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Evaluation of caving mining methods through multi-criteria decision-making: an integrated analytic hierarchy process–analytic network process methodology

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Abstract

The increasing scale, depth and complexity of modern cave mining operations have elevated the importance of transparent, auditable and defensible decision-making in cave design and planning. Traditional approaches often rely on expert judgement applied in an informal or weakly structured manner which can obscure assumptions, hide uncertainty, and make it difficult to compare fundamentally different design options or hazard mitigation strategies. In cave mining, risk is fundamentally a function of uncertainty, with lack of knowledge representing the highest level of risk severity; consequently, reliance on comparative financial criteria alone to select alternatives can be misleading where long-term assumptions such as metal prices, discount rates and cost escalation are themselves highly uncertain.

This paper presents a novel integrated analytic hierarchy process–analytic network process (AHP–ANP) framework for multi-criteria decision-making in cave mining, applied to the selection of an appropriate caving variant – specifically the comparison of macroblock panel caving versus panel caving. The framework decomposes the decision into a four-level hierarchy of goals, criteria, subcriteria, and technical factors, with rubric-anchored scoring that converts expert judgement into structured, consistent, and traceable ratings. AHP is applied where criteria are hierarchical and largely independent; ANP captures the interdependencies and feedback loops that a pure hierarchy cannot model. Pairwise comparison scores were assigned by a panel of 3 specialists with a combined cave mining experience of approximately 120 years, with all consistency ratios confirmed below the accepted threshold of 0.10.

The results demonstrate that macroblock panel caving is primarily profitability-led, with decision sensitivity concentrated in operational delivery and construction enablement, while panel caving is more balanced across knowledge confidence, risk exposure, and profitability. The paper shows that structured decision frameworks substantially support expert judgement and improve its clarity, consistency, and defensibility – particularly for high-impact decisions made under conditions of limited knowledge – while remaining practical for integration into real project environments.

Keywords: *block and panel caving, decision-making, multi-criteria decision-making, analytic hierarchy process, analytic network process, acceptability criteria, risk, lack of knowledge, mining alternatives*

1 Introduction

Large-scale cave mining projects combine capital-intensive, long-horizon development with geological and geomechanical environments that are inherently uncertain. Decisions taken during early study and project definition phases establish constraints that persist throughout the life of a project and cannot be reversed once construction and production commence. Existing cave mining decision frameworks – including Brown (2007), the SME Handbook (Laubscher 2011), and Laubscher et al. (2017) – provide comprehensive technical

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guidance on design factors and hazard identification (Flores 2014), but do not offer a structured, quantitative mechanism for comparing competing mining variants or explicitly weighting uncertainty as a decision driver. This paper addresses that gap through an integrated analytic hierarchy process–analytic network process (AHP–ANP) process that makes trade-offs between knowledge confidence, production capacity, profitability, and risk-explicit, auditable, and yields-consistent results.

Despite significant advances in geological modelling, numerical analysis, and mine planning tools (Brown 2012), the performance of many major underground mining operations and projects have fallen short of expectations (Flores et al. 2004). Such outcomes are rarely attributable to deficiencies in technical effort or professional competence. Instead, experience indicates that shortcomings arise from the way decisions are formulated, justified, and governed when multiple, interdependent criteria must be considered simultaneously.

Caving mining operations involve complex technical, geomechanical, operational, and strategic decisions that demand a structured and defensible evaluation framework. This paper presents the application of the AHP, the ANP, and multi-criteria decision-making (MCDM) to enhance decision quality across the full life cycle of caving projects. The principal contributions are:

- an integrated AHP–ANP criteria structure specifically developed for cave mining method selection, consolidating and reorganising leading design methodologies into a unified four-level hierarchy of goals, criteria, subcriteria, and technical factors
- a rubric-based scoring framework that anchors expert judgement to explicit, evidence-linked ratings on a 1–9 scale, converting qualitative domain knowledge into structured, auditable, and quantitative inputs to the MCDM model
- an applied comparison of macroblock panel caving and panel caving, demonstrating how the framework reveals fundamental differences in decision character, risk appetite, and governance requirements between the 2 variants.

2 Analytic hierarchy process/analytic network process and multi-criteria decision-making applied to cave mining

2.1 Analytic hierarchy process

The analytic hierarchy process (Drake 1998; Saaty 1990, 2000) involves several phases that guide decision-makers through the process of structuring a decision problem, producing preferences, and synthesising judgements to arrive at a decision. Figure 1 shows the general flow of tasks in implementing the AHP analysis methodology.

Definition of the hierarchical structure is the first task. The next step in the AHP methodology is assignment of scores of importance in a pairwise comparison of factors. This is done using a judgement scale defined by Saaty (1990) representing the intensity with which one element dominates another with respect to the parent attribute. The scale is 1 = equal dominance, 3 = moderate, 5 = strong, 7 = very strong, 9 = extreme (2, 4, 6 and 8 are intermediate values).

2.2 Analytic network process

The ANP (Saaty & Vargas 2006, 2013) is an extension of the AHP that allows for the modelling of complex decision problems with interdependencies among criteria and alternatives. The ANP involves several phases that guide decision-makers through the process of structuring the decision problem, eliciting preferences, and synthesising judgements. Figure 2 summarises a typical ANP.

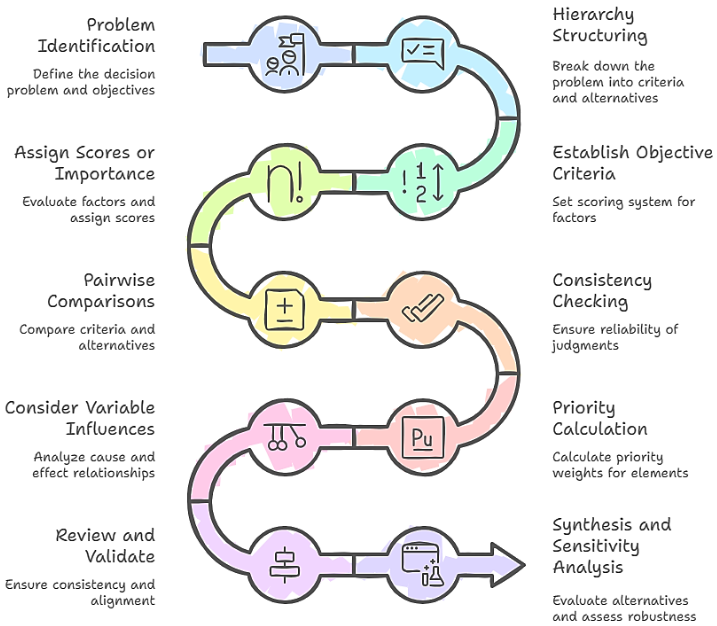

Figure 1 Generalised description of the analytic hierarchy process

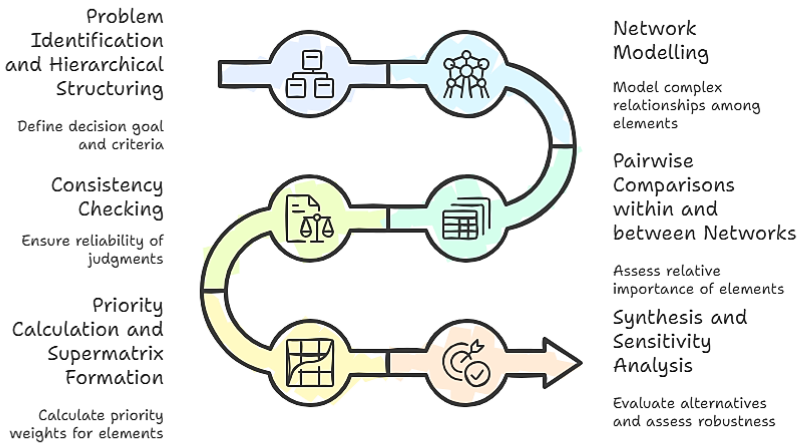

Figure 2 Generalised description of the analytic network process

2.3 Multi-criteria decision-making

MCDM (Figure 3) is a structured approach used to evaluate and rank multiple alternatives (options or choices) against a set of criteria. It is particularly useful in situations where decisions involve multiple conflicting objectives or criteria that need to be balanced. Within cave mining, the MCDM framework supports decision processes where outcomes are governed by numerous, often competing drivers: safety and hazard exposure, environmental constraints, ore quality and value, geological–geotechnical conditions, mine design and sequencing, operational efficiency, ventilation, and life-of-asset economics (capex/opex). It highlights that these decisions are intrinsically multi-dimensional and system-coupled, with criteria that are interdependent (i.e. changes in one domain can propagate through feedbacks to others), making purely single-metric or siloed assessments prone to bias or omission.

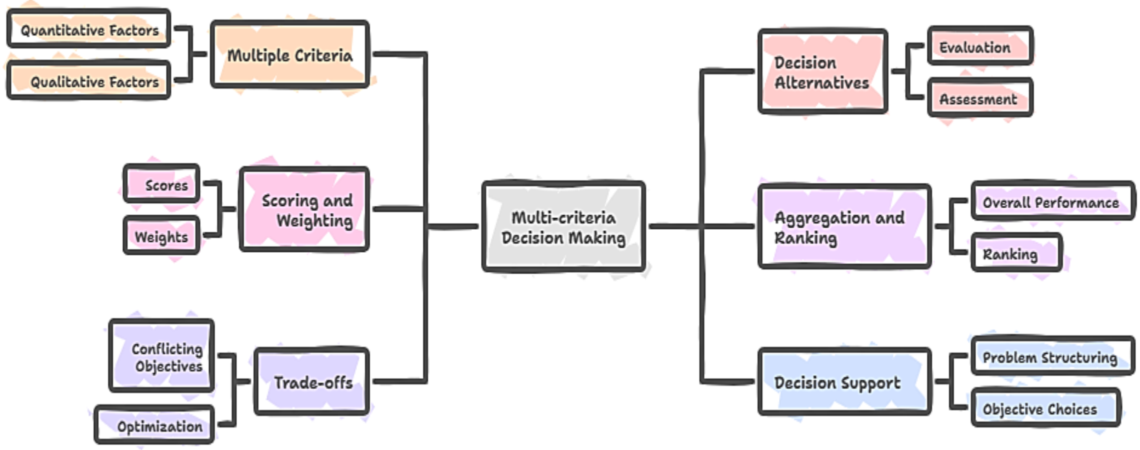

Figure 3 Key features of the multi-criteria decision-making process

3 Cave mining methodologies and the design technical factors framework for the analytic hierarchy process/analytic network process

Cave mining methods operate within environments characterised by high uncertainty, complex geomechanical behaviour, and strong interdependencies between design decisions. To support transparent, defensible and consistent decision-making, this paper consolidates the principal cave-mining design methodologies in the literature and reorganises them into unified criteria–subcriteria–technical factors structure suitable for AHP and ANP modelling.

Across leading methodologies – Bieniawski (1992), Brown (2004, 2007), the SME Mining Engineering Handbook (Laubscher 2011), Ferguson (2015), and Laubscher et al. (2017) – successful cave mine design must integrate technical understanding, risk management, operational performance, and system-level interactions, rather than adopting a linear or prescriptive design sequence. However, while each methodology identifies the relevant technical factors within its own domain, none provides a structured mechanism for weighting those factors against one another, comparing competing mining variants quantitatively, or making the influence of uncertainty explicit in the decision process. This paper advances beyond these foundations by consolidating their technical factors into a unified four-level hierarchy – goals, criteria, subcriteria, and technical factors – and embedding them within an AHP/ANP MCDM framework that supports quantitative comparison, sensitivity testing, and auditable governance.

3.1 Brown (2004, 2007)

Brown's methodology is firmly fixed in providing technical support to develop a cave mining design, subject it to an analysis of the known risks, and subsequently how to monitor and manage the performance of the mining design (Table 1). However, a means to select a mining variant or undercutting strategy for specific mining environments is left for the engineering professional to solve.

Table 1 Major geomechanics issues and activities related with block/panel caving mines (Brown 2007)

Stage/phase	Technical factors	
Preliminary studies	Geotechnical model formulation Caveability assessment Fragmentation assessment Mining method selection	Identification of potential major hazards Subsidence prediction Risk analysis
Mine planning, design and construction	Undercut level selection and undercutting strategy Excavation sequencing Extraction level design and construction, including support and reinforcement	Subsidence prediction Infrastructure location, design and construction
Mining operations	Undercutting and caving initiation Draw management Monitoring (e.g. by seismic monitoring) and managing cave propagation (e.g. by draw control, rock mass conditioning and cave inducement)	Monitoring excavation (including extraction level) performance Management of major operational hazards including uncontrolled collapses, rockbursts, mud rushes and air blasts Monitoring the development of surface subsidence

3.2 SME Mining Engineering Handbook

The SME Mining Engineering Handbook (Laubscher 2011) highlights 25 key parameters that should be reviewed prior to adopting a cave mining method (Table 2). Some parameters are specific to the orebody and mining method. Other parameters are common to all cave mining approaches and must be considered when evaluating the suitability of cave mining.

Table 2 Parameters to be considered before implementation of cave mining (Laubscher 2011)

Caving stages	Cave mining implementation parameters	
Orebody information	Caveability Primary fragmentation	Draw heights Induced cave stresses
Mine design and planning	Drawpoint/drawzone spacing Layout Excavation stability Support Practical excavation size Drawpoint interaction Sequence	Undercutting sequence (pre/advance/post) Development Method of draw Draw column stresses Dilution Tonnage drawn Ore/grade extraction
Mine operation	Drilling and blasting Rate of draw Secondary fragmentation	Secondary blasting/breaking Support repair
Hazard assessment	Rockburst potential Subsidence	

3.3 Laubscher et al. (2017)

Laubscher's contribution comprises the collation of numerous design topics, considered in isolation, and requires a means of constructing a model to support a cave mining design and a method to select a mining design and variant for a specific mining environment (Table 3).

Table 3 Design topics (Laubscher et al. 2017)

Design topics (technical factors)		
Role of management	Load–haul-dump (LHD) horizontal layouts	Ore grade extraction
Geological investigations	LHD incline drawpoint and front cave layouts	Drawpoint support repair
Geotechnical investigations	Grizzly and slusher Layouts	Rock mass response to block caving
Rock mass classification	Induced stress	Subsidence
Mining limits	Roadways	Mining costs/productivity
Caveability	Preconditioning/forced/induced caving	Physical and numerical modelling
Air blast potential	Excavation stability	Mine planning, planning schedules and stope dossiers
Rockburst potential/high stress Damage	Extraction level support	Environmental issues
Mud flow/mud push and water inflow potential	Draw column heights	Ancillary development/infrastructure location
Primary fragmentation	Mining sequence	Underground research projects
Secondary fragmentation	Angle of draw	
Secondary breakage	Potential draw rate	
Drawpoint spacing	Draw strategy	
Undercutting	Dilution	
Ore handling systems	Draw control	

3.4 Criteria–subcriteria–technical factors for analytic hierarchy process and analytic network process caving mining method

The synthesis of these methodologies shows that cave mine design depends on several core domains: orebody knowledge, geotechnical conditions, cavability, fragmentation, layout and sequencing, infrastructure, draw control, operational hazards, and monitoring systems. Each methodology also emphasises the need to assess risks, subsidence, induced stresses, and excavation performance, establishing a comprehensive set of technical factors essential for structured decision analysis.

The principal design objectives, the associated decision criteria used in this paper, and the key technical factors influencing performance are summarised in Table 4.

Table 4 Applied caving design criteria

Decision criterion	Design objective	Functions/properties (outcomes)	Key technical factors (sources of uncertainty)
Knowledge/ uncertainty (KNU)	System predictability and control	Maximising safety and operational stability through predictable system behaviour	Confidence in geological and geotechnical characterisation that controls caveability, fragmentation and cave propagation. Stress regime and hydro understanding impact stability, damage, potential seismicity
Production capacity (PCR)	Production achievement	Optimising ramp-up and production capacity with confidence in schedules; and optimising recovery through predictable cave and draw behaviour	The undercut geometry and execution approach that enables cave initiation and stable draw Layout and physical capacity of the production system. Readiness to start caving safely and on schedule. How the cave expands, ramps, and behaves through time
Profitability (PFT)	Economic value	Minimising cost through reliable productivity and controlled dilution	Practicality/cost of establishing the footprint and enabling the cave. Cost and success likelihood of initiating cave. Capital intensity and footprint efficiency and Operational performance drivers
Risk (RSK)	Loss prevention	Minimising technical and operational risk arising from uncertainty	Major physical hazard classes that can cause fatalities, prolonged shutdowns, or asset loss Events that drive economic underperformance Model and execution uncertainty that threatens technical success

This framework provides the basis for converting complex cave mining knowledge into an AHP hierarchy or ANP network. The structure supports rigorous comparison of design variants, undercutting strategies, sequencing options, and operational configurations. The AHP enables prioritisation within a hierarchical structure, while the ANP captures feedback loops and interdependencies.

By embedding the consolidated criteria → subcriteria → technical factors within an AHP/ANP-based MCDM framework, organisations can establish a transparent, auditable, and quantitative process for evaluating mining strategies. This supports better alignment with corporate objectives, reduces ambiguity in engineering judgement, and enhances both design quality and operational readiness across the life cycle of caving projects.

The consolidation of these methodologies into a unified four-level hierarchy demonstrates that cave mining method selection is inherently a multi-criteria problem. No single technical domain – whether geomechanical, operational, or economic – can determine the preferred variant in isolation; it is the structured weighting of their interactions that produces a defensible and transparent decision.

4 Implementation of analytic hierarchy process/analytic network process and multi-criteria decision-making for caving mining methods

Block (macroblock) and panel caving decisions sit at the intersection of geology, geomechanics, design, schedule, economics, and low-probability/high-consequence hazards where 'best' is rarely defined by a single metric and uncertainty is often the dominant driver of outcomes. The AHP provides a way to convert complex multi-factor decision criteria analysis into a decision-making structure by decomposing the problem into acceptability hierarchy criteria. Table 5 summaries the levels of caving hierarchy model.

Table 5 Caving mining method hierarchy framework

1st level	Goals	Top level strategic objective of the model (knowledge, productivity, profitability and risk)
2nd level	Criteria	They are the major domains that contribute to achieving the goal (mining environment, geomechanics, rock engineering, mining design, mine planning, construction, operations, risk)
3rd level	Subcriteria	Specific aspects under each criterion (e.g. rock mass knowledge, rock mass response, rock engineering, undercutting, cave growth, mining reserves, cave establishment, cave initiation, cave production, opex, hazards)
4th level	Technical factors	They are the core elements in the hierarchy. Each factor is evaluated in terms of local importance and weighted based on its contribution to the subcriteria and ultimately the goal (e.g. mining-induced stresses, mining experience, lessons learned, adjacent rock mass, cave propagation, draw control, dilution, ramp-up, preconditioning, construction rule, crushing/sizing, ventilation airways, materials handling, draw control propagation, monitoring, major collapses, rock bursts, mud rushes, air blasts, water– slurry rushes, etc.)

The AHP/MCDM caving framework is structured as a decision hierarchy from the overall objective through to goals down to technical factors (Figure 4). Detailed technical quantitative or qualitative evidence informs factors supporting each subcriterion for rigorous, rubrics-based expert assessment.

Evidence is systematically weighted and scored against the criteria, subcriteria and technical factors that govern geotechnical and geomechanics aspects, cave commissioning, draw strategy and performance, cost, and safety. The AHP caving framework is used to rank alternatives in terms of caving mining options by combining expert judgement with measurable technical indicators and explicitly testing sensitivity, which is useful to evaluate trade-offs, to highlight where additional data will most improve confidence, and to create a consistent governance pathway for selecting caving strategies that are technically credible, economically resilient, and operationally safe.

4.1 Practical Implementation of analytic hierarchy process methodology

The typical phases of the AHP can be summarised on those bullet points:

- Define the decision problem: clarify the goal, scope, criteria, and alternatives to be assessed.
- Build the hierarchy: structure the decision into levels (goal → criteria/subcriteria → alternatives/factors).
- Set how importance will be judged: establish a scoring/weighting scale (often expert-based) to reflect relative importance.
- Evaluate and compare: assign scores and conduct pairwise comparisons between criteria and/or alternatives to express preferences.

- Check consistency: test whether the comparisons are logically consistent (and adjust if needed).
- Calculate priorities (weights): convert comparisons into numerical priority weights for criteria and alternatives (e.g. eigenvector method).
- Consider cause-effect influences: reflect on how variables influence the decision process and outcomes.
- Review and validate: re-check inputs, comparisons, and results with stakeholders to ensure alignment with objectives.
- Synthesise and test robustness: combine weights to rank alternatives and run sensitivity analysis to see how results change with different assumptions.

4.2 Practical implementation of analytic network process methodology

The ANP extends the AHP by replacing the linear hierarchy with a network of interdependent clusters and nodes, allowing feedback and lateral influences between criteria, subcriteria, and alternatives that a strict hierarchy cannot capture. The typical phases of ANP implementation are as follows:

1. Define the decision problem: clarify the goal, scope, criteria, and alternatives, as in AHP – but explicitly map the interdependencies and feedback relationships between elements that are expected to influence one another.
2. Build the network structure: rather than a top-down hierarchy, construct a network of clusters (e.g. mining environment, geomechanics, operations) with directional influence arcs representing how elements within and between clusters affect one another. In cave mining, for example, rock engineering controls influence cave initiation outcomes, which in turn feed back into draw control effectiveness.
3. Set importance judgements: establish a scoring and weighting scale, again using Saaty's 1–9 intensity scale, applied to pairwise comparisons within each cluster and across influence relationships.
4. Conduct pairwise comparisons: compare elements with respect to their influence on each other – both within clusters (inner dependence) and between clusters (outer dependence). This produces a set of local priority vectors.
5. Construct the supermatrix: assemble the local priority vectors into an unweighted supermatrix, where each column represents the influence of one element on all others. This matrix captures the full network of interdependencies simultaneously.
6. Weight and converge the supermatrix: the unweighted supermatrix is transformed into a weighted supermatrix (by normalising cluster influences) and then raised to limiting powers until it converges – the resulting stable columns yield the global ANP priorities, which reflect all direct and indirect influences within the network.
7. Check consistency: as in AHP, each set of pairwise comparisons is tested using the consistency ratio (CR), with $CR < 0.10$ required for acceptance.
8. Review and validate: results are reviewed with stakeholders to confirm that the network structure and influence relationships reflect the real-world system being modelled.
9. Synthesise and test robustness: global priorities are used to rank alternatives, and sensitivity analysis is conducted to assess how changes in interdependency weights or cluster importance affect the final ranking.

4.3 Why the analytic hierarchy process and analytic network process are used together

AHP and ANP are complementary rather than competing methodologies. AHP is applied where the decision structure is hierarchical and criteria are reasonably independent – in particular, for the prioritisation of top level goals and rubric-based scoring of technical factors. ANP is applied where interdependencies and feedback loops are too significant to ignore – for example, where rock engineering controls influence cave initiation behaviour, which in turn affects draw control effectiveness and production capacity. The AHP provides the structural backbone and initial criteria weighting; the ANP captures system-level interactions that a pure hierarchy would obscure. Together, they produce a framework that is both tractable for expert elicitation and sufficiently sophisticated to reflect the genuine complexity of caving systems.

4.4 Pairwise comparison and evaluation of factor importance

A central feature of the AHP/ANP methodology is its matrix format and the ability to subsequently calculate consistency diagnostics. There are many papers, including the original Saaty (1990) paper, that outline the mechanics of the calculation process in detail, so they are not repeated here. Instead, a simplified description is provided to illustrate the main steps in the process.

Through the initial pairwise matrix that is formed with each element a_{ij} representing the relative importance of factor i relative to factor j. The diagonal elements are always 1, since $i = j$, i.e. it is the importance of a factor relative to itself.

The second step in the matrix evaluation process is to normalize the matrix, which is carried out such that $\sum w_i = 1$, where w is the weight of each pairwise comparison.

Finally, the consistency statistics are calculated. The CR evaluates the logical reliability of a decision-maker's evaluations by comparing the consistency of their normalised factor weight matrix against the expected consistency of a randomly generated matrix of the same size, ensuring their judgements are intentional and not arbitrary. If this value is less than 0.1 the result is acceptable, $0.10 < CR \leq 0.20$: borderline, and if $CR > 0.20$: re-evaluation is required.

4.5 Expert panel

Pairwise comparison scores were provided by a panel of 3 specialists with a combined cave mining experience of approximately 120 years: Dr Alex Catalan, Rock Mechanics and Caving Consultants, Australia; Dr Gavin Ferguson, Seltrust Associates Limited, UK; and Professor Stephen McKinnon, formerly Chair in Mine Design, Department of Mining Engineering, Queen's University, Canada. Professor McKinnon additionally contributed to the construction of the AHP framework and to the interpretation of results.

4.6 Expert elicitation process

Scores were assigned independently by each panel member prior to group discussion, minimising anchoring bias that can arise when experts score collaboratively from the outset. Discrepancies were resolved through iterative review conducted via video conference and written correspondence, with final scores agreed by consensus. All pairwise comparison matrices were recorded and retained.

4.7 Consistency ratio results

CRs were calculated for all pairwise comparison matrices. All CRs fell below the accepted threshold of 0.10, with several approaching zero, confirming the logical reliability and internal consistency of the expert judgements underlying the model.

For this evaluation, the entire process has been implemented in Power BI and multiple dashboards have been generated to facilitate graphical output for interpretation.

The four-level hierarchy, rubric-anchored scoring, and integrated AHP–ANP methodology together provide a governance pathway that is both rigorous and practical. By making the weighting of technical factors explicit and traceable, the methodology ensures that decisions on caving method selection are grounded in structured evidence rather than informal judgement – and that the influence of uncertainty on outcomes is visible, quantified, and open to independent scrutiny at every level of the hierarchy.

5 Cave mining hierarchical overall framework

The AHP/MCDM framework is a structured governance mechanism to support strategic cave mining decisions where geotechnical uncertainty, operational coupling, and capital commitment must be evaluated transparently and defensibly. Accordingly, the model architecture is organised in four key decisions pillars, Table 6.

Table 6 Top objectives

Top objectives	Analytic hierarchy process interpretation
G1 — knowledge and uncertainty (KNU)	High weight means preference alternatives with better characterisation, lower epistemic uncertainty, and higher confidence in predictions
G2 — production capacity (PCR)	Emphasises design throughput, scheduling realism, reserve conversion, and bottleneck risk
G3 — profitability (PFT)	Focuses on capex/opex drivers, constructability, operational efficiency, and value delivery
G4 — risk (RSK)	Elevates hazards, financial shocks, and technical failure modes

Figure 4 shows the AHP/ANP MCDM framework in a structure the decision hierarchy which will be used at the macroblock (MB)/panel caving (PC) assessment. The framework decision hierarchy is configured from the top objective level to goals through to technical factors:

- 1st level. Goals → strategic outcomes (knowledge, productivity, profitability and risk)
- 2nd level. Criteria → engineering and planning domains (e.g. geomechanics, mine planning)
- 3rd level. Subcriteria → specific aspects within each domain (e.g. cave initiation, draw control)
- 4th level. Technical factors → technical variables (e.g. undercutting rate, rock mass response) and weights/importances to each factor based on expert judgement and data are assigned.

These top objectives are interdependent (MCDM). High-productivity operations require safe working environments to be able to generate and maintain a production capacity that will generate sufficient income to pay back the investment and provide profits to reward the investors. Thus, the objective of the AHP/MCDM methodology is to support the cave mining engineering design process to achieve decisions that fall within the acceptability criteria and risk tolerance agreed with investors and corporate management. Hence the requirement to identify, describe and clearly define the numerous technical factors which support these business pillars.

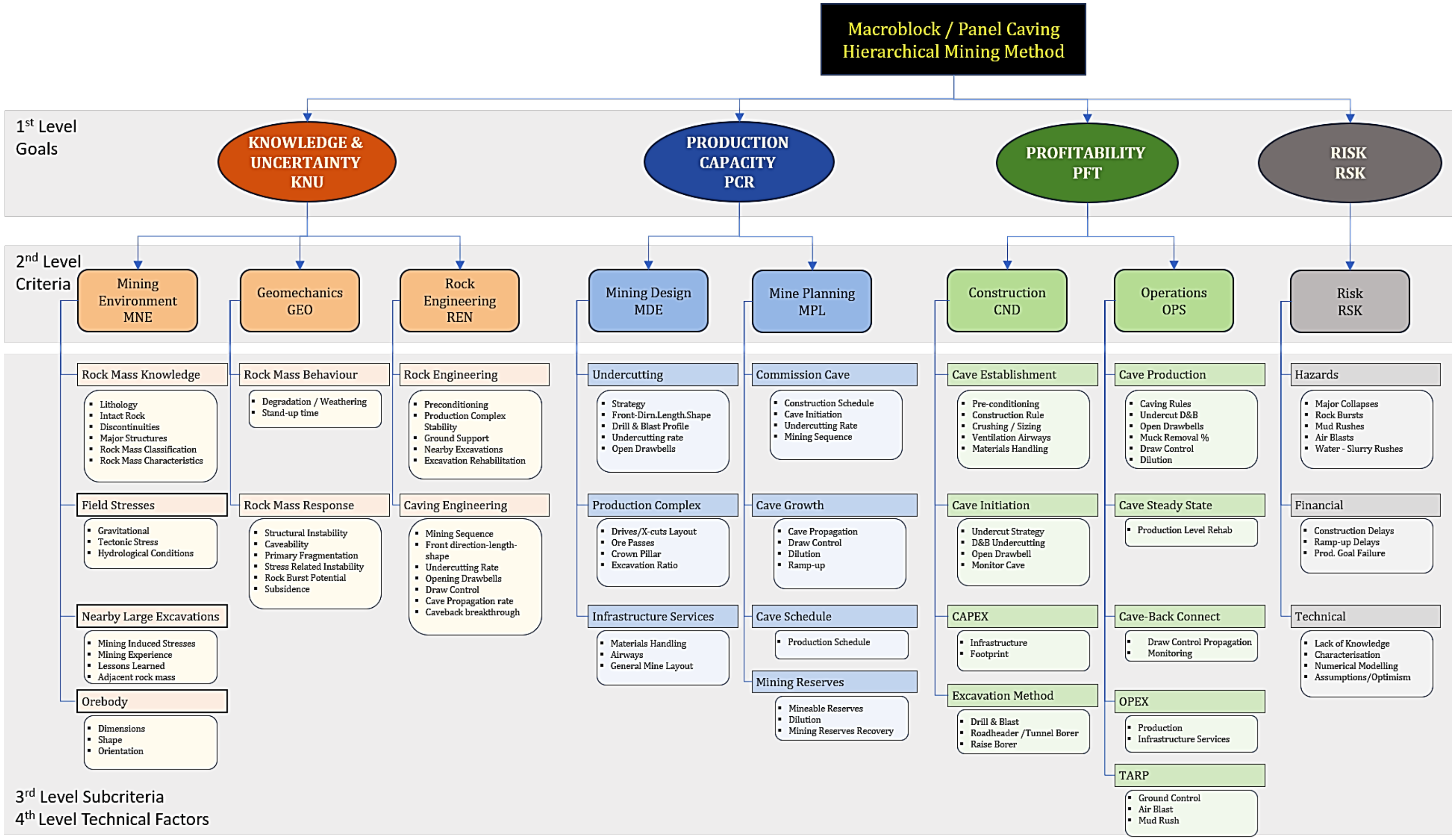

Figure 4 Macroblock/panel caving mining method – hierarchical structure applied to caving mining method

6 Application of analytic hierarchy process/multi-criteria decision-making for macroblock panel versus panel caving

The AHP structures decision problems into a goal–criteria–subcriteria–alternatives hierarchy and uses pairwise comparisons to derive ratio-scale priorities for criteria and alternatives. Within this framework, rubric scores for technical factors are incorporated at the subcriteria level and inform the relative performance of options or the relative exposure of risks. The AHP is used to convert these inputs into weights and rankings through the comparison matrices and consistency checks.

The AHP's pairwise mechanism is well suited to qualitative evidence made quantitative, typically via Saaty's 1–9 intensity scale, which maps 'equal' to 'extreme' importance in a consistent way; our rubrics adopt the same 1–9 ratings so that factor scores can be directly interpreted in the AHP initiation process and, when needed, sensitivity can be run on alternative scales.

6.1 Rubric-based evaluation framework as input to the analytic hierarchy process/analytic network process multi-criteria decision-making caving model

The cave mining decision-making framework begins with rubric-based scoring at the technical-factor level (1–9 anchors with clear evidence requirements). Rubrics convert domain judgements (e.g. about capacity adequacy, dilution risk, schedule credibility, or model uncertainty) into structured, consistent ratings that are traceable to assumptions, metrics, and notes. Those ratings then become the inputs to MCDM. In short, rubrics standardise expert judgement; MCDM aggregates it.

For example, mining environment (MNE) criterion of knowledge and uncertainty (KNU) goal, the rubric objective captures the confidence level in the geological–geotechnical understanding that supports caving environment; 'lack of information'; uncertainty or rock mass knowledge. Its overall assessment is indicated in Table 7.

Table 7 Mining environment (MNE) – knowledge and uncertainty rubric scoring (1–9)

Score	Uncertainty/ knowledge	MNE interpretation (what it means in practice)
9	Very low uncertainty/ excellent knowledge	Evidence is data-rich and reconciled; uncertainty is negligible at the decision scale. The underlying characterisation/assumptions are validated and support predictive use in cave design and operating controls across rock mass, stress/hydro, legacy interaction, and orebody geometry
8	Low/very low	Strong confidence with minor residual gaps that are unlikely to change decisions. Remaining uncertainty is limited and managed through monitoring/verification plans
7	Low	Good confidence at the decision scale; key drivers are identified and uncertainty is bounded and manageable. Some sensitivity exists, but decisions remain robust
6	Moderate/low	Generally reliable understanding but with meaningful gaps; decisions require explicit scenario bracketing and tighter monitoring/controls to manage residual uncertainty
5	Moderate	Baseline understanding is adequate, but uncertainty is still meaningful. Multiple plausible interpretations exist for some drivers; contingencies are required and outcomes may be sensitive to assumptions

Score	Uncertainty/ knowledge	MNE interpretation (what it means in practice)
4	Moderate/ high	Significant gaps or variability remain; conservative assumptions are needed because uncertainty can influence caveability/fragmentation/propagation expectations or control settings
3	High	Weakly constrained; several plausible interpretations exist; high likelihood of surprises or revisions to key drivers that control cave behaviour, stress response, or interaction effects
2	High/very high	Very limited constraints on key drivers; high probability that critical assumptions are wrong without major additional investigation/validation
1	Very high uncertainty/ poor knowledge	Insufficient characterisation to support credible design/operating decisions; the subcriterion is dominated by assumptions rather than evidence. Major additional investigation is required

Guideline: higher score = highest knowledge/lower uncertainty/higher confidence in the mining environment understanding and predictability.

In the caving decision-making framework, the MNE objective is decomposed into its 4 subcriteria that represent the dominant uncertainty sources in a cave mine (Table 8) and each subcriterion is supported by technical factors and key assumptions/case inputs, how uncertainty is parameterised for scoring and scenario comparisons using a specific rubric for each subcriteria.

To apply this rubrics-based approach, the criteria and their subcriteria have been implemented across the following functional domains, each with dedicated 1–9 technical factor rubrics and scorecards: mining Environment (MNE), geomechanics (GEO), rock engineering (REN), mining design (MDE), mine planning (MPL), construction (CND), operations (OPS), the risk-focused domains hazard (HAZ), financial (FIN), and technical (TEC). These domains collectively provide the structured, evidence-linked inputs used by the AHP/ANP-based MCDM caving model for scenario ranking, sensitivity testing, and prioritisation.

Table 8 Mining environment (MNE) L2 criteria weighting

Subcriterion (level 2)	Technical factors	Score guidance (1/3/5/7/9)	MB panel Final score	Panel Final score
A1.1 rock mass knowledge	Lithology variability: number of domains and contact uncertainty Intact rock: UCS/CI scatter/COV, anisotropy Discontinuities: joint sets, persistence, infill, DFN calibration quality Major structures: fault/shear zones, karst/voids, dykes Rock mass classification: RMR/Q/GSI distribution and confidence	9: Validated and predictive; dense drilling/oriented core; DFN calibrated; boundaries robust 7: Well constrained; robust domaining/DFN and parameter bounds at decision scale 5: Bounded/bracketed; baseline domaining and parameters, but uncertainty meaningful 3: Weak constraints; multiple plausible models; high boundary/DFN uncertainty 1: Assumption-driven characterisation; major gaps in domains/structures/parameters	6	6

Subcriterion (level 2)	Technical factors	Score guidance (1/3/5/7/9)	MB panel Final score	Panel Final score
A1.2 field stresses	Rock mass characteristics: brittleness index, Hoek–Brown parameters confidence intervals Gravitational stress model confidence Tectonic stress magnitude/orientation uncertainty Hydrologic conditions: pore pressure, drainage response, saturation zones	9: Validated; multiple measurements; low misfit; calibrated hydro and stress model. 7: Measured and mostly constrained; moderate uncertainty; calibration reasonable. 5: Bracketed ranges (wide but defined); moderate confidence; scenario management required. 3: Weak constraints; sparse measures; large scatter/misfit; hydro uncertain. 1: Stress/hydro largely unknown; no credible model.	6	6
A1.3 nearby large excavations	Mining-induced stress changes/abutments Mining experience: legacy damage, rehabilitation requirements Lessons learned Adjacent cave depletion effects	9: Greenfield or fully surveyed/validated interactions; robust modelling and history. 7: Interactions understood; history/lessons largely available; bounded uncertainty. 5: Bracketed interactions (e.g. adjacent zone 300–600 m); moderate uncertainty. 3: Weak constraints; uncertain geometry/stand-offs; limited history. 1: Legacy interactions unknown/unmanaged; no credible stand-off basis.	6	7
A1.4 orebody	Dimensions: thickness/height continuity Shape: irregularity and edge complexity Orientation: dip/strike uncertainty, structural alignment	9: Validated footprint/geometry; tight boundary/orientation uncertainty; high confidence. 7: Well constrained; minor boundary/orientation uncertainty; continuity largely supported. 5: Bracketed geometry; uncertainty meaningful (e.g. ±15–25 m; ±10–15°). 3: Weak constraints; high boundary/edge uncertainty; continuity uncertain. 1: Geometry/orientation largely unknown; boundary/continuity uncontrolled.	6	7

Note: Uniaxial compressive strength (UCS); Confidence Interval (CI); Coefficient of Variation (COV); Discrete fracture network (DFN); Rock mass rating (RMR); Q-System (Q); Geological Strength Index (GSI)

6.2 Results of analytic hierarchy process multi criteria decision-making caving model

This section presents a structured comparison of macroblock and PC variants, explicitly recognising that decision outcomes are governed by the degree of knowledge available and the uncertainty associated with key technical assumptions. The AHP implementation is structured as a four-level hierarchy visible in the hierarchical structure applied to caving mining method (Figure 4).

The AHP analysis results for the mining environment and their L4 technical factors are shown in Table 9 and are classified in Table 10. The AHP results are primarily governed by baseline of the knowledge related to the rock mass and the effect of caves or large excavation closer on the MB. Stress field plays an important role in the PC. They are classified as main drivers or dominant drivers of uncertainty.

Table 9 Mining environment (MNE) MB versus panel caving weighting (L4 technical factors)

Mining environment			
Subcriterion	**Final technical factor weight**	**MB**	**PC**
A1.1 rock mass knowledge	Lithology variability: number of domains and contact uncertainty	7%	7%
	Intact rock: UCS/CI scatter/COV, anisotropy	3%	7%
	Discontinuities: joint sets, persistence, infill, DFN calibration quality	16%	2%
	Major structures: fault/shear zones, karst/voids, dykes	10%	7%
	Rock mass classification: RMR/Q/GSI distribution and confidence	3%	7%
	Rock mass characteristics: brittleness index, Hoek–Brown parameters confidence intervals	16%	12%
A1.2 in situ stresses	Gravitational stress model confidence	7%	12%
	Tectonic stress magnitude/orientation uncertainty	7%	12%
	Hydrologic conditions: pore pressure, drainage response, saturation zones	1%	2%
A1.3 nearby large excavations	Mining-induced stress changes/abutments	10%	4%
	Mining experience: legacy damage, rehabilitation requirements	2%	4%
	Lessons learned	2%	4%
	Adjacent cave depletion effects	10%	4%
A1.4 orebody	Dimensions: thickness/height continuity	3%	4%
	Shape: irregularity and edge complexity	2%	7%
	Orientation: dip/strike uncertainty, structural alignment	2%	7%

Note: Uniaxial compressive strength (UCS); Confidence Interval (CI); Coefficient of Variation (COV); Discrete fracture network (DFN); Rock mass rating (RMR); Q-System (Q); Geological Strength Index (GSI)

6.3 Results of analytic network process multi criteria decision-making caving model (L3 subcriteria)

Table 10 summarises the results obtained from the ANP model for the MB and the PC mining option of L3 subcriteria.

The MB's relatively higher emphasis on nearby excavations/interaction effects and rock mass behaviour implies the plan should assume more variability and step-change events (instability, interaction-driven damage, rehabilitation details).

Because the model weights rock engineering plus caving engineering much higher for PC, the planning focus should shift toward making execution rules achievable and applicable, not just technically correct.

Table 10 Knowledge and uncertainty L3 subcriteria analytic network process macroblock (MB) versus panel caving (PC) weighting

Mining environment		
Subcriterion Final L3 subcriteria weight	**MB**	**PC**
A1.1 rock mass knowledge	1%	1%
A1.2 in situ stresses	4%	4%
A1.3 nearby large excavations	2%	2%
A1.4 orebody	4%	4%
Geomechanics		
Subcriterion Final L3 subcriteria weight	**MB**	**PC**
A2.1 rock mass behaviour	4%	2%
A2.2 rock mass response	4%	4%
Rock engineering		
Subcriterion Final L3 subcriteria weight	**MB**	**PC**
A3.1 rock engineering	2%	7%
A3.2 caving engineering	4%	7%

6.4 Results of the analytic network process multi criteria decision-making caving model (L2 criteria)

The integrated L2 ANP macroblock and PC results are shown in Table 11:

- For MB PC, the model puts even more weight on operational delivery, plus a strong 'enablement' layer (construction + environment + planning).
- For PC, the model outcomes are most sensitive to how the cave is operated, how credible the plan is, and how engineering controls and mining environment knowledge support execution.

Table 11 L2 Criteria macroblock (MB) versus panel caving (PC) weighting

Final L2 criteria weight	MB	PC
Mining environment	12%	11%
Geomechanics	7%	6%
Rock engineering	6%	14%
Mining design	11%	12%
Mine planning	13%	16%
Construction	15%	13%
Operations	30%	19%
Risk	6%	10%

6.5 Goal assessment for macroblock versus panel caving (L1 goal)

This work builds and applies an AHP/ANP multi-criteria decision model to compare MB PC versus PC, rolling up from L4 technical factors → L3 subcriteria → L2 criteria → goal-level priorities.

The outputs provide a transparent way to see what drives the decision most, where confidence is strongest/weakest, and which levers (operations, planning, design, construction, knowledge, risk) most influence the final assessment. L1 goal results are shown in Table 12 and Figure 5 (overall summary dashboard – Power BI Implementation):

- MB PC configuration is being evaluated primarily through value delivery/capital efficiency, it is 'profitability-led'.
- PC decisions are framed as more sensitive to confidence in the knowledge base and risk exposure, while still strongly valuing profitability and deliverability, it is 'more balanced' and more uncertainty/risk conscious.

Table 12 L1 goal (top level)

Goal (top level)	Macroblock	Panel caving
Knowledge and uncertainty	27%	33%
Production capacity	23%	26%
Profitability	45%	31%
Risk	6%	9%

The integrated AHP–ANP results reveal that MB PC and PC are not simply technical alternatives but reflect fundamentally different risk appetites and governance requirements. MB PC demands rigorous operational discipline and explicit governance gates to prevent profitability considerations from diluting risk controls; PC demands sustained knowledge confidence and long-duration operational consistency as the primary conditions for success. For project teams, the practical implication is clear – method selection should be driven not only by geological and geomechanical suitability, but by an honest assessment of organisational capability to meet the specific execution demands that each variant imposes.

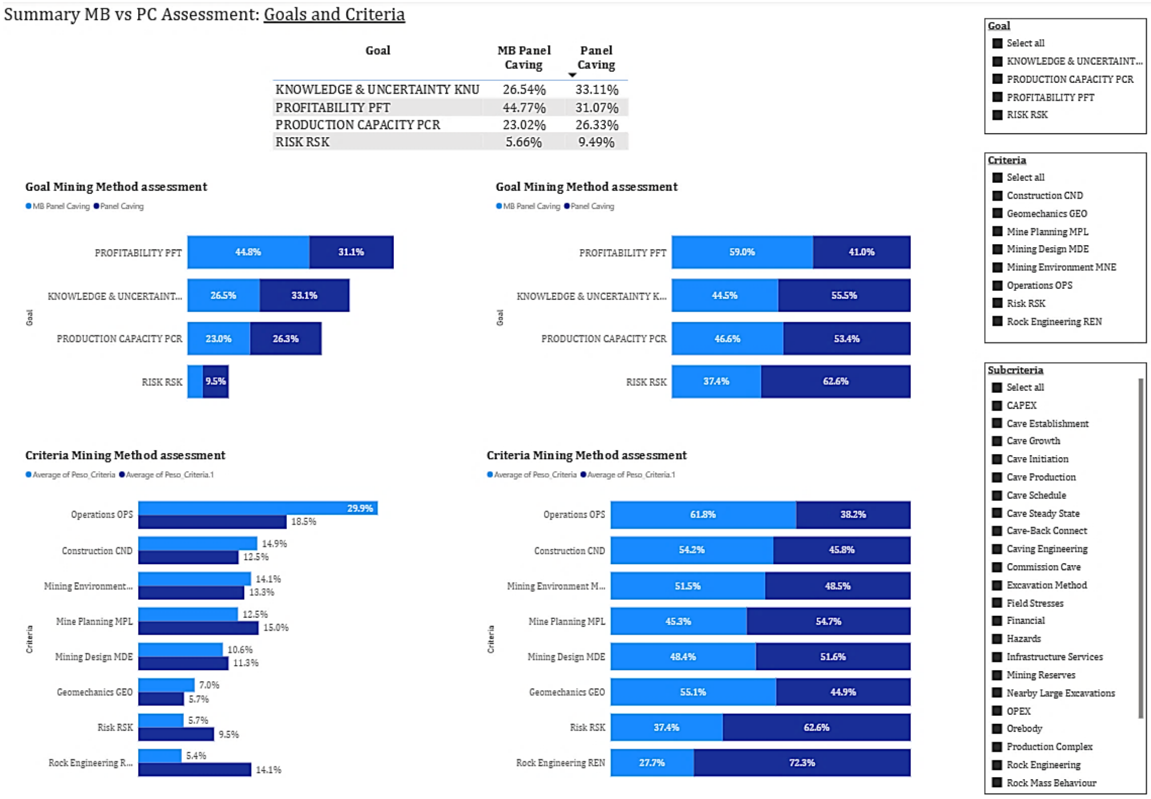

Figure 5 Overall goals assessment for macroblock versus panel caving (L1 goal)

7 Conclusion

1. AHP/ANP MCDM provides a transparent, auditable way to convert expert judgement into defensible priorities under uncertainty. The model decomposes the decision into goals → criteria → subcriteria → technical factors, applies rubric-anchored scoring, and uses AHP/ANP logic (including interdependencies via supermatrix) to generate prioritised drivers and trade-off visibility with sensitivity testing.
2. No single mining method is universally best'; the preferred method is conditional on uncertainty tolerance and execution capability. MB and PC each have strengths and weaknesses; selection depends on confidence in rock mass characterisation, cave behaviour predictability, draw control effectiveness, and organisational ability to execute and respond.
3. Operational delivery and readiness dominate outcome sensitivity. Across the integrated results, the model repeatedly shows decision sensitivity concentrated in operational/planning control levers (discipline, sequencing, draw/undercut governance, trigger action response plans), rather than solely in static design assumptions.
4. Risk must be treated as a first-class decision pillar with explicit 'acceptability gates'. The structure acceptability hierarchically: safety is non-negotiable, uncertainty must be bounded, and residual risk must be within tolerances before lower-level trade-offs are allowed.
5. Regarding to MB PC – specific conclusions:
    a. The integrated approach tends to be more profitability-led and heavily influenced by operational delivery plus construction/enablement, which increases the risk of 'risk dilution' unless governance gates are explicit.
    b. Macroblock performance is sensitive to repeated uncertainty events (initiation/connect cycles), and therefore requires stronger assurance around execution discipline, interaction effects, and continuity controls.
6. Regarding to PC – specific conclusions:
    a. The integrated approach is more balanced, with relatively higher influence of knowledge confidence and risk, meaning uncertainty reduction and control effectiveness can materially alter the decision outcome.
    b. PC concentrates uncertainty into sustained system controls (front geometry, draw control, monitoring, trigger action response plans), so long-duration operational discipline is the critical success requirement.

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