Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/NA11.20260092
Published: June 9, 2026

An AI-Governance Framework for Intelligent Decision-Making in Mineral Resource Management

Oladeji. O. Ige
Department of Materials Science and Engineering
Obafemi Awolowo University, Ile-Ife, Nigeria
Department of Industrial Engineering, Durban University of Technology
Durban, South Africa
Institute of System Science, Durban University of Technology
Durban, South Africa
ige4usa@yahoo.com

Felix Mora-Camino
Department of Industrial Engineering
Durban University of Technology
Durban, South Africa
felixmora@id.uff.br

Oludolapo. A. Olanrewaju
Institute of System Science
Durban University of Technology
Durban, South Africa
oludolapoo@dut.ac.za

Abstract

Mineral resources constitute the backbone of industrial and socio-economic growth, yet persistent governance weaknesses continue to limit their developmental impact in many resource-rich economies. Artificial Intelligence (AI) and Multi-Criteria Decision-Making (MCDM) offer transformative capabilities for improving decision quality, transparency, and sustainability within mineral resource management (MRM). However, a systematic bibliometric review of 287,601 academic records across six major databases revealed no study within the defined search scope simultaneously addressing mineral resource management, artificial intelligence, and regulatory policy frameworks—a tri-disciplinary void representing a critical barrier to intelligent governance. This conceptual paper proposes an AI-governance framework—the Intelligent Decision-Making System (IDMS)—which integrates regulatory governance, strategic coordination, and investment analytics through AI-enhanced MCDM techniques. Drawing on Decision Theory, governance practice in resource-rich economies, and Computational Intelligence Theory, the IDMS framework introduces a tri-layer structure (macro, meso, micro) that aligns top-down policy constraints with bottom-up data-driven optimization, forming a continuous learning system for sustainable resource governance. An illustrative AHP–TOPSIS application ranking three hypothetical mining projects demonstrates the framework's analytical operability. As a theoretical contribution, this framework provides foundations for harmonizing institutional accountability with computational efficiency and contributes to Sustainable Development Goals (SDGs) 9, 12, and 16. The paper concludes with five testable research propositions (P1—AI-MCDM integration improves decision quality; P2—feedback mechanisms enhance adaptability; P3—multi-criteria evaluation produces balanced outcomes; P4—hybrid human-algorithm structures optimize performance; P5—tri-layer architectures manage governance

complexity), theoretical implications, and a conceptual implementation roadmap for intelligent mineral management systems.

Keywords
Multi-Criteria Decision-Making, Artificial Intelligence, Decision Support Systems, Mineral Resource Management, and Intelligent Decision-Making Systems

1. Introduction
Mineral resources remain critical to industrialization and socio-economic development, yet many resource-rich African nations continue to experience poor outcomes—a paradox widely described as the structural disconnect between resource wealth and development outcomes (Franks et al, 2023). Despite accounting for nearly one-third of global mineral endowments, Africa attracts less than 15 percent of global mining investment (Franks et al, 2023; Vandome and Dechambenoit, 2020). This disparity arises from fragmented policy regimes, limited institutional capacity, and weak integration of analytical intelligence in decision processes as constraints identified in the Africa Mining Vision (African Union, 2009). The convergence of AI and MCDM presents a unique opportunity to transform legacy management systems into intelligent, transparent, and data-driven frameworks. Nevertheless, most studies examine either the technological dimension—focusing on automation, optimization, and predictive analytics—or the regulatory dimension—addressing institutional reforms and governance compliance (Corrigan and Laye, 2022). Few attempt to integrate both into a single coherent system. While AI applications in mining operations have matured (Corrigan and Laye, 2022; Dumakor-Dupey and Arya, 2021), and MCDM methods are well-established in resource contexts (Sitorus *et al*. 2019), their integration for governance applications remains largely unexplored.

This paper builds on our earlier work (Ige and Olanrewaju, 2025; Ige *et al.* 2026). It identifies a tri-disciplinary gap between AI, multi-criteria decision-making, and mineral resource governance. It advances an enhanced AI-governance framework called IDMS. This framework features refined architecture, ethical foundations, and analytical insights. The goal is to move beyond mere gap identification to foster effective interdisciplinary collaboration.

The structural absence of integrated frameworks is independently confirmed here by the systematic bibliometric review in Section 2.4.1—the most comprehensive evidence to date that no study simultaneously addresses all three domains. Despite extensive work in AI-driven optimization (Duan *et al.*, 2019; Lepenioti *et al.*, 2020) and governance-oriented frameworks (Franks et al., 2023; Vandome and Dechambenoit, 2020; African Union, 2009), no unified theoretical architecture explicitly integrates all three domains. As demonstrated by the systematic bibliometric review in Section 2.4.1, which screened 287,601 records across six major databases, no study simultaneously addresses mineral resource management, artificial intelligence, and regulatory policy frameworks. Unlike existing studies that treat AI, governance, and investment analysis separately, this study proposes a structurally integrated and feedback-driven architecture—the Intelligent Decision-Making System (IDMS).

Mineral endowment continues to shape national development trajectories, yet many resource-rich economies experience persistent governance inefficiencies that limit the translation of mineral wealth into sustainable outcomes. This paradox reflects structural challenges in institutional coordination, regulatory implementation, and analytical capacity within decision-making systems. Emerging advances in artificial intelligence (AI) and multi-criteria decision-making (MCDM) offer new opportunities to enhance decision quality in complex, multi-dimensional environments. AI enables large-scale data processing and predictive modelling, while MCDM techniques support structured evaluation of competing economic, environmental, and social objectives. However, these capabilities have largely been applied in isolation from governance systems, resulting in fragmented analytical and policy approaches.

Building on prior work that identified a structural gap across these domains, this study develops an integrated Intelligent Decision-Making System (IDMS) that aligns computational intelligence with regulatory governance and investment analytics.

1.1 Research Objectives
This conceptual paper pursues three primary objectives:

1. To develop an intelligent theoretical framework that unifies regulatory governance, strategic coordination, and investment analytics within mineral resource management.
2. To propose mechanisms enabling continuous learning and adaptation in mineral resource policy-making through AI-MCDM integration.

3. To establish a theoretical foundation for future empirical research on intelligent decision-support systems in resource governance.

1.2 Contribution and Scope

Our contribution is purely theoretical and conceptual, providing an architectural foundation for intelligent decision-making that future empirical work can validate and refine. This paper extends preliminary work presented at previous conferences by: (a) formalizing the tri-layer theoretical architecture, (b) explicating integration mechanisms between layers, (c) grounding the framework in established theoretical traditions, and (d) proposing research directions for empirical validation. As a conceptual contribution, this paper focuses on framework development and theoretical argumentation rather than empirical testing. We acknowledge that actual performance validation awaits future research involving data collection and case application.

The paper generates five testable research propositions (detailed in Section 5.1) to guide future empirical investigation: **P1**—AI-MCDM integration improves decision quality over fragmented approaches; **P2**—feedback mechanisms enhance governance adaptability; **P3**—explicit multi-criteria evaluation yields more balanced economic, environmental, and social outcomes; **P4**—hybrid human-algorithm structures outperform both full automation and pure intuition; and **P5**—tri-layer hierarchical architectures manage governance complexity more effectively than flat structures.

This study builds upon prior works by the authors (Ige and Olanrewaju, 2025; Ige *et al.*, 2026), which identified a tri-disciplinary gap through systematic analysis. While the studies focused on gap identification, the present paper advances a more comprehensive framework by developing the Intelligent Decision-Making System (IDMS) with enhanced architectural detail, ethical considerations, and analytical demonstration.

2. Literature Review and Theoretical Foundations

2.1 Mineral Resource Management Challenges

African mineral governance often reflects a striking imbalance between the continent's abundant natural resources and the developmental outcomes they generate. While revenues from mineral extraction can significantly boost fiscal income, weak regulatory frameworks and limited local beneficiation capacity perpetuate dependence on raw commodity exports.

The Africa Mining Vision (African Union, 2009) represents a continental effort to transform mineral wealth into sustainable development, yet implementation remains challenged by weak institutional capacity (Franks *et al.*, 2023). Sustainable mineral supply requires effective resource governance (Franks *et al.*, 2023; Vandome and Dechambenoit, 2020), particularly as global transitions to low-carbon economies increase demand for critical minerals (Sovacool *et al.*, 2020). Despite policy frameworks, the gap between regulatory intent and implementation outcomes persists across mineral-rich African nations (Vandome and Dechambenoit, 2020).

Several challenges constrain effective governance in this sector. First, fragmented policy coordination among government agencies leads to inefficiencies and overlapping regulatory functions. Second, limited technical capacity in contract negotiation and compliance monitoring often results in unfavourable outcomes for host communities and domestic economies. Third, environmental and social considerations remain poorly integrated into management strategies, leading to ecological degradation and community disempowerment.

Weak enforcement mechanisms further undermine governance integrity, allowing regulatory violations to persist. Insufficient stakeholder participation reduces policy legitimacy and silences affected groups. Finally, the absence of intelligent decision-support systems hampers long-term planning and adaptive policy formation. Collectively, these deficiencies result in suboptimal resource allocation, revenue leakages, and missed opportunities for sustainable development.

2.2 Artificial Intelligence in Resource Management

AI techniques, including neural networks, natural-language processing (NLP), and machine learning (ML) algorithms, are becoming increasingly prevalent in various sectors, particularly in exploration, production optimization, and safety monitoring (Dumakor-Dupey and Arya, 2021; Hyder *et al.*, 2019). Applications span mineral resource estimation, blast optimization, and autonomous technologies (Corrigan and Laye, 2022). Yet, their application in governance and policy evaluation remains nascent.

The evolution of AI for decision-making in big data contexts (Duan *et al.*, 2019) and prescriptive analytics capabilities (Lepenioti *et al.*, 2020) provide foundations for intelligent governance applications. While AI applications in public sector governance demonstrate potential for evidence-based policy-making (Wirtz et al., 2019), mineral resource governance represents a relatively unexplored application domain.

Several promising pathways exist for embedding AI in governance. Text mining can analyze policy documents to identify inconsistencies and regulatory gaps. Predictive analytics enables proactive assessment of compliance risks, while pattern recognition enhances interpretation of large regulatory datasets. Furthermore, automated monitoring systems could streamline implementation tracking and support evidence-based policy revisions.

AI-driven decision-support tools can also facilitate complex, multi-stakeholder negotiations by identifying consensus points and minimizing bias. Despite these potential benefits, the application of AI within mineral governance introduces a range of ethical challenges that require careful consideration. One key issue relates to transparency, as algorithmic systems may produce outputs that are difficult to interpret or audit, particularly in high-stakes decision contexts (Diakopoulos, 2015; Saaty, 1980; Lepri *et al.*, 2018). Ensuring that such systems remain explainable and subject to institutional oversight is therefore essential. Bias in data-driven models presents an additional concern, as reliance on historical datasets may inadvertently reinforce existing inequalities in resource allocation and environmental prioritization (Diakopoulos, 2015; Saaty, 1980; Lepri *et al.*, 2018). Addressing this requires deliberate incorporation of fairness-aware modelling practices and inclusive participation in decision criteria formulation. Data governance also emerges as a critical consideration, particularly in resource-dependent regions where mineral-related datasets represent strategic national assets. Ensuring appropriate control over data access, usage, and ownership is essential to maintaining analytical sovereignty and preventing asymmetrical dependencies. To mitigate these risks, the proposed framework adopts a human-in-the-loop structure in which AI supports, rather than replaces, institutional decision-making processes, thereby preserving accountability while enhancing analytical capability.

2.3 Multi-Criteria Decision-Making Methods

Multiple-Criteria Decision-Making (MCDM) methods provide structured approaches to complex decision problems involving multiple, often conflicting, objectives (Belton and Stewart, 2002). Techniques including the Analytic Hierarchy Process (AHP) (Saaty, 1980), Fuzzy AHP, and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) provide systematic approaches to evaluating alternatives across multiple objectives. They enable decision-makers to prioritize competing factors through structured analysis that accommodates both quantitative and qualitative dimensions.

MCDM applications span diverse domains, with comprehensive reviews documenting their evolution and application patterns (Mardani *et al.*, 2015). In mineral resource contexts, MCDM methods address equipment selection, processing technology choices, and strategic planning decisions (Sitorus *et al.*, 2019). Fuzzy extensions effectively handle uncertainty inherent in governance contexts (Kahraman *et al.*, 2015). In the mineral resource context, MCDM is particularly valuable where objectives such as economic profitability, environmental protection, social equity, and technical feasibility must be balanced. When integrated with AI, MCDM enhances predictive modelling, improves uncertainty management, and enables adaptive weighting of socio-economic and governance criteria. This combination of methods contributes directly to sustainable development by reconciling competing interests and improving the rigor of investment evaluations and policy formulations.

2.4 The Tri-Disciplinary Research Gap

Existing scholarship demonstrates significant advancement within the individual domains of mineral resource management, artificial intelligence, and multi-criteria decision-making (Dumakor-Dupey and Arya, 2021; Sitorus *et al.*, 2019). Nevertheless, their convergence remains limited, with most studies addressing either operational optimization or policy-level considerations independently. Prior analysis systematically examined this intersection and identified a clear absence of frameworks that simultaneously integrate governance constraints, analytical intelligence, and investment decision processes (Ige and Olanrewaju, 2025; Ige *et al.*, 2026). While partial intersections between two domains were observed, no unified architecture addressing all three dimensions was established within the defined scope.

The present study extends this foundation by moving beyond gap identification to propose a structured integration framework that operationalizes the interaction between regulatory systems, strategic coordination mechanisms, and data-driven investment analytics. The five specific gaps characterizing the current scholarship are:

1. Absence of comparative frameworks: No conceptual models systematically integrate regulatory governance with AI-enhanced investment analytics.
2. Lack of integration mechanisms: Theoretical guidance is missing on how to connect policy constraints with computational optimization.
3. Fragmented disciplinary communication: AI researchers seldom collaborate with scholars in governance or policy studies.
4. Missing architectural frameworks: No coherent structures currently guide integration of AI–MCDM approaches with institutional governance.
5. Inadequate theoretical foundations: Hybrid systems combining human judgment and algorithmic reasoning lack formal theoretical grounding.

2.4.1 Search Strategy and Evidence of Tri-Disciplinary Gap

A structured bibliometric search across six major academic databases – Scopus, Web of Science, IEEE Xplore, Wiley Online Library, SpringerLink, and ScienceDirect – screened 287,601 records using Boolean keyword logic combining artificial intelligence, multi-criteria decision-making, and mineral resource governance terms (Ige and Olanrewaju, 2025; Ige *et al.*, 2026). Sequential filtering against inclusion criteria that required simultaneous treatment of all three domains yielded zero qualifying studies. Convergence efficiency – defined as the proportion of records addressing at least two of the three domains simultaneously – was 0.54%, confirming a near-total structural absence of integrated frameworks. Full methodological details, including search protocol, keyword strings, and PRISMA screening stages, are reported in (Ige and Olanrewaju, 2025; Ige *et al.*, 2026). The complete screening process is summarised in Figure 1 using a PRISMA-style flow diagram.

2.5 Theoretical Anchors

The IDMS model draws on two theoretical traditions and one governance-practice perspective. Decision Theory supports rational decision-making under uncertainty, providing foundations for optimal choice among alternatives. Core concepts include utility maximization, risk assessment through probability distributions, and sequential decision-making under incomplete information. Decision theory undergirds the computational optimization components of IDMS. Governance practice in resource-rich African economies demonstrates how rules, norms, and accountability structures influence policy outcomes (Vandome and Dechambenoit, 2020). This evidence emphasizes that formal regulations alone are insufficient—effective governance requires alignment between de jure rules and de facto practices, supported by monitoring mechanisms and stakeholder participation. This governance perspective informs the IDMS macro and meso layers. Computational Intelligence Theory demonstrates how algorithms can emulate adaptive reasoning, learning from data to improve performance over time. Unlike static rule-based systems, computational intelligence approaches can handle ambiguity, discover patterns in complex data, and adapt to changing conditions. This theory provides the theoretical foundation for incorporating AI across the layers of an Intelligent Decision-Making System (IDMS). These theoretical and empirical foundations jointly underpin the shift from static, rule-based systems to dynamic, learning-oriented mineral governance.

3. The Intelligent Decision-Making System (IDMS): A Conceptual Framework

3.1 Framework Overview

The Intelligent Decision-Making System (IDMS) frames mineral resource management (MRM) as a multi-level adaptive system, where regulatory, strategic, and investment decisions interact dynamically. It aligns top-down policy goals with bottom-up operational realities through three principles: integration, addressing regulatory, strategic, and investment factors simultaneously; adaptation, enabling learning and policy adjustment; and intelligence, leveraging both computational algorithms and human judgment.

The IDMS framework operationalizes concepts introduced in the AI-Investment Decision Matrix (Ige et al*.,* 2026), extending beyond investment analytics to incorporate regulatory governance and strategic coordination layers. This multi-technique integration reflects contemporary trends in hybrid MCDM frameworks (Mardani *et al.*, 2015) and AI-enhanced decision support systems (Ige et al., 2026), adapted specifically for mineral governance contexts.

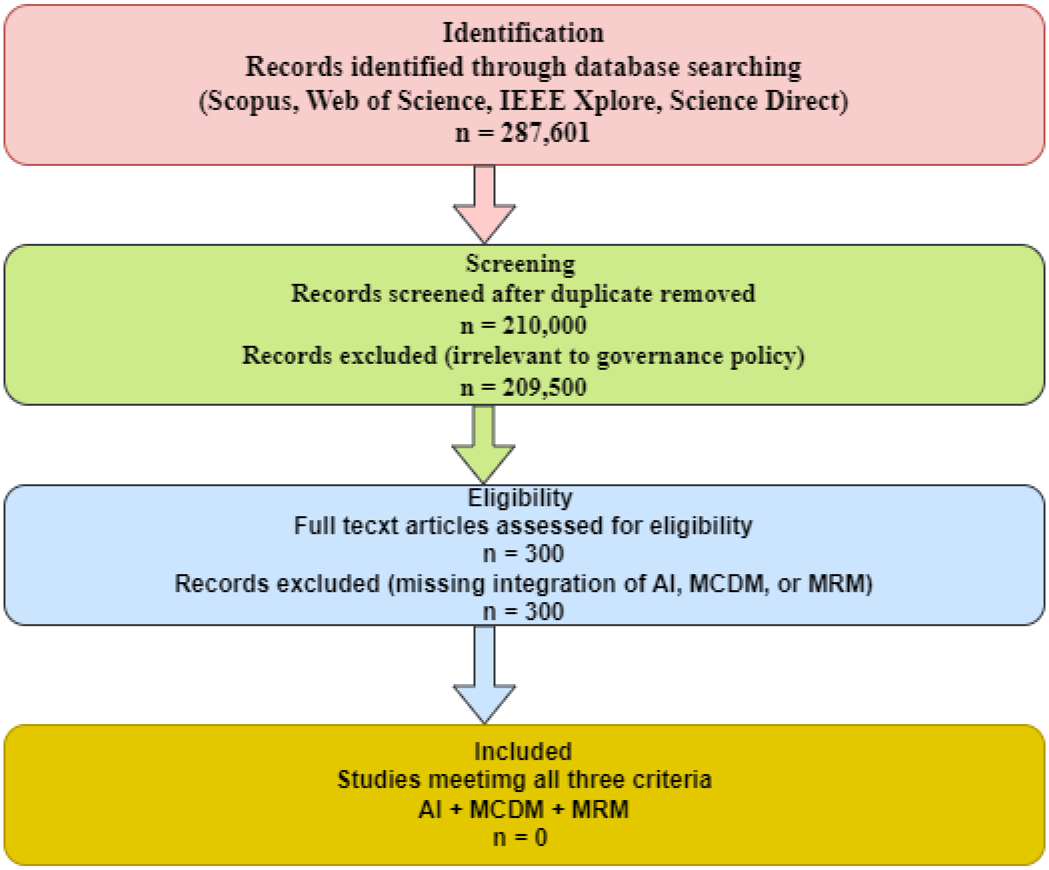

Figure 1. PRISMA Style Flow Diagram – Identification of the AI-MCDM-MRM Tri-Disciplinary Research Gap

3.2 Tri-Layer Architecture

The IDMS comprises three interconnected layers, each targeting a specific governance level as illustrated in Figure 2 (see next page). The IDMS integrates regulatory, strategic, and investment layers, each enhanced with AI-MCDM tools, to support adaptive, intelligence-driven mineral resource governance.

Macro Layer—Regulatory Governance: Defines legal and sustainability boundaries (e.g., mining codes, environmental regulations, fiscal regimes). AI-MCDM tools include NLP for policy analysis, AHP for weighting objectives, and legal ontologies for coherence assessment. Critically, the macro layer is not a self-governing system: authority over criteria selection, weighting, and threshold-setting resides with the designated regulatory institution, not the algorithm. This design explicitly addresses conflicts of interest — for instance, a ministry that simultaneously promotes investment and enforces environmental compliance—by requiring that competing objectives be encoded as separate, explicitly weighted criteria subject to independent audit (Franks *et al.*, 2023). The role of AI at this layer is therefore circumscribed: it processes and surfaces information, flags regulatory inconsistencies, and models trade-offs, but normative choices remain the prerogative of accountable human institutions.

Meso Layer—Strategic Integration: Bridges policy and execution through stakeholder coordination, performance monitoring, and risk management. Tools include fuzzy AHP for trade-offs, network analysis for stakeholder mapping, and scenario analysis for strategic planning.

Micro Layer—Investment Analytics: Provides data-driven insights for project evaluation and operational optimization. Tools include ML classification models (e.g., SVM), multi-objective optimization, and TOPSIS for ranking alternatives.

Together, the layers synthesize policy, strategy, and investment decisions, enabling adaptive, intelligence-driven mineral resource governance.

Table 1 contrasts the objectives, analytical tools, and decision bases that characterize AI-enabled regulatory and investment frameworks. It highlights their complementary functions within the IDMS, showing how governance-driven policy mechanisms (macro/meso layers) align with investment-focused analytics (micro layer) to achieve intelligent, data-informed mineral resource governance. Taken together, Table 1, Table 2, and Figure 2 collectively fulfil the function of a unified visualization: Figure 2 provides the architectural overview of the tri-layer system, Table 1 maps how AI inputs interact with socio-economic and governance criteria at each layer, and Table 2 specifies the AI-MCDM tool assignments per governance function. Readers seeking a single integrated view of how AI, environmental, and socio-economic criteria interact within the IDMS are directed to read Figure 2 and Table 2 in conjunction.

3.3 Theoretical Mechanism

The macro layer defines regulatory and sustainability constraints, the meso layer translates them into measurable strategies, and the micro layer applies AI–MCDM analytics for investment optimization (Table 2). A feedback loop ensures continuous learning, linking outcomes back to policy refinement and adaptive governance.

In practice, a regulatory agency could apply the IDMS by first encoding policy constraints within the macro layer (e.g. environmental thresholds, fiscal royalty requirements, and land-use regulations), translating them into measurable KPIs at the meso layer (e.g. compliance scores, stakeholder alignment indices), and subsequently evaluating investment alternatives at the micro layer using AI-MCDM tools such as TOPSIS or machine learning classification models. For example, a mining ministry in a resource-rich economy could use the framework to rank competing project proposals against weighted criteria spanning environmental impact, community benefit, and economic return – producing a transparent defensible decision record. Similarly, mining firms can use the framework to align project selection with regulatory expectations while optimizing financial and sustainability outcomes, thereby reducing the risk of license revocation or reputational harm. The Intelligent Decision-Making System (IDMS) operates as a dynamic, learning-oriented framework that continuously links regulatory governance, strategic coordination, and investment analytics. Its functionality depends on structured information flows across three interdependent layers.

At the Macro layer, institutional data—such as policy directives, regulatory standards, and sustainability objectives—define the decision boundaries. These boundaries form the upper constraints within which optimization occurs.

The Meso layer acts as the system's interpretive hub, translating policy mandates into measurable strategies through stakeholder consultation, key performance indicators (KPIs), and multi-criteria assessments. This layer produces actionable outputs—such as performance indices, compliance metrics, and alignment indicators—that bridge governance intentions and investment actions.

The Micro layer executes optimization by processing real-time data from markets, environmental systems, and operations. Using AI and MCDM algorithms (e.g., Support Vector Machines, neural networks, and fuzzy AHP), it generates predictive insights and optimized investment portfolios that inform upper-level review.
Feedback and learning cycle close the loop, where investment outcomes and monitoring data return to the Macro layer. Machine learning models then recalibrate policy thresholds and sustainability benchmarks, ensuring continuous improvement in regulatory responsiveness and decision accuracy. This iterative process institutionalizes adaptive governance—transforming static regulation into a living, data-informed system of intelligent decision-making.

To illustrate the workflow concretely: consider Zambia's Ministry of Mines, which must evaluate three competing applications for a new copper concession in the Copperbelt Province. Using the IDMS, the Ministry first encodes its binding constraints at the macro layer—including a 30% local-content requirement, a maximum acid mine drainage threshold, and a minimum royalty rate—as formal decision criteria (Step 1). These are translated at the meso layer into measurable KPIs: a community employment index, an environmental compliance score, and a royalty-revenue projection (Step 2). The micro layer then processes each applicant's submissions against these criteria using a TOPSIS ranking, producing a ranked shortlist with a documented, auditable rationale that the Ministry can defend to parliament, affected communities, and investors (Steps 3–4). When production data become available post-award, the feedback loop (Step 5) recalibrates the environmental threshold weight if monitoring reveals deterioration—as demonstrated in Section 4.7.4. To operationalize the IDMS framework, a structured workflow can be defined.

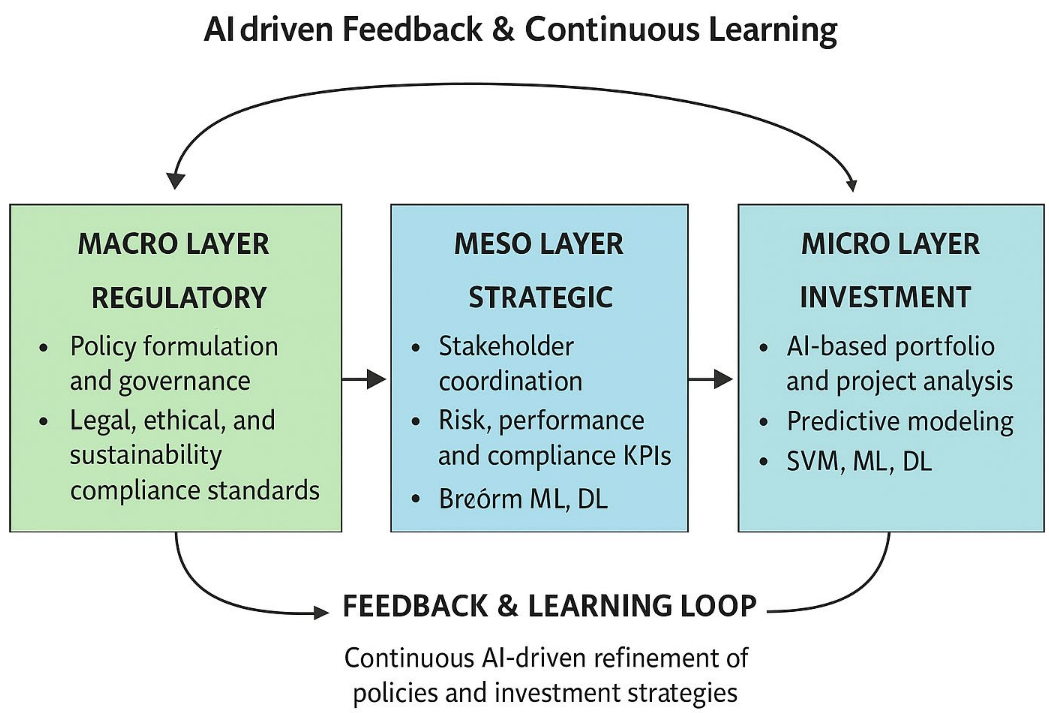

Figure 2. Tri-Layer Intelligent Decision-Making System (IDMS) Framework

Table 1. Comparative Summary of Traditional versus IDMS Approaches

Dimension	Traditional Approach	IDMS Framework
Decision Basis	Expert intuition and discretion	Data-driven analysis with expert oversight
Integration	Sequential, fragmented	Simultaneous, unified
Transparency	Opaque, implicit trade-offs	Explicit criteria and weights
Adaptability	Static policies	Dynamic learning through feedback
Sustainability	Sequential consideration	Multi-criteria integration
Stakeholder Input	Ad-hoc consultation	Structured participatory methods
Complexity Handling	Limited analytical capacity	Computational optimization
Accountability	Diffuse responsibility	Traceable decision processes

Step 1: Policy Encoding (Macro Layer) – Regulatory constraints, sustainability thresholds, and fiscal policies are translated into formal decision criteria and boundary conditions.
Step 2: Criteria Structuring (Meso Layer) – These constraints are converted into measurable indicators, including compliance scores, stakeholder alignment indices, and risk metrics using MCDM techniques such as AHP or fuzzy AHP.

Step 3: Analytical Processing (Micro Layer) – AI models (e.g., machine learning classifiers, optimization algorithms) process real-time and historical data to evaluate and rank investment alternatives using methods such as TOPSIS or multi-objective optimization.

Step 4: Decision Output – The system produces ranked alternatives, policy compliance scores, and risk-adjusted investment recommendations.

Step 5: Feedback and Learning – Outcomes are fed back into the system to recalibrate criteria weights, update predictive models, and refine policy thresholds, enabling adaptive governance over time.

3.4 Theoretical Justification for Tri-Layer Structure

The theoretical justification for the tri-layer structure is grounded in three complementary foundations—two theoretical and one practice-based—that reinforce each other effectively. First, decision theory suggests that complex problems can be made more manageable by breaking them down into hierarchical sub-problems, allowing for clearer information flows. In the IDMS, each layer addresses a distinct decision problem—regulatory design at the macro, coordination at the meso, and investment selection at the micro—while vertical interfaces ensure coherent information flow between them.

A key insight from governance practice in resource-rich economies is that institutional pressures for change influence organizations at three distinct levels: macro (rules), meso (coordination), and micro (practices). The tri-layer structure facilitates this alignment by implementing explicit interface specifications that guide interactions among the different layers. Computational intelligence theory highlights the benefits of layered architectures, a principle also seen in deep learning. A layered architecture facilitates a progressive and task-specific transformation of input data. Each layer within the IDMS processes information at the appropriate level of abstraction relevant to its particular decision problem, enhancing both efficiency and effectiveness.

Table 2 links specific artificial-intelligence and multi-criteria decision-making (MCDM) methods to distinct governance activities across the IDMS. It illustrates how AI techniques such as NLP, Bayesian learning, and neural networks combine with MCDM approaches like AHP, TOPSIS, and VIKOR to support policy analysis, compliance assessment, investment ranking, and performance monitoring within adaptive decision cycles.

3.5 Distinguishing Features

The IDMS framework presents several distinctive theoretical contributions that enhance our understanding and implementation of decision-making processes. Firstly, it introduces a concept of bidirectional integration, which sets it apart from traditional hierarchical models characterized by one-way information flows. In IDMS, feedback mechanisms are crucial as they allow insights from lower layers to inform and refine policies at higher levels. Moreover, the framework emphasizes hybrid intelligence by explicitly blending computational analytics, such as AI optimization, with human judgment through stakeholder deliberation. This approach successfully navigates the pitfalls of relying solely on either automation or intuition, creating a more balanced decision-making process. Another significant aspect of IDMS is its focus on multi-criteria explicitness. The framework employs structured multi-criteria decision-making (MCDM) methods to make trade-offs clear and transparent, rather than leaving them to implicit expert judgment or political negotiations. Furthermore, IDMS promotes adaptive learning through its feedback mechanisms, thereby transforming mineral governance from a reactive administrative model into one of proactive adaptive management, fostering continuous improvement. Lastly, by incorporating sustainability integration, the framework ensures that environmental, social, and governance (ESG) considerations are embedded in every step of the decision-making process, reinforcing its commitment to sustainable outcomes.

Figure 3 presents an integrated visualization of the IDMS, illustrating how AI-driven inputs (e.g., predictive analytics, pattern recognition outputs) are systematically mapped onto multi-criteria dimensions, including economic performance, environmental sustainability, and governance compliance. These inputs are processed through MCDM structures to generate transparent and traceable decision outputs. The figure highlights the interaction between computational intelligence and structured decision criteria across all three layers, demonstrating how data-driven insights are translated into accountable governance outcomes.

4. Theoretical Implications and Discussion

4.1 Resolving Theoretical Tensions

The IDMS framework navigates three key tensions in resource governance. First, it balances Governance and Automation by viewing AI as a supportive tool rather than a replacement for human judgment. This approach enhances decision-making while ensuring that human control over normative choices remains intact through a tri-layer structure. Second, it reconciles Policy Consistency with Adaptation. While stable frameworks are essential for predictability, they can also become outdated. IDMS incorporates structured feedback to allow for controlled policy evolution. It ensures policies maintain consistency during decision cycles but can adapt based on outcomes, fostering flexibility without sacrificing stability. Lastly, IDMS integrates sustainability within governance by utilizing multi-criteria evaluation methods. This approach treats economic, environmental, and social dimensions not as sequential processes but as interconnected objectives, enabling simultaneous optimization for sustainable development. This approach aligns with recognition that sustainable mineral supply requires effective resource governance (Ali *et al.*, 2017), particularly for critical minerals essential to low-carbon transitions (Sovacool *et al.*, 2020).

In summary, IDMS offers a modern framework for effective resource governance that embraces both human oversight and adaptive processes.

Figure 4 illustrates the dynamic interaction mechanism of the IDMS, showing how information flows bidirectionally across the macro, meso, and micro layers. It highlights the feedback loop through which investment outcomes and monitoring data recalibrate policy thresholds at the regulatory level, enabling continuous adaptive governance.

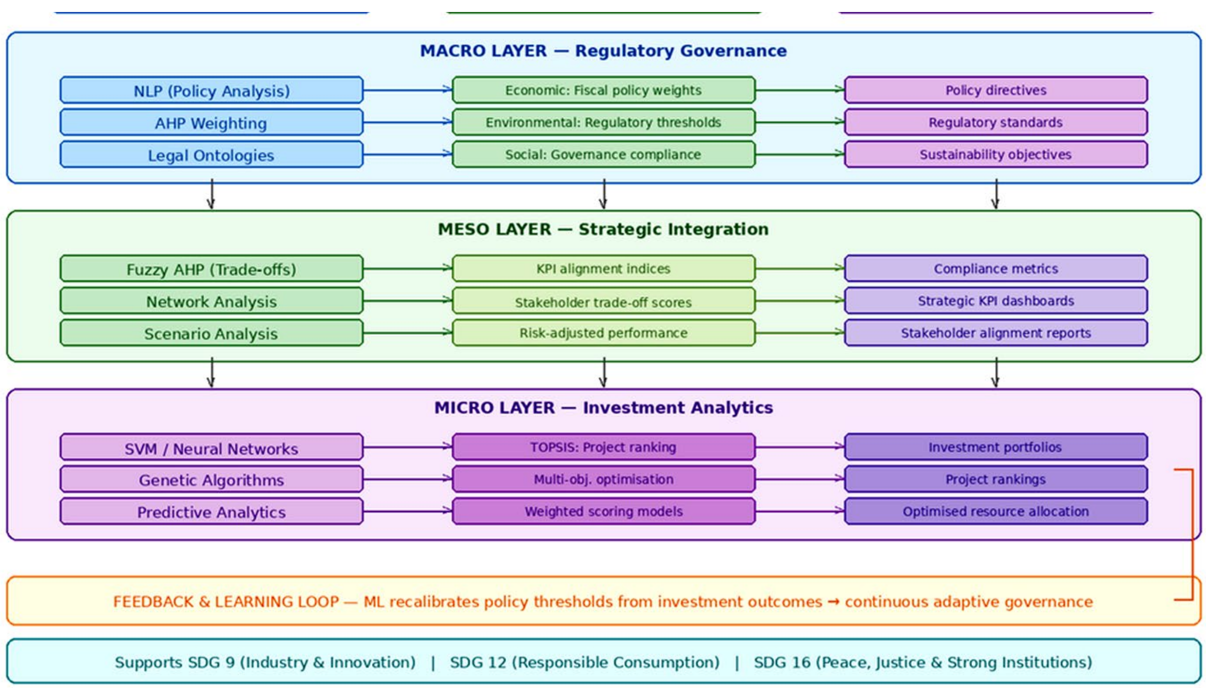

Figure 3. Integrated AI-MCDM-Governance Flow Model – AI inputs mapped to socio-economic, environmental, and governance criteria across the IDMS tri-layer structure

4.2 Conceptual Advantages

IDMS provides key advantages over traditional methods. Decision rationales are made transparent through the application of explicitly defined criteria and algorithms. The structured approach ensures consistency, minimizing arbitrary variations in similar decisions. IDMS utilizes multi-criteria frameworks to integrate and consider the diverse perspectives of its stakeholders. Additionally, it offers traceability, allowing for accountability through documented processes. Finally, once set up, the framework can efficiently handle a high volume of decisions with minimal extra effort.

First, the model remains conceptual and has not yet undergone empirical validation. The absence of field data creates two key limitations: it prevents quantitative calibration of feedback loops and empirical weighting of decision criteria. Consequently, we cannot fully assess the interoperability between AI and MCDM components. Future studies should pilot the framework using real-world datasets to evaluate its performance and refine parameter sensitivity.

Second, contextual variation in governance structures poses implementation challenges. The contextual realities of African mineral economies diverge significantly from those in the Global North, the primary source of existing AI-policy scholarship. Variations in institutional maturity, data infrastructure, and regulatory enforcement may affect the fidelity of implementation. Consequently, future adaptations of the IDMS should incorporate regional policy variables, informal governance practices, and socio-economic priorities unique to resource-rich African states.

Third, the framework's technical assumptions introduce practical constraints. The macro-layer NLP component assumes access to digitized, standardized policy documents—an assumption that breaks down where regulations are paper-based or multilingual without official translations. Likewise, ML algorithms at the micro layer require historical investment data for training, which may be limited or proprietary in emerging mining sectors.

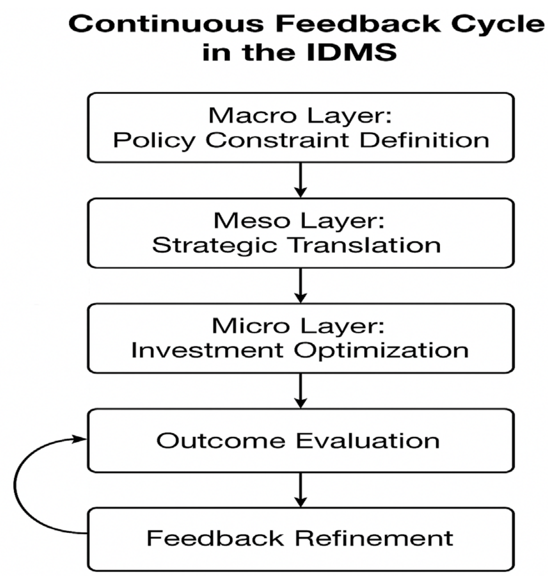

Figure 4. The three layers of the conceptual Intelligent Decision-Making System mechanism

Table 2. Mapping of AI-MCDM Tools to IDMS Layers

Layer	Governance Function	AI Tools	MCDM Methods	Expected Theoretical Benefits
Macro	Policy Analysis	NLP, Text Mining	AHP	Automated gap detection, priority weighting
Macro	Compliance Monitoring	ML Classification	Fuzzy Sets	Risk prediction, uncertainty handling
Meso	Stakeholder Coordination	Network Analysis	Fuzzy AHP	Influence mapping, trade-off quantification
Meso	Strategic Planning	Scenario Analysis	Multi-Criteria Scenarios	Robustness testing, adaptive planning
Micro	Project Evaluation	SVM, Neural Networks	TOPSIS	Classification accuracy, alternative ranking
Micro	Portfolio Optimization	Genetic Algorithms	Multi-Objective MCDM	Pareto efficiency, preference articulation
All Layers	Performance Monitoring	Predictive Analytics	Weighted Scoring	Real-time evaluation, iterative adjustment

4.3 Limitations and Contextual Considerations

Although the proposed Intelligent Decision-Making System (IDMS) presents a theoretically coherent framework, several limitations and contextual factors must be acknowledged. In the first instance, the model remains conceptual and has not yet undergone empirical validation. The absence of field data creates two key limitations: it prevents quantitative calibration of feedback loops and empirical weighting of decision criteria. Consequently, we cannot fully assess the interoperability between AI and MCDM components. Future studies should pilot the framework using real-world datasets to evaluate its performance and refine parameter sensitivity. Secondly, contextual variation in governance structures poses implementation challenges. The contextual realities of African mineral economies diverge significantly from those in the Global North, the primary source of existing AI-policy scholarship. Variations in institutional maturity, data infrastructure, and regulatory enforcement may affect the fidelity of implementation. Consequently, future adaptations of the IDMS should incorporate regional policy variables, informal governance practices, and socio-economic priorities unique to resource-rich African states. Also, the framework's technical assumptions introduce practical constraints. The macro-layer NLP component assumes access to digitized, standardized policy documents—an assumption that breaks down where regulations are paper-based or multilingual without official translations. Likewise, ML algorithms at the micro layer require historical investment data for training, which may be limited or proprietary in emerging mining sectors.

Finally, ethical and transparency considerations demand ongoing scrutiny. Algorithmic governance introduces potential risks of opacity, bias, and exclusion, particularly in contexts where decision-making is politically sensitive or captured by vested interests. Sustaining accountability, therefore, requires open audit mechanisms and participatory oversight. A specific ethical challenge of direct relevance to African mineral governance is data sovereignty—the question of who owns, controls, and benefits from the data that powers IDMS decisions. In the African context, mineral data assets include geological surveys held by national agencies, environmental baselines maintained by regulatory bodies, investment records held by mining companies, and community impact assessments often funded by international donors. The IDMS framework proposes that primary mineral governance data be classified as state-held public assets. Mining companies and AI providers may access this data under licensing agreements that mandate usage audit trails, data-retention limits, and an explicit prohibition on secondary commercialisation. This aligns with emerging continental frameworks such as the African Union's Data Policy Framework (African Union, 2022) and mirrors principles adopted in the EU Data Governance Act (European Parliament and Council of the European Union, 2022), adapted for the specific power dynamics of resource-rich economies where persistent governance gaps have historically constrained the translation of resource wealth into development outcomes. Embedding data sovereignty protocols into the macro-layer of the IDMS is therefore not merely a legal compliance matter but a prerequisite for the framework's institutional legitimacy.

While AI applications in the public sector are expanding (Wirtz, *et al.*, 2019), institutional realities in African mineral economies diverge from the contexts that dominate the existing literature. Contextualizing the IDMS within regional assessments (Vandome and Dechambenoit, 2020) and continental policy frameworks such as the African Mining Vision (African Union, 2009) is essential for its effective deployment.

While the bibliometric analysis provides strong indicative evidence of a tri-disciplinary gap, it is acknowledged that variations in terminology and emerging interdisciplinary research may yield partial overlaps not captured within the defined search scope. As such, the findings should be interpreted as demonstrating a structural absence of fully integrated frameworks rather than an absolute absence of related studies.

4.4 Prerequisites for Implementation

Successful deployment of the IDMS framework presupposes a set of institutional, technical, and data conditions that must be assessed before implementation begins. Recognizing these prerequisites is essential to avoid the "digital divide" risk—where technically advanced frameworks are rendered inoperable by infrastructure deficits common in many resource-rich African states.

Institutional prerequisites—A designated regulatory authority with a legal mandate to deploy and oversee algorithmic decision-support tools; formal data-sharing agreements among mining ministries, environmental agencies, and statistical offices; and a stakeholder governance board with representation from government, industry, civil society, and affected communities.

Technical prerequisites—A minimum viable digital infrastructure including digitized policy and licensing records, an interoperable data platform accessible to each IDMS layer, and staff capacity to operate and interpret AI-MCDM outputs. Where ministries still operate on paper-based records, a digitization phase—estimated at 12–24 months—should precede full IDMS deployment.

Data prerequisites—A minimum of three years of historical investment and compliance data for ML model training; standardized environmental baseline datasets; and a data-quality audit confirming acceptable completeness and consistency thresholds. In data-sparse environments, transfer learning from analogous mining jurisdictions or simulation-based synthetic datasets may serve as interim substitutes pending field data accumulation.

These prerequisites are not barriers to conceptual adoption but planning milestones that ensure IDMS implementation is context-sensitive, sustainable, and equitable across varying levels of institutional maturity.

4.5 Conditions for Applicability

The framework is theoretically most appropriate under specific conditions (Table 3). This table highlights the contexts in which AI-MCDM frameworks are likely to be effective versus those that may limit their successful application. Recognizing these boundary conditions is essential for responsible and context-sensitive implementation.

Table 3. Contextual Conditions Influencing the Applicability of AI-MCDM Frameworks

Favourable Conditions	**Challenging Conditions**
Complex decision environments with multiple competing objectives	Simple decision contexts with clear priorities
Institutional capacity to support technical implementation	Severe resource and capacity constraints
Stakeholder willingness to engage with structured analytical methods	Strong preferences for discretionary human-centered processes
Regulatory cultures valuing transparency and evidence-based policy	Regulatory cultures prioritizing flexibility over standardization
Sufficient data availability for computational methods	Minimal data availability

4.6 Conceptual Evaluation Framework

As a conceptual contribution, the present study does not report empirical performance outcomes but establishes a comprehensive framework that links evaluation logic with methodological direction for future research. The proposed framework provides both (a) a conceptual evaluation schema for assessing the Intelligent Decision-Making System (IDMS) and (b) a methodological pathway for empirical validation once field data become available.

The conceptual evaluation framework for Intelligent Decision-Making Systems (IDMS) delineates key performance dimensions that facilitate the assessment of effectiveness across governance layers. Five dimensions are proposed: Decision Quality (coherence of prioritisation), Adaptability (stable yet responsive learning), Transparency (clarity of criteria and weights), Sustainability Integration (SDG alignment across economic, environmental, and social objectives), and Stakeholder Legitimacy (inclusiveness and fairness of the process). To guide future empirical validation, a methodological pathway is proposed, comprising a series of steps for reproducible research. These include the operationalization of IDMS layers into measurable units, the development of a data collection blueprint to identify pertinent sources, and the formulation of an Algorithmic Integration Plan leveraging AI techniques for various analytical needs. Additionally, the pathway outlines simulation and modelling designs to replicate feedback and adaptive learning processes, alongside a validation protocol that emphasizes transparency and ethical accountability in disclosing model parameters and assumptions. This comprehensive framework and methodology aim to compare IDMS with conventional governance models in future empirical studies.

Figure 5 illustrates the structured sequence for future empirical validation of the IDMS. It begins with conceptual framework development and proceeds through framework operationalization, data blueprinting, algorithmic integration, simulation design, and validation protocol definition—culminating in a transparent, reproducible pathway for empirical application once data become available.

4.7 Illustrative Application of the IDMS Framework: AHP–TOPSIS Project Ranking

To demonstrate the analytical operability of the IDMS micro-layer, this section presents a fully reproducible AHP–TOPSIS evaluation of three hypothetical mining projects. The exercise is illustrative rather than empirical: the projects and scores are constructed to represent realistic governance trade-offs encountered in African mineral economies. All data are hypothetical and labelled accordingly. This section grounds the abstract framework in concrete decision logic, consistent with the paper's applied orientation.

4.7.1 Projects and Evaluation Criteria

Three hypothetical projects are evaluated: Project A—a lithium mining venture in the Democratic Republic of Congo (DRC); Project B—a copper mining operation in Zambia; and Project C—a coal extraction project in South Africa. Five evaluation criteria are defined across all three IDMS layers: C1 (Return on Investment, economic, micro-layer), C2 (Geopolitical and Operational Risk, macro-layer), C3 (Environmental Impact Score, macro-layer), C4 (Infrastructure and Regulatory Readiness, meso-layer), and C5 (Strategic Mineral Demand Alignment, meso-layer). These criteria reflect the multi-dimensional governance objectives embedded in the IDMS tri-layer architecture.

4.7.2 Step 1: AHP Criteria Weighting

Pairwise comparisons using Saaty's AHP scale (Saaty, 1980) yield the following normalised criterion weights: C1–ROI = 0.30; C2–Risk = 0.12; C3–Environmental = 0.08; C4–Infrastructure = 0.18; C5–Strategic Demand = 0.32. The AHP Consistency Ratio (CR) is computed as CR = CI / RI, where the Consistency Index $CI = (\lambda max - n) / (n - 1)$ and RI is the Random Index for $n = 5$ criteria (RI = 1.12). The calculated CR = 0.047, which is below the 0.10 threshold stipulated (Saaty, 1980), confirming acceptable pairwise consistency. The highest weight assigned to C5 (Strategic Mineral Demand) reflects the IDMS macro-layer priority of aligning investment decisions with national and continental resource strategy, as articulated in the Africa Mining Vision (African Union).

4.7.3 Step 2: TOPSIS Ranking

The TOPSIS closeness coefficient for each project is computed as $CCi = Si- / (Si+ + Si-)$, where Si+ is the Euclidean distance to the positive-ideal solution A+ and Si− is the distance to the negative-ideal solution A−. Raw performance scores (scale 1–10, hypothetical) and the resulting TOPSIS outputs are summarized in Table 4.

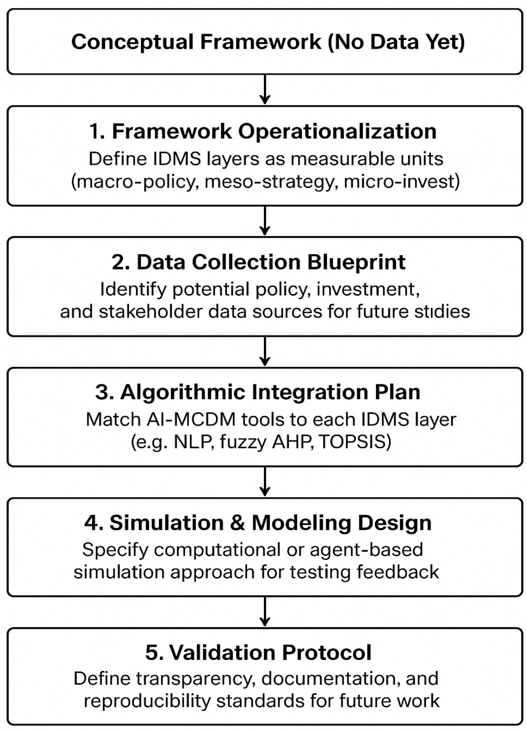

Figure 5. Methodological Pathway for Future Empirical Validation of the Intelligent Decision-Making System (IDMS)

Table 4. AHP–TOPSIS Illustrative Ranking of Three Hypothetical Mining Projects

Project	C1 ROI	C2 Risk	C3 Env.	C4 Infra.	C5 Strat.	S+	S−	CC (Rank)
A – DRC Lithium	9	7	6	5	10	0.082	0.145	**0.64 (1st)**
B – Zambia Copper	8	5	5	7	8	0.095	0.120	0.56 (2nd)
C – SA Coal	6	4	8	9	6	0.140	0.080	0.36 (3rd)
AHP Weight	*0.30*	*0.12*	*0.08*	*0.18*	*0.32*	—	—	*CR = 0.047*

Note: All project scores are hypothetical and constructed for illustrative purposes. S+ = distance to positive-ideal; S− = distance to negative-ideal; CC = TOPSIS closeness coefficient (higher = better). CR = AHP Consistency Ratio (<0.10 acceptable).

4.7.4 Step 3: Interpretation and Feedback Loop Demonstration

Project A (DRC Lithium) ranks first (CC = 0.64), driven by its high strategic mineral demand alignment (C5 = 10) and strong return on investment (C1 = 9), which together account for 62 percent of the total weight. Project B (Zambia Copper) ranks second (CC = 0.56), offering a more balanced profile with lower risk and stronger infrastructure readiness. Project C (SA Coal) ranks third (CC = 0.36), primarily penalised by its low strategic demand alignment in the context of the global low-carbon transition—despite having the strongest infrastructure score (C4 = 9). This output illustrates how the IDMS micro-layer produces transparent, defensible rankings that directly reflect the weighted priorities established at the macro and meso layers.

The IDMS feedback loop is illustrated through a hypothetical post-decision scenario: suppose Project A is licensed and after two operating years, environmental monitoring data reveal that its C3 (Environmental Impact) performance has deteriorated to a score of 3, significantly below the initial score of 6. Within the IDMS feedback mechanism, this outcome triggers a weight recalibration at the macro-layer: the AHP pairwise weight for C3 is increased from 0.08 to 0.15 to reflect elevated regulatory priority for environmental compliance. A re-run of the TOPSIS ranking with updated weights yields CC scores of A = 0.51, B = 0.59, C = 0.38—elevating Project B above Project A for the next licensing cycle. This adaptive recalibration operationalizes Proposition P2 (feedback enhances governance adaptability) and demonstrates the HITL dimension: the weight adjustment is validated by the regulatory agency's governance board before being applied, ensuring that algorithmic learning remains institutionally accountable.

A sensitivity analysis confirms model robustness: reducing C5 (Strategic Demand) from 0.32 to 0.20 reduces Project A's dominance, increasing Project B's CC to 0.61 and narrowing the gap to 0.03—demonstrating that the ranking is responsive to policy priority shifts without being fragile to minor weight perturbations. This sensitivity property is consistent with TOPSIS best-practice recommendations (Sitorus *et al.*, 2019) and reinforces the analytical credibility of the IDMS micro-layer.

5. Research Propositions and Future Directions

As a conceptual contribution, this paper generates several research propositions for future empirical investigation. This section consists of core research propositions, empirical validation pathway, and extended research directions.

5.1 Core Research Propositions

P1: Integration of regulatory governance and investment analytics through AI-MCDM frameworks will improve decision quality compared to fragmented approaches.
P2: Feedback mechanisms enabling policy learning from investment outcomes will enhance governance adaptability compared to static regulatory frameworks.
P3: Explicit multi-criteria evaluation will produce more balanced decisions across economic, environmental, and social dimensions compared to implicit trade-offs.
P4: Hybrid human-algorithm decision structures will outperform both pure automation and pure intuition across transparency, efficiency, and legitimacy metrics.
P5: Tri-layer hierarchical architectures will be more effective than flat structures for managing complexity in mineral resource governance.

5.2 Empirical Validation Pathway

Future research should prioritize empirical validation of the proposed framework through multiple complementary strategies. This includes conducting simulation studies to develop computational models of the IDMS components and evaluate their behavior under varying conditions, such as data quality, stakeholder alignment, and resource availability. Furthermore, case studies should be conducted to implement the framework in a specific mineral governance landscape. This includes the tar sands sector, to evaluate its practical feasibility and identify potential challenges to implementation. A comparative analysis would further strengthen the validation by benchmarking IDMS recommendations against traditional decision-making approaches, thereby quantifying the added value in terms of decision quality, implementation cost, and stakeholder satisfaction. Finally, longitudinal studies should be conducted to track governance outcomes over time and evaluate whether the framework's feedback mechanisms effectively foster the intended adaptive learning processes.

5.3 Extended Research Directions

Looking beyond validation, several promising research directions warrant further exploration. One area of focus is the development of hybrid computational methods, which enable the integration of various AI techniques, such as deep learning, reinforcement learning, and graph neural networks, with multi-criteria decision-making (MCDM) approaches. Another key direction involves participatory AI-MCDM, which aims to develop strategies that promote meaningful stakeholder involvement in AI-driven decision-making processes—particularly for individuals without a technical background.

This inclusivity is crucial for the effectiveness and acceptance of such systems. Additionally, it's essential to examine the adaptability of these frameworks across different cultural and institutional contexts, particularly those that diverge from traditional Western governance models. This cross-cultural adaptation can provide valuable insights into the diverse governance challenges present in various regions. Dynamic policy learning is another significant area for research. By extending the framework to explicitly model policy evolution through the use of online learning algorithms or Bayesian approaches, we can understand how policies can adapt over time in response to new information and changing conditions.

Furthermore, the development of ethical AI frameworks is critical. We need to formalize sector-specific definitions of fairness, establish accountability mechanisms, and outline transparency requirements and strategies for bias mitigation to ensure that AI systems operate fairly and responsibly. Lastly, it is worth investigating the applicability of intelligent decision-making systems (IDMS) to other natural resource sectors such as forestry, fisheries, water, and energy. These sectors face governance challenges that may be like those currently addressed and can benefit from the insights gained in this context. This table summarizes the conceptual research agenda emerging from the IDMS framework (Table 5). It presents sequential phases for empirical validation—framework operationalization, indicator development, pilot testing, and cross-sectoral benchmarking—together with propositions linking AI integration, regulatory maturity, and sustainable investment outcomes. While Table 6 presents a conceptual cross-sector comparison illustrating the transferability of the Intelligent Decision-Making System (IDMS) framework. By mapping parallels across energy, agriculture, manufacturing, and environmental governance, the table demonstrates the framework's scalability and theoretical generalizability beyond the mineral resource domain.

Table 5. Research Propositions for Empirical Validation

Proposition	Theoretical Basis	Suggested Validation Method
P1: Integration improves decision quality	Decision Theory	Comparative case studies
P2: Feedback enhances adaptability	Institutional Learning Theory	Longitudinal analysis
P3: Multi-criteria produce balanced outcomes	Stakeholder Theory	Outcome measurement across dimensions
P4: Hybrid structures optimize performance	Computational Intelligence Theory	Simulation experiments
P5: Tri-layer architecture manages complexity	Systems Theory	Structural equation modelling

Table 6. Cross-Sector Application Potential of the IDMS Framework

Sector / Domain	Illustrative Application	Parallel to IDMS Layers	Key Adaptation Requirements	Key Insights for Adaptation
Energy and Utilities	AI-based optimization of renewable energy grids and carbon policy compliance	Macro: regulatory energy policies Meso: performance and sustainability KPIs Micro: investment in green technologies	Real-time data integration, grid stability constraints	Demonstrates adaptability of IDMS for balancing regulation, sustainability, and investment in dynamic energy systems.
Agriculture and Food Systems	Smart farming, yield forecasting, and	Macro: agricultural policy and subsidies	Seasonal variability	Extends IDMS toward sustainable resource and

	resource allocation through AI-driven governance	Meso: supply chain monitoring Micro: AI-based investment in Agro-tech	modelling, smallholder inclusion	risk management under environmental constraints.
Manufacturing / Industry 4.0	AI-enhanced supply chain risk modelling and production optimization	Macro: compliance and standards Meso: production strategy Micro: process automation investment	Supply chain complexity, rapid technological change	Shows transferability of the three-tier model to industrial digital transformation governance.
Environmental Management	AI models for climate adaptation and ecological monitoring	Macro: environmental regulation Meso: policy-performance integration Micro: AI analytics for impact assessment	Uncertainty quantification, long time horizons	Illustrates how IDMS can inform adaptive governance in sustainability-focused sectors.

6. Conclusion

This paper introduces the Intelligent Decision-Making System (IDMS), a novel framework that combines AI-enhanced multi-criteria Decision-Making with regulatory governance for effective mineral resource management. It addresses a significant research gap at the intersection of artificial intelligence, policy, and mineral management, as revealed by a systematic review of over 287,000 academic records, which identified no integrated studies simultaneously addressing all three domains. IDMS employs a tri-layer architecture comprising macro (regulatory), meso (strategic), and micro (investment analytics) levels, enhanced by continuous feedback mechanisms. It lays the theoretical groundwork for mitigating governance-automation tensions through hybrid human-algorithm structures, enabling adaptive policy responses via structured learning, and incorporating sustainability through multi-criteria evaluation. While offering a substantial conceptual contribution, the framework acknowledges limitations that require empirical validation through data collection, case studies, and comparative analyses. The implementation process is guided by management of technical and data complexities, alongside ethical considerations like transparency and bias. Future research should focus on validating the IDMS's efficacy compared to traditional methods, adapting it for varying resource contexts, and ensuring stakeholder participation in AI-driven systems. Ultimately, effective governance of mineral resources is essential for converting wealth into sustainable prosperity. By providing a robust foundation for intelligent and adaptive decision systems, IDMS aims to enhance governance outcomes, supporting resource-rich nations in aligning their mineral endowments with Sustainable Development Goals and fostering long-term human flourishing.

The framework provides a pathway for transitioning from resource extraction to intelligent resource governance – where decisions are not only data-informed but institutionally accountable, sustainability-oriented, and adaptive to the evolving realities of mineral economies. The path from conceptual framework to implemented system will require sustained collaboration among computer scientists, governance scholars, policy practitioners, and affected communities—but the potential for transformative impact on resource governance justifies this investment.

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Biographies

Oladeji Ige (0000-0002-1090-8376) is a Researcher in the Department of Materials Science and Engineering at Obafemi Awolowo University, Ile-Ife and Department of Industrial Engineering, Durban of Technology, Durban. He is known for his contributions to materials science and engineering. His publications reflect a strong focus on the innovative applications of materials, intensifying the importance of sustainability and efficiency in material design. His current research focuses on AI + X, where X = mineral resources and materials degradation mechanisms.

Félix Mora-Camino, an aeronautical engineer from ENSICA with Dr.Ing and DSc degrees from the University of Toulouse, has served as a professor of Control and Computer Science at the Federal University of Rio de Janeiro (Brazil) and the Air Force Academy of Marrakech (Morocco). In recent years, he has led the Automation Laboratory at ENAC (French Civil Aviation School), taught Control Theory and Flight Control Design, and worked as a senior researcher at LAAS-CNRS. He is a member of AIAA and the Institute of System Science at Durban University of Technology.

Oludolapo Olanrewaju (0000-0002-3099-9295) obtained his Doctorate in Industrial Engineering from Tshwane University of Technology. He is a rated researcher with NRF. His research interests include Artificial Intelligence, Modelling, and Lean applications. He has co-authored more than 250 publications which include journals, conference proceedings, and book chapters. He is a recipient of awards both locally and internationally.