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TOWARDS A MULTIDIMENSIONAL PERSPECTIVE FOR DECISION OPTIMISATION: INTEGRATING SOCIAL, MATHEMATICAL, AND TECHNOLOGICAL DIMENSIONS

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ABSTRACT. Ineffective decision-making remains a persistent challenge for organisations operating in complex, uncertain, and data-intensive environments. This paper explores the interrelationships among decision-making, optimisation, and digitalisation, aiming to develop an integrated perspective on organisational decision support. A structured literature review is conducted, drawing on insights from operations research (OR), decision sciences, and digital transformation. The findings highlight that contextual and human factors shape decision-making, while optimisation provides the analytical structure required to address complex problems. Furthermore, digitalisation enhances these capabilities by enabling improved data integration, processing, and real-time analysis. While each domain contributes individually, their combined application enables more robust, adaptive, and data-driven decision processes. This paper proposes a multidimensional framework that conceptualises decision optimisation as a socio-technical process involving the interaction between human judgement, analytical modelling, and digital technologies. The study contributes to the literature by bridging traditionally fragmented research areas and providing a holistic foundation for more effective decision support systems. Practically, the findings emphasise the need for organisations to align optimisation methods, digital capabilities, and contextual considerations to improve decision quality, resilience, and long-term sustainability.

Keywords: Artificial intelligence, decision-making, decision support, digitalisation, optimisation, machine learning, multidimensional, sustainability

JEL Classification: C61, D83, M15, D81

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Introduction

Ineffective decision-making remains a significant challenge for many contemporary organisations. A global survey by McKinsey & Company (2023), involving over 1,200 business leaders, estimated that ineffective decision processes may cost a typical Fortune 500 company approximately 530,000 days of managerial time, equating to nearly $250 million in wasted wages. Beyond financial implications, effective decision-making is critical for navigating increasingly complex organisational environments and sustaining a competitive advantage (Institute of Directors, 2024). These realities underscore the central role of decision-making in organisational adaptability and sustainability.

However, achieving optimal decision-making is inherently challenging, particularly in large-scale contexts characterised by multiple interdependent variables, uncertainty, and dynamic conditions. Operations research (OR) and related optimisation techniques have traditionally been employed to address such complexity by providing structured, quantitative decision-support approaches. Despite their strengths, conventional optimisation approaches often face limitations related to scalability, computational efficiency, and adaptability, particularly in increasingly data-intensive and dynamic operational environments (Cloirec, 2023).

In response to these challenges, organisations are increasingly using digitalisation to improve decision-making. The integration of digital technologies into business processes has led to the emergence of data-driven decision environments, where large volumes of structured and unstructured data can be leveraged to enhance analytical capabilities and operational efficiency (McKinsey & Company, 2024). Among these technologies, artificial intelligence (AI) has emerged as a key driver, with the potential to improve decision speed and accuracy, reduce reliance on manual processes, and mitigate human error (Palanivelu & Vasanthi, 2020).

Nevertheless, a critical gap remains in understanding how to effectively integrate decision-making, optimisation, and digitalisation within a unified framework. Existing research often addresses these domains in isolation, failing to elucidate their combined, integrated potential. This fragmentation highlights the need for a holistic perspective that captures the interdependencies between human, analytical, and technological components of decision systems. In this context, the following research question is posed: *What is the conceptual overlay among decision-making, optimisation, and digitalisation, and how can a multidimensional perspective contribute to adaptability and sustainability in dynamic organisational environments?*

Accordingly, this paper presents a structured literature review that synthesises insights across three interconnected dimensions: decision-making (as a social dimension), optimisation (as a mathematical dimension), and digitalisation (as a technological dimension). By integrating these perspectives, the paper seeks to advance a multidimensional understanding of decision optimisation in industrial engineering contexts. The contribution of this paper lies in identifying key relationships and gaps in the underlying conceptual decision domains, thereby providing a foundation for the development of more integrated and effective decision-support systems.

Decision-making in organisational systems

Decision-making as a multi-level organisational process

From a social dimension perspective, decision-making is widely regarded as a fundamental human activity that guides goal-directed behaviour when multiple alternatives are available (Hansson, 2011). Within organisational systems, it serves as a critical functional process that supports sustainability, resilience, strategic alignment, accountability, risk management, and continuous improvement (Alkhadi, 2024). However, the effectiveness of organisational decision-making is increasingly being challenged by the complexity of contemporary business environments, where decisions must often be made rapidly and under conditions of uncertainty.

Developing a clear understanding of the factors that influence decision-making is, therefore, essential, particularly in environments characterised by high levels of uncertainty and rapid change (Kozioł-Nadolna & Beyer, 2021). While numerous variables may affect decision processes, these can be broadly structured into three interrelated contextual domains (Kamal *et al.*, 2015). The first is the individual context, which reflects the decision maker's personal characteristics. The second is the organisational context, which represents the structural and environmental conditions within which decisions are made. The third is the decision context, which concerns the nature and complexity of the decision itself. Together, these levels provide a holistic view of organisational decision-making.

Individual influences on decision-making

At the individual level, organisational decision-making is shaped by a range of personal attributes, including differences in personality, perspectives, risk tolerance, and prior experiences, all of which influence how decisions are approached and the outcomes that follow (Kamal *et al.*, 2015). Established personality dimensions, such as extraversion, agreeableness, conscientiousness, neuroticism, and openness to experience, have been found to play a significant role in determining decision-making styles (Bayram & Aydemir, 2017). Rather than relying on a single approach, individuals typically apply a combination of decision styles depending on the circumstances they face. Factors such as age, gender, prior experiences, and sociodemographic background may further influence these tendencies, particularly in relation to risk perception and judgment (Meier, 2021). These influences highlight the interpretive and socially embedded nature of decision-making. Understanding individual-level factors is therefore essential for promoting decisions that are not only rational but also consistent with the broader organisational environment.

Organisational influences on decision-making

Decision-making does not occur in isolation but is strongly shaped by the organisational environment in which it takes place. Effective decisions depend on the alignment between internal organisational capabilities and external environmental conditions, both of which influence organisational adaptability and sustainability (Atuahene *et al.*, 2023). Frameworks such as SWOT provide a useful basis for analysing these influences by distinguishing between internal strengths and weaknesses and external opportunities and threats (Ramsudeen, 2025). In this context, analysing internal conditions enables a more informed assessment of the organisation's capacity to respond to external pressures (Halmaghi *et al.*, 2017). Together, these dimensions shape the conditions under which organisational decisions are formulated and implemented.

Internal organisational influences

The internal environment comprises the conditions and factors within an organisation that influence its operations and decision-making processes (Atuahene *et al.*, 2023). These factors are typically evaluated in terms of strengths and weaknesses, reflecting their positive or negative impact on performance (Ramsudeen, 2025). In this regard, literature often considers organisational culture as central to the internal environment, as it shapes shared values, norms, and assumptions that guide behaviour and coordination (Halmaghi *et al.*, 2017).

Culture also influences how information is interpreted, how decisions are approached, and how conflict is managed, ultimately defining the organisation's identity (Al-Fahim, 2024). The Competing Values Framework (Figure 1) is often used to categorise culture into four types based on an organisation's degree of flexibility and strategic focus. These types include *clan cultures*, which are internally focused and emphasise collaboration and well-being; *adhocracy cultures*, which prioritise innovation and adaptability; *hierarchical cultures*, which focus on stability and control; and *market cultures*, which are externally focused and drive competitiveness and measurable outcomes (Cameron & Quinn, 2011; Lawrence, 2024).

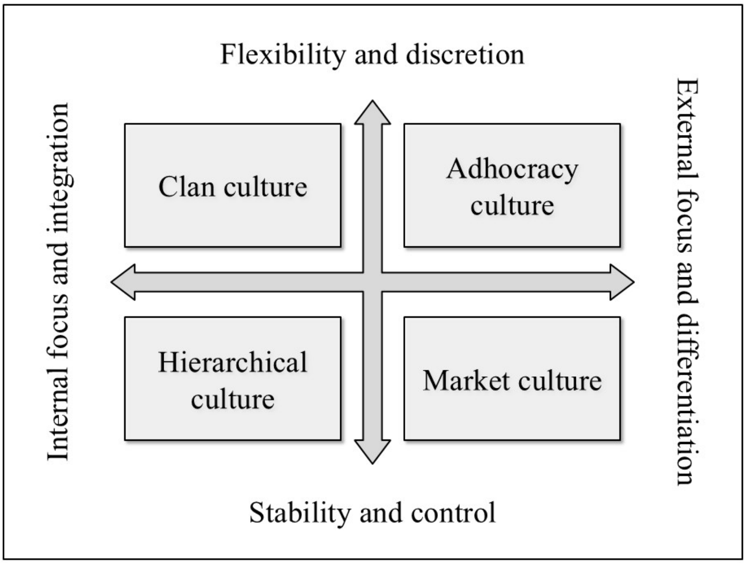

Figure 1. The Competing Values Framework
Source: Adapted from Cameron and Quinn (2011)

Leadership and management style further shape decision processes by influencing how problems are approached and how authority is distributed (Rosita *et al.*, 2023). Common leadership styles include directive, analytical, conceptual, and behavioural approaches, each of which affects organisational decision-making processes differently (Sulich *et al.*, 2021). Understanding these internal influences allows decision-making to be interpreted as part of a broader organisational system rather than as an isolated activity. Understanding when management styles are most effective enables individuals to better interpret the organisational culture in which they operate (Alsaqqa, 2016).

Overall, decision-making within organisations emerges from the interactions between culture, leadership, and strategic adaptability, highlighting the importance of understanding the internal environment as an integrated system rather than a set of isolated factors.

External organisational influences

The external environment is a crucial component of organisational analysis, encompassing factors beyond the organisation’s boundaries that influence its operations, strategic direction and overall performance (Fajembimo & Isaac, 2025). An organisation’s ability to interpret and respond effectively to external forces is therefore vital for sound decision-making (Atuahene *et al.*, 2023). These influences are typically assessed in terms of the opportunities they present and the threats they pose, both of which originate outside the organisation and remain beyond its direct control (Ramsudeen, 2025). As a result, organisations must adopt a structured, proactive approach to monitor and adapt to external changes throughout the business lifecycle. The PESTLE framework is widely applied in this regard, providing a systematic analysis of political, economic, social, technological, legal, and environmental (natural) factors shaping the external environment. The considerations of these factors are described as follows (Çitilci & Akbalik, 2020; Ramsudeen, 2025):

- **Political factors:** Government policies and regulations, political risks, trade restrictions, etc.
- **Economic factors:** Interest rates, taxes and tariffs, minimum wage levels, economic growth, unemployment levels, inflation and exchange rates, etc.
- **Social factors:** Demographics, population, non-governmental organisations, health and insurance systems, values, lifestyles of stakeholders, etc.
- **Technological factors:** Innovations, copyrights, technology and related trends, etc.
- **Legal factors:** Legislation, labour and consumer rights/laws, wages, job security, etc.
- **Environmental factors:** Environmental policies, climate, nature, raw materials, consumption trends, etc.

This framework demonstrates universal applicability across organisational contexts and may provide value to a wide range of industries. Importantly, when combined with decision-making and strategic planning, the PESTLE framework's adaptability and comprehensive structure enable organisations to formulate strategic plans and make data-driven decisions (Ramsudeen, 2025).

This analysis should enable contemporary organisations to anticipate challenges, identify emerging opportunities, and align strategic initiatives with changing environmental conditions.

Decision context and situational complexity

Beyond individual and organisational influences, decision-making is fundamentally shaped by its context. This refers to the environment in which individuals or groups evaluate alternatives and reach conclusions, requiring responsiveness to situational conditions and constraints (Ryan, 2022). In contemporary organisational settings, this context is characterised by uncertainty, complexity, and rapid change, often necessitating decisions under pressure and with incomplete information (Panpatte & Takale, 2019). As a result, decision-making extends beyond simple optimisation to managing trade-offs among competing objectives.

Uncertainty is a central feature of this context, arising from incomplete information, limited understanding of variables, and dynamic environmental conditions (Wienclaw, 2021). While some forms of uncertainty can be reduced through improved data and clearer causal insight (Wu & Shang, 2020), increased data availability may also lead to information overload, thereby complicating decision quality (Shahrzadi *et al.*, 2024). Consequently, effective decision-making under uncertainty requires a balance between analytical methods and managerial judgment.

Organisational complexity further intensifies these challenges. Defined by the degree of differentiation and interdependence within systems (Gorzeń-Mitka & Okręglicka, 2014), increased complexity makes decision processes more difficult to design and manage, often exceeding cognitive limits and leading to suboptimal outcomes (Beyer & Ullrich, 2022). In such contexts, structured approaches such as multi-criteria decision-making may provide valuable support by enabling systematic evaluation across competing criteria.

Uncertainty and complexity jointly give rise to risk, which may be partially quantifiable but also influenced by unknown variables (Wu & Shang, 2020). While these conditions introduce potential threats, they may also create opportunities for innovation (Gorzeń-Mitka & Okręglicka, 2014). Decision-making in this context, therefore, involves not only mitigating risk but also recognising and leveraging emerging opportunities.

Stakeholder involvement represents another critical aspect. Decisions typically involve multiple internal and external stakeholders (Osika *et al.*, 2023), and incorporating their perspectives improves decision quality, alignment, and legitimacy (Smith, 2024). However, conflicting interests and information asymmetries can increase complexity and require careful management of stakeholder engagement (Rosyada *et al.*, 2024).

Taken together, these contextual factors demonstrate that organisational decision-making is not merely a technical activity, but a socio-technical process shaped by uncertainty, complexity, risk, and stakeholder dynamics. This reinforces the need for structured and adaptive approaches that support decision-makers in increasingly complex environments.

Mathematical optimisation for decision support

Role of optimisation in decision support

From a mathematical dimension perspective, optimisation plays a fundamental role in decision support by providing structured mathematical and algorithmic frameworks for identifying optimal decisions under defined constraints. Through mathematical modelling, statistical reasoning, and computational algorithms, optimisation enables decision-makers to systematically evaluate alternatives and select solutions that maximise or minimise a defined objective function (Rodriguez, 2024).

In terms of decision support, optimisation is closely aligned with prescriptive analytics, as it moves beyond describing or predicting outcomes to recommend optimal courses of action (Lepenioti *et al.*, 2020). However, the effectiveness of optimisation is not isolated; it depends on integration with broader analytical processes to ensure that solutions are both contextually relevant and practically implementable (Abolghasemi, 2023).

Contemporary decision environments are characterised by increasing complexity, uncertainty, and scale. As a result, organisations are required to navigate competing objectives and trade-offs to achieve feasible, balanced outcomes (Cloirec, 2023). These challenges are particularly pronounced in sustainability-oriented applications, where economic, environmental, and social objectives must be considered simultaneously (Ferdous *et al.*, 2024; Gunantara, 2018). This complexity highlights the importance of structured optimisation approaches as a foundation for advanced decision support.

Problem formulation and structural characteristics of optimisation models

At the core of any optimisation problem lies a formal structure defined by decision variables, objective function(s), constraints, and domain sets. These collectively define the mathematical representation of the decision problem and determine how solutions are generated and evaluated (Sohrabi & Azgomi, 2018). However, in practical applications, these elements are influenced by additional structural characteristics that shape model complexity and solution behaviour. Optimisation problems can thus be described across six key aspects (Rizk-Allah & Hassanien, 2022):

· **Objective structure:** Problems may be classified as single-objective, multi-objective, or many-objective problems.

· **Constraint presence:** Problems may be classified as constrained or unconstrained depending on whether restrictions are imposed on variables or the objective function.

· **Landscape properties:** Objective functions may be unimodal (single optimum) or multimodal (multiple optima), affecting solution complexity.

· **Function form:** Models may take a linear or nonlinear form, which significantly influences the selection of appropriate solution techniques.

· **Variable composition:** Decision variables may be continuous, discrete (e.g. binary), or a combination of both, leading to mixed-variable problems.

· **Uncertainty profile:** Problems may be deterministic, with fully known parameters, or stochastic, where uncertainty is explicitly incorporated.

Together, these aspects define the structural nature of optimisation problems and influence both the model formulation and the selection of the solution strategy. In real-world contexts, optimisation problems are often constrained, data-intensive, and subject to incomplete information (Van der Blom *et al.*, 2023). These characteristics play a critical role in determining model feasibility and solvability.

Trade-off modelling in multi-objective optimisation

In practical decision-making environments, optimisation rarely involves a single objective. Instead, decision problems typically involve multiple, often conflicting objectives that must be balanced simultaneously. This complexity is further intensified by diverse stakeholder preferences, which limit the effectiveness of intuition-based decision-making (Parkinson *et al.*, 2013).

To address such complexity, multi-objective optimisation (MOO) provides a structured framework for analysing and managing competing objectives (Ferdous *et al.*, 2024; Gunantara, 2018). In many cases, MOO problems are transformed into a single-objective optimisation (SOO) problem using scalarisation techniques (Singh & Deb, 2020). One of the most widely used methods is the weighted-sum approach, which aggregates multiple objectives into a single function based on their relative importance (Kalayci *et al.*, 2019). However, different scalarisation methods may yield different solutions, requiring careful evaluation and comparison of outcomes.

Unlike SOO, which produces a single optimal solution, MOO generates a set of optimal trade-off solutions known as the Pareto-optimal front (Sayyaadi, 2020). Each solution on this front represents a different balance between objectives, where improvement in one objective results in a deterioration of at least one other. The Pareto-optimal front, therefore, provides a structured way to visualise and evaluate trade-offs, enabling decision-makers to select solutions aligned with strategic priorities (Alamo *et al.*, 2021).

As such, trade-off modelling is a central element of MOO and plays a key role in supporting balanced, transparent, and defensible decision-making.

Computational complexity and solution feasibility

As optimisation problems increase in size and complexity, their computational requirements, particularly in terms of processing time and memory, also increase significantly (Bröchin *et al.*, 2024; Chowdhary, 2025). As the problem scale grows, even small adjustments to the model formulation can lead to notable differences in solution time and computational effort. This becomes especially critical in practical application scenarios where large, data-driven problems must be solved within realistic time limits. In this context, computational complexity theory offers a structured lens for assessing the resources required to solve optimisation problems (Pantsar, 2021).

Within this framework, problems are classified according to their time and space requirements. Time complexity is particularly important, as it directly influences scalability and practical feasibility (Chowdhary, 2025). A key distinction is made between class P problems, which can be solved in polynomial time, and NP problems, where solutions can be verified efficiently but may be computationally expensive to obtain (Bossaerts & Murawski, 2017). This distinction highlights a central challenge in optimisation: as problem size increases, exact solution methods may become impractical or infeasible within realistic time constraints.

Consequently, there is often a need to balance model accuracy with computational efficiency. This trade-off is essential to ensure that optimisation solutions remain implementable in real-world decision-making environments.

Optimisation solution approaches and method comparison

Selecting an appropriate optimisation method is a critical step in the decision-making process, as method suitability depends on problem structure, size, uncertainty, and computational constraints (Rizk-Allah & Hassanien, 2022). In general, optimisation techniques can be grouped as deterministic, stochastic, and hybrid approaches, each with its own limitations and advantages.

Deterministic methods, such as linear programming (LP), integer programming (IP), and nonlinear programming (NLP), are suitable for well-structured problems with clearly defined mathematical formulations. These methods may be limited in large-scale, nonlinear, or nonconvex problems due to computational complexity (Azevedo *et al.*, 2024; Padamwar & Pandey, 2019).

Stochastic and heuristic methods are designed to better handle complexity and uncertainty. These approaches, including genetic algorithms, simulated annealing, tabu search, particle swarm optimisation, and ant colony optimisation, focus on exploring the solution space to identify high-quality, near-optimal solutions rather than guaranteeing global optimality. They are particularly useful in large-scale or poorly structured problems but often require careful parameter tuning (Rizk-Allah & Hassanien, 2022).

Hybrid methods combine deterministic and stochastic approaches to leverage the strengths of both. By integrating structured optimisation with exploratory search mechanisms, hybrid methods can improve solution quality, robustness, and convergence behaviour. However, they also introduce additional complexity in design and implementation and must be carefully balanced against computational cost (Azevedo *et al.*, 2024; Duan *et al.*, 2023).

Table 1 provides a comparative overview of common optimisation methods, highlighting the differences in problem suitability, convergence speed, scalability, and application domains.

Table 1. Comparative overview of common optimisation methods

Method	Problem type	Convergence Speed	Scalability	Applications
LP	Linear	High	High	Production planning, transportation and network optimisation
IP	Discrete	Moderate	Moderate	Project scheduling, facility location and resource allocation
NLP	Nonlinear	Moderate	Moderate	Engineering design, financial modelling and data analysis
Genetic algorithm	Any	Moderate	High	Scheduling and optimisation problems with complex search spaces
Simulated annealing	Any	Low to moderate	Moderate	Combinatory optimisation and parameter estimation
Tabu search	Any	Moderate	High	Travelling salesman problem and job scheduling
Particle swarm optimisation	Any	Moderate	High	Function optimisation and neural network training
Ant colony optimisation	Combinatory	Moderate	High	Vehicle routing, scheduling and network optimisation

Source: Adapted from Padamwar & Pandey (2019)

Overall, no single optimisation method is universally superior. The selection of an appropriate approach depends on problem-specific characteristics and practical considerations, such as computational resources, implementation complexity, and available expertise (Thomas *et al.*, 2023). Increasingly, hybrid approaches are preferred in complex real-world applications due to their ability to balance efficiency and solution quality.

Digitalisation and organisational decision-making

Digitalisation and the emergence of decision intelligence

From the technological perspective, the transition from Industry 4.0 to emerging paradigms such as Industry 5.0 reflects a sustained trajectory of technological advancement and the continuous evolution of industrial systems (Madsen *et al.*, 2025). Within this context, organisations increasingly engage in digitalisation, defined as the integration of digital technologies into organisational processes Madsen *et al.*, 2025), as a strategic transformation that reshapes operations, decision-making practices, and organisational interactions (Chaushi *et al.*, 2024).

A central outcome of digitalisation is its ability to enhance organisational decision-making by improving data availability, integration, and analytical capabilities. By enabling the collection and processing of large volumes of data, digital technologies improve the timeliness and accuracy of decisions (Kržan & Šanko, 2023). In addition, their connectivity and intelligence facilitate the generation of actionable insights, thereby strengthening organisational responsiveness and decision quality (Lenka *et al.*, 2017).

As a result, digitalisation can be understood as a foundational enabler of decision intelligence**,** supporting organisations in navigating complex, uncertain, and data-rich environments while improving sustainability, resilience, and competitiveness.

Digital technologies as enablers of analytical decision support

A diverse set of digital technologies underpins this transformation, including the Internet of Things (IoT), blockchain, cloud computing, robotics, big data analytics, and AI (Dvouletý *et al.*, 2025; Yamin, 2024). While these technologies differ in functionality, their primary contribution lies in enabling analytical tools and platforms that support decision-making.

Rather than directly improving decision-making, digital technologies give rise to intermediary analytical capabilities structured to enhance decision support. These capabilities can be broadly categorised into three interrelated domains (Elmojarrush *et al.*, 2025):

(i) Data analytics and business intelligence (BI) tools transform raw data into structured and actionable insights.

(ii) Forecasting and market analysis tools enable organisations to anticipate future trends and uncertainty.

(iii) Innovation-oriented digital capabilities support continuous improvement, adaptability, and value creation.

Across these domains, digital value is realised through tools such as BI dashboards, data warehouses, predictive analytics platforms, and AI-enabled decision models. These tools turn data availability into actionable insights, enabling more informed, forward-looking decisions. Consequently, the intersection of digital technologies and decision-making has become a central focus of contemporary research, with increasing emphasis on AI as a key enabling layer within decision-support ecosystems (Aleessawi & Djaghouri, 2025).

Artificial intelligence-enabled technologies in decision-making

AI has emerged as a critical driver of digital transformation, enabling organisations to improve efficiency, productivity, and decision accuracy while reducing human error (Alkhadi, 2024; Li *et al.*, 2024). Beyond operational improvements, AI contributes to enhanced organisational performance across economic, operational, and sustainability dimensions (Nobilo, 2024). Empirical evidence supports these benefits. For example, PwC (2023) reports that AI adoption often leads to improvements in decision-making quality, efficiency, revenue growth, cost reduction, and customer service performance. Among these, decision-making benefits significantly from enhanced data processing capabilities, enabling faster and more accurate insights.

Within AI, analytical AI is particularly relevant in complex, uncertain decision-making environments. It focuses on extracting actionable insights from large and heterogeneous datasets using machine learning (ML) and deep learning (DL) techniques (Sarker, 2022). Analytical AI can thus be conceptualised as a hierarchical structure in which ML serves as the foundational layer, while DL represents a more advanced subset capable of modelling complex, nonlinear relationships (Sarker, 2022). In this regard, ML enables systems to learn from data and improve performance without explicit programming, while deep learning extends these capabilities by identifying deeper patterns within dynamic datasets (Aleessawi & Djaghouri, 2025; Patil *et al.*, 2023). As such, ML serves as a core enabling mechanism in analytical AI, supporting automated learning and enhancing decision-makers' ability to generate meaningful, data-driven insights (Namvar *et al.*, 2023).

Together, these capabilities improve the speed, accuracy, and scalability of analytical processes, supporting more adaptive and sustainable organisational performance.

Machine learning-enabled decision architectures

ML extends beyond a purely technical function, emerging as a strategic enabler that reshapes how organisations approach decision-making (Kaggwa *et al*., 2024). Within this context, ML-enabled decision systems can be understood through three interrelated layers: information systems (IS) as the foundational infrastructure, decision support systems (DSS) as the functional layer, and business intelligence systems (BIS) as a key analytical sub-system. Together, these components reflect a broader shift towards data-driven, intelligent decision-making environments.

At the foundational level, IS provides mechanisms for collecting, processing, and distributing information across the organisation, thereby supporting operational efficiency and evidence-based decision-making (Alola, 2023). However, traditional IS may struggle to cope with the scale and complexity of modern data environments. The integration of ML technologies transforms these into intelligent information systems (IIS), enabling advanced capabilities such as data mining, pattern recognition, and predictive analytics. Empirical findings demonstrate that such systems significantly enhance decision quality, with notable improvements in both speed and accuracy across diverse organisational contexts (Velasco *et al*., 2025). As such, ML-enhanced IS are best viewed as enabling platforms that strengthen data readiness rather than as standalone decision-making tools.

Building on this foundation, DSS provide structured, interactive support for decision processes by integrating data, analytical models, and human expertise. These systems encompass various forms—including data-driven, model-driven, and knowledge-driven DSS—each tailored to different decision requirements (Fernando & Baldelovar., 2022). Recent developments in DSS incorporate techniques such as knowledge bases, fuzzy logic, multi-agent systems, natural language processing, genetic algorithms, and neural networks, with ML serving as a key enabling component (Panda, 2021). The incorporation of ML into DSS enhances their ability to generate predictive and prescriptive insights, supporting applications ranging from production planning to healthcare decision-making (Sauer *et al.*, 2024). Despite these advancements, the role of human judgement remains critical, reinforcing the importance of human-centric design principles.

Finally, BIS represent a specialised subset of DSS focused on transforming data into actionable insights for strategic, tactical, and operational decision-making. While traditional BIS primarily support descriptive and diagnostic analytics, integrating ML enables more advanced predictive capabilities, such as forecasting customer behaviour and evaluating operational outcomes (Tripathi *et al.*, 2023). In this way, ML-enhanced BIS bridges historical data with forward-looking intelligence, strengthening organisations' ability to respond proactively to complex challenges.

These layers thus illustrate how ML functions as a critical enabler of modern decision-making architectures, enhancing analytical capability, supporting human judgement, and aiding more responsive and effective organisational decisions.

Organisational considerations for machine learning adoption

Effective deployment of ML within organisations goes beyond having advanced technology; it also depends on organisational readiness. Digitalisation should be viewed as socio-technical transformation that simultaneously influences technological systems, operational processes, and organisational structures (Chaushi *et al.*, 2024). Consequently, the adoption of ML-based solutions is shaped by a set of interconnected organisational factors rather than purely technical considerations.

These factors can be conceptualised into five key themes: data integration and quality, technological infrastructure, organisational culture, talent acquisition, and strategic outcomes. Within these themes, organisations encounter both challenges and opportunities (Ara *et al.*, 2024).

Table 2. Challenges and opportunities of machine learning adoption in organisations

Theme	Challenges	Opportunities
Data integration and quality	Inaccuracies and inconsistencies in data and a lack of real-time data integration	Implement robust data governance frameworks and utilise advanced data processing technologies
Technological infrastructure	Legacy systems incompatible with ML complexities and difficulties in integrating advanced analytics	Modernise technological infrastructure to support ML, and invest in scalable and flexible technology solutions
Organisational culture	Resistance to change and innovation, and low data literacy among staff	Foster a data-driven culture, and emphasise education and training in data literacy
Talent acquisition	Shortage of skilled ML and analytics professionals, and a lack of a competitive market for talent	Develop strategic education and training programs, and focus on workforce development and retention strategies
Strategic outcomes	Initial high investment costs and implementation challenges	Enhanced decision-making capabilities, operational efficiencies, personalised customer experiences and market agility

Source: Adapted from Ara et al. (2024)

These are summarised in Table 2. Based on this, common barriers include poor data quality, incompatibility between legacy systems, resistance to organisational change, and shortages of skilled personnel. Conversely, successful adoption offers opportunities to make better decisions, improve operational efficiency, and deliver more responsive, customer-focused processes.

Complementing this perspective, the need for integrated interventions spanning both technical and organisational domains is evident. These include establishing robust data governance and validation frameworks, investing in scalable, interpretable technological infrastructure, and promoting organisational readiness through targeted training, change management initiatives, and the cultivation of a data-driven culture (Iyelolu & Paul, 2024).

This reinforces the view that ML adoption is inherently socio-technical, and successful implementation depends not only on algorithmic sophistication but also on the alignment of organisational capabilities, structures, and strategic objectives.

A multidimensional perspective of organisational decision optimisation

A multidimensional perspective on DS and DSS emerges from integrating decision-making, optimisation, and digitalisation rather than considering these domains in isolation, as illustrated in Figure 2.

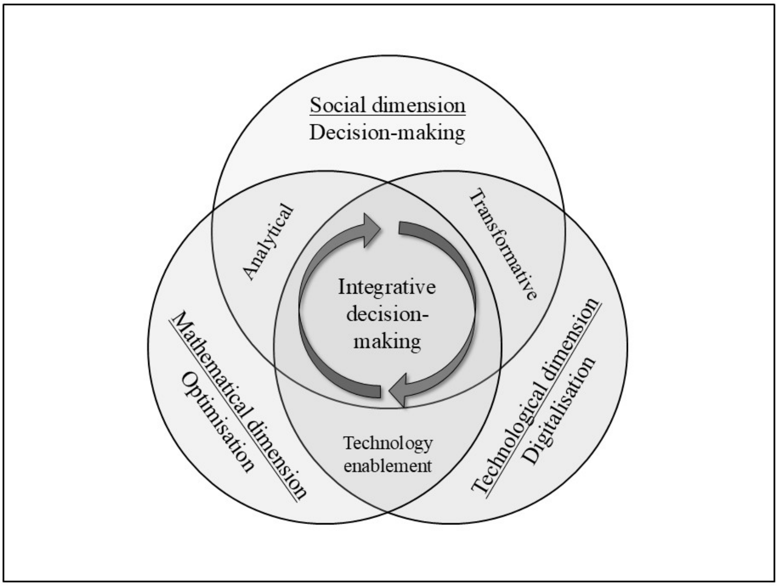

Figure 2. Multidimensional perspective of decision optimisation
Source: Author's adaptation

This reflects the inherently socio-technical nature of organisational decision systems, in which analytical, technological and transformative perspectives interact to address complex, dynamic problems.

Per Figure 2, the illustrated intersections of the foundational decision-support dimensions result in the analytical, transformative and technology enablement perspectives, clarified as follows:

(i) The overlap between the decision-making and optimisation dimensions provides an *analytical* perspective in which quantitative models structure complex problems while contextual factors such as uncertainty, stakeholder preferences, and strategic objectives define what constitutes an optimal solution. Optimisation strengthens the rigour and consistency of decision processes, and the decision context determines the relevance and applicability of the resulting solutions, particularly in environments with competing objectives and constraints.

(ii) The intersection between the optimisation and digitalisation dimensions reflects the *technology enablement* perspective in the context of advanced analytics, where data-driven methods, ML, and scalable computational tools enhance the ability to solve large-scale, complex, and dynamic optimisation problems. These technologies support improved data processing, model accuracy, and real-time responsiveness, thereby extending the practical applicability of optimisation in data-intensive environments.

(iii) The overlay between the digitalisation and decision-making dimensions highlights the *transformative* nature of decision environments through data-driven insights, DSS, and human-AI collaboration, improving both the speed and quality of decisions. While digitalisation enhances information availability and analytical capability, effective decision-making remains dependent on human judgement, particularly in interpreting results, managing uncertainty, and aligning outcomes with organisational objectives.

At the core of these interactions is an iterative, integrated decision-making perspective that combines human judgement, analytical modelling, and digital technologies to support adaptive, context-aware decision-making. This integration enables continuous feedback among data, models, and decision-makers, facilitating learning, adaptability, and improved responsiveness to changing conditions. Together, this multidimensional perspective provides a strong foundation to enhance organisational resilience, sustainability, and decision effectiveness in increasingly complex and uncertain environments.

Concluding discussion

Inefficient decision-making remains a persistent challenge in contemporary organisations, particularly in complex, dynamic environments characterised by uncertainty, interdependencies, and competing objectives. As such, this paper sought to address a gap in the existing literature by examining the conceptual relationships among decision-making, optimisation, and digitalisation, with the aim of developing a more integrated perspective on organisational decision support in the digital era.

The paper highlights that decision-making is inherently contextual and human-centred, shaped by individual, organisational, and situational factors. In contrast, optimisation provides the analytical rigour required to structure complex problems through mathematical modelling and systematic evaluation of alternatives. Digitalisation, enabled by advances in AI-related technologies, extends these capabilities by enabling data-driven insights, scalability, and adaptive decision-making. While each of these domains contributes independently to improved decision outcomes, their true value emerges through their interaction.

In response to the research question, this paper identifies the conceptual overlap among decision-making, optimisation, and digitalisation as a multidimensional integration of human judgment, analytical modelling, and technological capability. This integrated perspective demonstrates that optimisation enhances decision quality, digitalisation expands analytical capacity, and decision context ultimately determines the relevance and applicability of outcomes. Accordingly, decision optimisation should be understood not as a purely technical exercise, but as a socio-technical process that requires alignment between these interdependent dimensions.

From a theoretical standpoint, this paper contributes to the literature by proposing a structured, multidimensional perspective that bridges the traditionally siloed domains within OR, DSS, and digital transformation. This framework advances the understanding of decision optimisation by emphasising the need for integration across analytical, contextual, and technological components. From a practical standpoint, the paper suggests that organisations should adopt a holistic approach to decision support. This includes aligning optimisation models with strategic objectives and contextual constraints, investing in robust data and digital infrastructures, and maintaining the critical role of human judgement in interpreting and implementing decisions. Importantly, no single optimisation method or digital tool is universally sufficient; rather, effectiveness depends on the appropriate combination and alignment of methods within a given context.

This paper is not without limitations, however. As a conceptual literature review, the proposed perspective has not been empirically validated, and its applicability may vary across different organisational settings. Furthermore, the rapid evolution of digital technologies presents an ongoing challenge in capturing the full scope of their impact on decision support.

Future research should therefore focus on empirically validating the proposed perspective within real-world organisational contexts. Further investigation into the integration of ML and optimisation techniques, as well as the role of human-AI collaboration in decision-making, would provide valuable insights. Additionally, domain-specific applications, such as in industrial and mining environments, may further refine and extend the practical relevance of this work.

In conclusion, as organisational environments continue to increase in complexity and uncertainty, the integration of decision-making, optimisation, and digitalisation will become increasingly critical. A multidimensional, adaptive, and context-aware approach to decision support offers a promising pathway towards enhancing organisational adaptability and long-term sustainability.

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