skilled Workforce	4	3	2	1	0	1	2	3	4	Data Complexity and overload
Lack of Skilled Workforce	4	3	2	1	0	1	2	3	4	Dynamic and Unpredictable Conditions in mining fields
Insufficient Training and Awareness	4	3	2	1	0	1	2	3	4	Lack of effective regulatory framework
Insufficient Training and Awareness	4	3	2	1	0	1	2	3	4	Compliance Costs and Administrative Burdens
Insufficient Training and Awareness	4	3	2	1	0	1	2	3	4	Limited External Stakeholder Engagement

Insufficient Training and Awareness	4	3	2	1	0	1	2	3	4	Loss of Routine Jobs through Automation
Insufficient Training and Awareness	4	3	2	1	0	1	2	3	4	Data Complexity and overload
Insufficient Training and Awareness	4	3	2	1	0	1	2	3	4	Dynamic and Unpredictable Conditions in mining fields
Lack of effective regulatory framework	4	3	2	1	0	1	2	3	4	Compliance Costs and Administrative Burdens
Lack of effective regulatory framework	4	3	2	1	0	1	2	3	4	Limited External Stakeholder Engagement
Lack of effective regulatory framework	4	3	2	1	0	1	2	3	4	Loss of Routine Jobs through Automation
Lack of effective regulatory framework	4	3	2	1	0	1	2	3	4	Data Complexity and overload
Lack of effective regulatory framework	4	3	2	1	0	1	2	3	4	Dynamic and Unpredictable Conditions in mining fields
Compliance Costs and Administrative Burdens	4	3	2	1	0	1	2	3	4	Limited External Stakeholder Engagement
Compliance Costs and Administrative Burdens	4	3	2	1	0	1	2	3	4	Loss of Routine Jobs through Automation
Compliance Costs and Administrative Burdens	4	3	2	1	0	1	2	3	4	Data Complexity and overload
Compliance Costs and Administrative Burdens	4	3	2	1	0	1	2	3	4	Dynamic and Unpredictable Conditions in mining fields
Limited External Stakeholder Engagement	4	3	2	1	0	1	2	3	4	Loss of Routine Jobs through Automation
Limited External Stakeholder Engagement	4	3	2	1	0	1	2	3	4	Data Complexity and overload

Limited External Stakeholder Engagement	4	3	2	1	0	1	2	3	4	Dynamic and Unpredictable Conditions in mining fields
Loss of Routine Jobs through Automation	4	3	2	1	0	1	2	3	4	Data Complexity and overload
Loss of Routine Jobs through Automation	4	3	2	1	0	1	2	3	4	Dynamic and Unpredictable Conditions in mining fields
Data Complexity and overload	4	3	2	1	0	1	2	3	4	Dynamic and Unpredictable Conditions in mining fields