

The Cybernetic Future of Investment Management: Insights from 42 Finance Middle Managers

Vera Alpár Dr.

`alpar.vera@uni-sopron.hu`

University of Sopron

Research Article

Keywords: Artificial intelligence, Information systems management, Human-AI collaboration, Cybernetic leadership, Capital allocation, Middle management, Qualitative research, financial decision making

Posted Date: September 18th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10928190/v1>

License:   This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: No competing interests reported.

Abstract

The rapid diffusion of artificial intelligence (AI) and digital platforms is fundamentally transforming organizational investment management. While prior information systems (IS) literature has largely focused on technological capabilities, less attention has been devoted to how managerial actors cognitively interpret and operationalize these systems in dynamic environments. Addressing this gap, this study explores how middle managers perceive the current and evolving role of AI in capital allocation and investment decision-making. Utilizing a qualitative exploratory design, we conducted semi-structured interviews with 42 middle managers working specifically within the financial sector of multinational organizations. The thematic analysis identifies five major transformation domains: augmented decision intelligence, adaptive capital allocation, decision velocity governance, trust and explainability and leadership transformation. The findings reveal a paradigm shift from static, periodic budgeting toward continuous, data-driven resource orchestration. Managers consistently describe AI as a cognitive extension that augments rather than substitutes human judgment, suggesting that future competitive advantage depends less on algorithmic sophistication and more on data quality, organizational adaptability and learning capabilities. Grounded in cybernetic leadership theory, dynamic capability theory and the human-in-the-loop paradigm, this study develops the Cybernetic Middle Management Decision Model (CMMDM). The model conceptualizes managerial decision-making as a recursive cycle of intelligence acquisition, contextual interpretation, adaptive decision commitment and recursive learning feedback, supported by trust, explainability and data quality as enabling conditions. The study contributes to the information systems and management literature by proposing a novel decision framework that explains how AI-mediated investment environments reshape managerial judgment, capital allocation and organizational learning. The findings further highlight how AI-enabled decision systems may contribute not only to investment effectiveness but also to broader questions of financial resilience, governance and systemic stability.

1. Introduction

Digital transformation has fundamentally altered how organizations allocate resources and evaluate investment opportunities. Traditional annual budgeting processes increasingly coexist with data-driven and adaptive decision systems that allow organizations to react continuously to changing market conditions. This transformation reflects a broader shift from static planning toward dynamic resource allocation and organizational adaptation.

The theoretical foundation of this paper – detailed in the 2nd chapter – draws on the cybernetic perspective of leadership, which argues that organizations increasingly operate as adaptive socio-technical systems characterized by recursive feedback loops, distributed intelligence and continuous learning. Within such environments leaders move away from direct control and increasingly focus on designing the conditions under which intelligent action can emerge.

The figure illustrates the evolving role of leadership in increasingly digital and AI-enabled organizational environments. Rather than functioning as centralized controllers of information and decisions, future leaders operate within interconnected socio-technical systems characterized by continuous feedback, distributed intelligence and dynamic interactions between human and artificial agents. Within such environments, effective leadership depends on three interrelated capabilities. First, leaders must facilitate productive human-AI collaboration by integrating analytical outputs with managerial judgement. Second, they must provide epistemic oversight by ensuring that automated recommendations remain transparent, explainable and proportionate to the complexity of the decision context. Third, leaders must continuously navigate uncertainty and volatility through adaptive learning and feedback-driven decision processes.

Consequently, leadership is no longer primarily defined by authority, control, or superior access to information. Instead, value creation increasingly stems from the ability to orchestrate interactions among data, technology, human expertise and organizational learning. This cybernetic perspective provides the theoretical foundation for investigating how middle managers experience the ongoing transformation of investment management and how they combine human judgement with AI-supported decision systems. Ultimately, these developments form the basis for the Cybernetic Middle Management Decision Model (CMMDM) proposed later in this study. The purpose is to investigate how middle managers perceive these developments in the field of investment management and how they envision the role of AI in future capital allocation processes.

The research addresses three questions:

- RQ1: How do finance middle managers currently balance human judgment, data analytics and algorithmic recommendations in financial investment decisions?
- RQ2: What organizational changes do finance managers observe in corporate investment planning and capital allocation processes?
- RQ3: How do financial sector managers envision the future role of AI in investment management by 2035?

Opening Vignette: „Voices from the Field“: During the interviews, one middle manager summarized the current transformation of investment management in the following way:

"Ten years ago, we spent months preparing investment plans and years evaluating whether they worked. Today, the dashboard tells us every morning whether we should continue, stop, or redirect capital."

Another respondent highlighted the changing role of managerial expertise:

"The algorithm brings options to the table. My job is no longer to calculate them. My job is to understand which option makes sense for the business."

A third manager emphasized the emerging limitations of AI-based decision support:

"The model is useful until something happens that has never happened before. Then experience becomes more valuable than any dataset."

These statements illustrate a broader transformation identified throughout the interviews. Investment management is no longer characterized by periodic planning, centralized budgeting and retrospective evaluation. Instead, organizations increasingly operate through continuous capital allocation, AI-supported analysis, real-time performance monitoring and adaptive decision cycles. Understanding how managers interpret these changes constitutes the central objective of this study.

2. Theoretical Background

Organizations increasingly operate in environments characterized by technological disruption, accelerating information flows and growing decision complexity. Traditional investment planning systems, which were primarily based on periodic reviews, hierarchical decision structures and relatively stable market assumptions, are being challenged by real-time analytics, artificial intelligence and continuously changing business conditions. As a result, investment management is evolving from a planning-oriented activity toward a dynamic process of sensing, interpreting, allocating and adapting.

The intellectual foundations of managerial decision-making can be traced to the concept of bounded rationality, which argues that decision-makers operate under conditions of imperfect information and cognitive limitations (Simon, 1957). Subsequent work in behavioral decision theory demonstrated that managerial decisions are influenced by heuristics, biases and contextual constraints rather than purely rational calculations (Kahneman & Tversky, 1979; Kahneman, 2011). These limitations become particularly important in complex investment environments characterized by uncertainty, ambiguity and rapidly changing information.

The growing availability of digital technologies and advanced analytics has fundamentally altered this landscape. Organizations increasingly rely on data-driven decision-making processes to improve performance, identify opportunities and allocate resources more effectively (Davenport & Harris, 2007; Brynjolfsson & McAfee, 2014). At the same time, the value of information depends not merely on its availability but on the organization's capability to transform data into actionable knowledge and strategic insight. Dynamic capability theory suggests that long-term organizational success depends on the ability to sense environmental changes, seize opportunities and continuously reconfigure resources in response to emerging conditions (Teece et al., 1997; Teece, 2007).

Within investment management, these developments have accelerated the shift from static budgeting toward adaptive capital allocation. Traditional annual planning cycles increasingly coexist with iterative resource-allocation approaches that rely on continuous monitoring, performance feedback and rapid reallocation of investments. Such approaches resemble the logic of real options and organizational experimentation, where investments are continuously reassessed rather than committed through irreversible long-term decisions (Bowman & Hurry, 1993; McGrath, 1997; Trigeorgis, 1996).

Artificial intelligence has become a central component of this transformation. Rather than simply automating routine activities, AI increasingly supports forecasting, risk evaluation, pattern recognition, scenario analysis and decision preparation. Recent research suggests that the greatest organizational value emerges not from full automation but from effective collaboration between human and artificial intelligence (Wilson & Daugherty, 2018; Jarrahi, 2018; Shrestha et al., 2019). This perspective is often described as the human-in-the-loop approach, in which AI functions as an analytical partner while humans retain responsibility for interpretation, ethical evaluation and final decision authority.

The management literature increasingly emphasizes that future organizational effectiveness depends on balancing algorithmic intelligence and human judgment (Raisch & Krakowski, 2021; Dwivedi et al., 2020). Although AI systems excel at processing large amounts of information, humans remain essential for contextual understanding, ethical reasoning, stakeholder management and strategic sensemaking. Consequently, managerial work is gradually shifting from information processing toward interpretation, orchestration and decision governance.

From a cybernetic perspective, organizations can be understood as adaptive systems that continuously learn through feedback, adjustment and environmental interaction. Cybernetic theory emphasizes that effectiveness is achieved not through prediction alone but through the capacity to monitor outcomes, compare them with objectives and continuously adapt behavior based on new information (Veitas & Weinbaum, 2015; Weiser et al., 2020). Such feedback-driven adaptation becomes increasingly relevant in investment management, where the speed of environmental change frequently exceeds the speed of traditional planning systems.

This perspective is further reinforced by research on organizational resilience, distributed intelligence and adaptive coordination, which suggests that organizations increasingly resemble learning systems rather than command-and-control structures (Avolio et al., 2008; Annarelli et al., 2021; Martín-Rojas et al., 2023). Under these conditions, decision effectiveness depends not only on choosing correctly but on the capability to continuously learn, recalibrate and respond to changing circumstances.

Taken together, the literature indicates a convergence between four major developments: data-driven decision-making, human-AI collaboration, adaptive capital allocation and cybernetic learning systems. However, existing research has primarily examined these areas independently. Limited attention has been devoted to understanding how middle managers integrate these dimensions into practical investment decisions. This gap provides the foundation for the present study and ultimately motivates the development of the Cybernetic Middle Management Decision Model (CMMDM) proposed in this paper. A complementary perspective on adaptive decision-making emerges from organizational learning and dynamic capability research. March (1991) argues that organizations face a persistent tension between **exploration** and **exploitation**. Exploration involves experimentation, innovation, risk-taking and the search for new opportunities, whereas exploitation focuses on efficiency, refinement, implementation and the utilization of existing knowledge. Sustainable organizational performance depends not on maximizing either logic, but on maintaining an effective balance between them. In contemporary

investment environments, middle managers increasingly operate at the intersection of these competing demands, simultaneously identifying new opportunities while ensuring the efficient allocation of organizational resources.

This tension is further elaborated by Iñigo and Albareda (2019), who propose an evolutionary framework of sustainability-oriented innovation based on three interconnected levels of dynamic capabilities: **adapting, expanding and transforming**. The first level focuses on continuous improvement, routine enhancement and skill development. The second level extends organizational capabilities through stakeholder collaboration, learning processes and innovation initiatives. The third level involves the reconfiguration of organizational processes and business models, enabling the creation of broader economic, social and environmental value. Importantly, the authors emphasize that capability development follows both **path-dependent** and **self-reinforcing** logics. Existing routines and previous decisions shape future possibilities, while successful learning processes strengthen organizational commitment, resource allocation and stakeholder engagement over time.

Together, these perspectives suggest that effective managerial decision-making extends beyond selecting the optimal investment alternative. Decision effectiveness increasingly depends on an organization's ability to continuously balance exploration and exploitation while simultaneously developing adaptive capabilities through learning and feedback. This understanding provides a critical theoretical foundation for the Cybernetic Middle Management Decision Model (CMMDM), which conceptualizes managerial decision-making as a recursive process of intelligence acquisition, contextual interpretation, adaptive commitment and continuous learning. Recent advances in generative artificial intelligence introduce a qualitatively new dimension to organizational decision-making. Unlike traditional analytical systems that primarily classify, predict, or optimize, generative AI is capable of producing synthetic scenarios, alternative strategic options, risk narratives, investment forecasts and decision-support content in real time. As a result, its role extends beyond information processing toward active participation in managerial sensemaking. In investment management, generative AI can support scenario development, portfolio planning, capital allocation assessments and strategic foresight by enabling managers to evaluate multiple alternatives simultaneously. However, the increasing influence of AI-generated outputs also raises important concerns regarding explainability, accountability, cognitive overreliance and systemic risk. Consequently, the challenge for future organizations is not whether generative AI should be integrated into decision-making processes, but how human judgement and AI-generated intelligence can be combined in a manner that preserves transparency, adaptability and organizational learning. This challenge reinforces the relevance of cybernetic perspective and provides additional justification for conceptualizing managerial effectiveness as a continuous process of intelligence acquisition, contextual interpretation, adaptive commitment and recursive learning.

3. Methodology of Research

This study employed a qualitative exploratory research design to investigate how finance middle managers perceive the ongoing transformation of investment management in the context of artificial

intelligence, advanced analytics and digital decision-support technologies. Given the limited empirical knowledge regarding managerial interpretations of AI-supported investment decision-making, a qualitative approach was considered the most appropriate method for capturing rich contextual insights, subjective experiences and forward-looking expectations. The research aimed not only to identify current practices but also to explore emerging patterns regarding the future evolution of financial investment management and leadership functions within multinational organizations. Data collection was conducted through semi-structured interviews with 42 middle managers working specifically within the financial sector or overseeing corporate finance operations in multinational companies operating across highly data-intensive environments, including financial services, banking, fintech, investment consulting and corporate financial divisions. Participants were selected using purposive sampling to ensure that interviewees possessed direct managerial responsibility for financial budgeting, corporate capital allocation, investment planning, digital financial transformation initiatives, or technology-related decision-making. The participating managers represented core functional areas such as corporate finance, financial strategy, treasury and investment risk management, thereby providing a broad range of insights into organizational financial processes.

The interview protocol consisted of seven open-ended questions designed to explore the relative influence of human expertise, data analytics and algorithmic decision support in financial investment management. Additional questions examined perceptions regarding the future role of artificial intelligence, changing financial managerial competencies, the acceleration of decision-making processes, risks associated with increasing automation and the characteristics of future investment-oriented organizations. The semi-structured format ensured consistency across interviews while allowing participants sufficient flexibility to elaborate on experiences, examples and context-specific observations. Interviews generated detailed qualitative material focusing on both contemporary practices and anticipated developments over the next decade.

3.1. Data Collection & Analysis

The collected interview data were analyzed using thematic analysis following the principles proposed by Braun and Clarke (2006). The analysis combined inductive and deductive coding procedures. During the first stage, interview transcripts were reviewed repeatedly to achieve familiarity with the data and identify recurring concepts, expressions and financial managers' concerns. In the second stage, initial codes were assigned to relevant text segments. Similar codes were subsequently grouped into higher-order categories, which were continuously refined through iterative comparison and interpretation. To enhance analytical rigor, themes were evaluated according to their recurrence across interviews, conceptual coherence and relevance to the research objectives. The analysis ultimately resulted in the identification of five overarching themes that describe the perceived transformation of financial investment management in the age of artificial intelligence. These themes were labelled as Augmented Decision Intelligence, Adaptive Capital Allocation, Decision Velocity Governance, Trust and Explainability and Leadership Transformation. Together, these thematic dimensions formed the basis for developing the conceptual framework presented in this study. The resulting framework integrates empirical insights

from financial managerial practice with cybernetic perspectives on leadership and organizational adaptation, offering a comprehensive interpretation of how human judgment, artificial intelligence and dynamic capital allocation are becoming increasingly intertwined within contemporary corporate finance systems.

3.2. Reliability and Trustworthiness

To strengthen the credibility and trustworthiness of the findings, the study followed established qualitative research procedures. Themes were derived through multiple rounds of coding and constant comparison across interview transcripts. Attention was paid to identifying both convergent and divergent viewpoints among respondents in order to avoid overemphasizing dominant narratives. Representative quotations were retained throughout the analysis to preserve participants' original meanings and support the interpretation of findings. The objective of the study was not statistical generalization but analytical generalization, providing an empirically grounded understanding of how finance middle managers interpret the evolving relationship between human judgment, artificial intelligence and financial investment decision-making in complex organizational environments.

4. Findings

The thematic analysis revealed five interrelated dimensions that collectively describe the emergence of a new investment management paradigm. Although the participants represented different multinational industries, a remarkable degree of convergence appeared across the interviews. The findings suggest that investment management is moving away from periodic planning, centralized control and static budgeting toward an adaptive system characterised by continuous capital allocation, real-time analytics, distributed intelligence and human-AI collaboration.

Table 1
Synthesis of Findings from 42 Semi-Structured Interviews

Key Area	Observed Phenomena	Identified Problems	Managerial Implications	Emerging Solutions
Financial Decision Making	Growing reliance on AI, predictive analytics and simulations	Finance managers face information overload and market complexity	Human judgment remains vital in ambiguous market situations	Human-in-the-loop decision structures
Capital Allocation	Shift from annual budgeting to continuous allocation	Traditional planning cycles are too slow for dynamic markets	Investment decisions become iterative rather than fixed	Adaptive Capital Allocation
ROI Expectations	Pressure for faster returns and measurable outcomes	Long-term investment evaluation models lose relevance	Managers must balance strategic value and short-term evidence	Milestone-based and phased funding
Data Management	Increased availability of data and analytics	Fragmented databases and poor data quality	Data quality becomes a strategic resource	Data governance and integrated information systems
AI Adoption	Rapid implementation of decision-support technologies	Lack of trust in algorithmic recommendations	Explainability becomes critical for adoption	Explainable AI (XAI) and transparent analytics
Organizational Structure	Greater local access to analytical tools	Growth of shadow IT and decentralized investment decisions	Investment authority moves closer to operational knowledge	Distributed decision-making systems
Risk Management	Expanded use of predictive analytics and simulations	AI struggles with unprecedented events and uncertainty	Human experience remains essential during crises	Hybrid risk assessment models
Corporate Governance	Faster decision cycles and increasing automation	Risk of accountability gaps in automated execution	Clear ownership of decisions becomes necessary	Decision Velocity Governance
Financial Leadership Competencies	Growing importance of data literacy and adaptability	Traditional managerial competencies become insufficient	Managers evolve from analysts to interpreters	Continuous learning and capability development

Key Area	Observed Phenomena	Identified Problems	Managerial Implications	Emerging Solutions
Human-AI Collaboration	Increasing interaction between managers and AI systems	Potential overreliance on algorithms	Balance between automation and judgment is required	Augmented Decision Intelligence
Organizational Learning	Continuous evaluation through dashboards and feedback loops	Learning often remains fragmented	Feedback must become part of decision systems	Recursive Learning Feedback
Future Financial Organizations (2035)	AI-integrated, decentralized, adaptive structures	Traditional hierarchical models become ineffective	Finance executives become facilitators of intelligence ecosystems	Cybernetic Middle Management Decision Model

The empirical evidence from the 42 finance middle managers reveals that the integration of AI triggers a fundamental shift toward new dynamic financial mechanisms and structural monetary solutions. Instead of adhering to traditional, rigid yearly budgeting cycles, organizations are increasingly adopting Continuous Capital Orchestration and Milestone-based Staged Funding. Under these newly emerged mechanisms, the corporate treasury relies on real-time AI analytics to dynamically shift liquid capital to high-yield projects, while subsequent funding tranches are automatically unlocked only upon the verification of predefined performance metrics. Furthermore, the findings highlight the institutionalization of a Two-Speed Velocity Governance model.

This monetary mechanism automatically approves low-risk, routine operational expenditures via automated algorithms, while redirecting high-impact, irreversible strategic investments into deep human oversight channels supported by parallel Monte Carlo simulations and advanced risk assessment models.

From the perspective of the finance middle managers, these technological solutions do not imply a transition toward fully autonomous financial management, but rather stress the absolute necessity of human-in-the-loop orchestration. The interviewed financial professionals strongly reject the narrative of managerial displacement, conceptualizing AI instead as a cognitive extension that enhances rather than substitutes human interpretation and fiduciary accountability. However, the respondents identify significant structural barriers to wide-scale financial AI adoption, pointing to data fragmentation and the inherent risks of algorithmic "black box" recommendations. Managers consistently emphasize that they will not authorize substantial capital deployment based on unexplainable machine outputs.

Consequently, they envision the future role of the finance leader evolving from a traditional quantitative data processor into a strategic interpreter, an ethical evaluator of risk and a coordinator of distributed

organizational intelligence. A closer examination of the interview data reveals a finding that initially appears paradoxical. While organizations are investing heavily in artificial intelligence, predictive analytics, automation and real-time decision-support systems, the findings do not indicate a movement toward fully automated investment management. Instead, the interviews suggest the emergence of a fundamentally different organizational logic.

Contrary to common expectations, increasing technological sophistication does not reduce the importance of middle managers. Rather, it amplifies the need for human interpretation, contextual understanding, ethical judgement and adaptive learning. As analytical capabilities become increasingly automated, managerial value shifts away from information processing and toward meaning-making.

An equally surprising observation concerns the relationship between data and decision quality. The respondents rarely viewed analytical models as the primary bottleneck of effective investment decisions. Instead, fragmented information systems, poor data quality, lack of trust and insufficient organizational learning mechanisms were identified as the most significant barriers. The findings therefore suggest that future decision effectiveness will depend less on the sophistication of algorithms and more on the organization's ability to transform information into actionable intelligence (see: Table 1.).

Collectively, these patterns indicate that investment management is evolving through a transition from **capital allocation** to **intelligence orchestration**. The central managerial challenge is no longer deciding where to invest resources once a year. Rather, it involves continuously integrating data, human judgement, organizational learning and adaptive resource allocation into an ongoing decision cycle.

This insight provides the foundation for the thematic findings presented in the following sections and ultimately leads to the development of the Cybernetic Middle Management Decision Model (CMMDM).

4.1 Augmented Decision Intelligence

The most dominant finding concerns the evolving relationship between human judgement and artificial intelligence in financial investment decision-making. Participants overwhelmingly rejected both purely intuition-based asset management and fully autonomous algorithmic execution systems. Instead, a hybrid logic emerged across almost all interviews.

Finance middle managers consistently described AI and advanced predictive analytics as mechanisms for expanding managerial cognition rather than replacing fiduciary responsibility. Data analytics, quantitative forecasting models and financial simulation tools increasingly provide the informational basis of corporate investment evaluations, yet final decision authority remains firmly associated with human interpretation, market context evaluation and institutional accountability.

Many respondents characterized AI as an analytical filtering mechanism that narrows financial alternatives rather than making final strategic choices. According to this perspective, algorithms identify market patterns, estimate default or return probabilities and generate stress-test scenarios, while finance

managers evaluate long-term strategic relevance, macroeconomic fit and broader stakeholder implications.

A recurring observation concerned the limits of algorithmic reasoning in complex or highly volatile market situations. Participants repeatedly argued that AI performs exceptionally well in analysing structured historical datasets and balance sheets, but struggles with highly dynamic contextual elements such as geopolitical shifts, shifting market sentiment, central bank interventions and unprecedented macroeconomic disruptions. Consequently, human judgment becomes increasingly important whenever financial investment decisions involve ambiguity, novelty, or systemic uncertainty.. *"Data analytics provides the evidence, but managerial experience provides the interpretation. We increasingly rely on AI to identify opportunities, yet the final responsibility remains with the decision-maker."* (Respondent 7)

"Algorithms help us process more information than ever before, but they cannot fully understand political uncertainty, organizational culture, or stakeholder expectations." (Respondent 18)

"Without advanced analytics we would simply be too slow to compete. Today, intuition without data is not sufficient for investment decisions." (Respondent 31)

Several respondents also highlighted a clear distinction between routine operational expenditures and strategic capital investments. Routine technology acquisitions, software subscriptions and predictable operational costs are increasingly managed through highly automated, data-driven approaches. In contrast, mergers and acquisitions (M&A), major digital infrastructure projects and international market-entry investments continue to depend heavily on deep managerial experience, industry expertise and intuitive financial judgment. An additional pattern emerged regarding financial crisis management. Finance managers generally reported strong confidence in AI-supported risk models under stable, predictable economic conditions. However, confidence declined substantially when discussing systemic shocks, market turbulence, or black swan events. Participants frequently emphasized that quantitative models trained on historical time-series data inevitably struggle when confronted with structural breaks for which no historical training data exists.

Collectively, these findings suggest that the financial sector is not moving toward autonomous AI-driven automation, but toward augmented decision intelligence. The future envisaged by participants is neither purely human-centred nor machine-controlled. Rather, it involves increasingly sophisticated forms of human-AI collaboration where technology extends quantitative analytical capabilities while human professionals retain absolute responsibility for interpretation, risk mitigation and strategic accountability..

4.2 Adaptive Capital Allocation

The second major theme concerns the radical transformation of corporate capital allocation processes. Across the financial sector, respondents reported a significant departure from traditional annual budgeting cycles and long-range capital planning frameworks.

Rather than operating within rigid yearly financial frameworks, Organizations are increasingly moving toward continuous, iterative and adaptive capital deployment systems. Participants described financial environments in which project funding decisions are reviewed frequently, reallocated dynamically by the corporate treasury and adjusted according to changing real-time financial performance metrics. A particularly noteworthy development involves the erosion of confidence in fixed, long-term planning assumptions. Finance middle managers indicated that rapid technological disruption and volatile market conditions have severely reduced the reliability of traditional discounted cash flow (DCF) and ROI forecasting models. Consequently, capital allocation is increasingly treated as an ongoing process of agile experimentation and continuous recalibration rather than a periodic administrative exercise.. *"The traditional three-to-five-year ROI horizon is disappearing. Senior management increasingly expects evidence of success within 12 to 18 months."* (Respondent 12)

"Capital allocation has become an ongoing process rather than an annual budgeting exercise. Investments are continuously reassessed based on live performance indicators." (Respondent 24)

Some of the respondents observed that project and asset portfolio performance is now monitored through real-time KPI dashboards, enabling the continuous reassessment of funding priorities. Financial resources can be increased, reduced, postponed, or terminated based on live performance data rather than waiting for annual review cycles. The interviews also revealed a substantial shift in return-on-investment expectations. Participants consistently reported increasing pressure from senior leadership to demonstrate early evidence of value creation. This acceleration is particularly evident in large-scale fintech integrations, corporate digital transformation initiatives and emerging technology investments.

To mitigate risk, finance managers repeatedly referred to pilot initiatives, milestone-based investments, phased approvals and staged funding mechanisms. Rather than committing massive amounts of capital upfront, organizations distribute financial exposure across multiple review gates, allowing capital commitment to evolve dynamically as new financial evidence and market feedback emerge.

These developments suggest a profound transition from fixed corporate budgeting toward adaptive capital allocation. Capital is no longer viewed as a static financial resource distributed periodically, but as a dynamic organizational capability that is continuously redirected toward high-yield opportunities and away from emerging financial risks.

4.3 Decision Velocity Governance

A third theme concerns the increasing importance of decision speed within corporate finance. Participants unanimously agreed that financial investment decisions must be made significantly faster than in previous decades to capture shifting market opportunities. However, rapid decision-making was not associated with reduced analytical rigor, weaker oversight, or compromised compliance.

Instead, respondents described the emergence of what may be termed decision velocity governance, where financial decision quality and regulatory compliance are preserved through embedded technological and procedural safeguards rather than lengthy manual approval hierarchies.

Numerous organizations now deploy AI-supported simulations, automated scenario analysis, predictive forecasting platforms and real-time algorithmic risk monitoring systems. These technologies enable finance managers to evaluate financial alternatives and capital projects more rapidly while maintaining maximum analytical depth and regulatory compliance. Several managers described the widespread use of automated Monte Carlo simulations and parallel scenario modelling, which allow corporate finance divisions to assess hundreds of potential market outcomes, volatility shocks and portfolio correlations within hours rather than weeks. Such capabilities significantly reduce the time required for comprehensive financial risk evaluation without sacrificing structural robustness. Another frequently mentioned mechanism is the implementation of data-driven Stage-Gate frameworks. Within these systems, predefined financial performance indicators and cost thresholds automatically trigger progression to subsequent investment phases, reducing bureaucratic delays while maintaining strict corporate accountability and audit trails.

Respondents also referred to predefined risk tolerance corridors. Financial investments operating well within acceptable risk-return corridors may proceed through accelerated approval channels, whereas decisions exceeding these volatility thresholds automatically trigger deeper qualitative review processes.

One particularly interesting pattern involved the emergence of what participants described as two-speed financial decision systems. Reversible, low-risk, or routine operational expenditures are increasingly delegated to agile, decentralized and algorithmically optimized processes. Conversely, strategic, irreversible, or high-impact capital investments continue to require comprehensive cross-functional analysis, human-in-the-loop validation and extensive executive governance procedures.

4.4 Trust and Explainability

Trust emerged as one of the most persistent themes throughout the interviews. While respondents generally expressed optimism regarding the future role of AI in corporate finance, substantial concerns remain regarding transparency, fiduciary accountability and explainability. Participants frequently referred to advanced financial AI systems as "black boxes" whose internal decision logic and risk calculations remain difficult to audit. This lack of transparency generates significant hesitation, particularly when high-value capital investments or compliance-heavy financial choices are involved. Finance middle managers repeatedly indicated that they are highly unlikely to approve significant capital deployment when they cannot adequately explain the underlying rationale of AI-generated recommendations to executive boards or external regulators. As a result, explainability appears to be becoming a critical prerequisite for organizational acceptance and financial compliance of advanced decision-support systems.

The interview findings suggest that managers perceive generative AI simultaneously as a source of enhanced decision intelligence and as a potential source of new organizational vulnerabilities. On one hand, respondents emphasized its ability to accelerate analysis and improve financial forecasting:

"Generative AI allows us to evaluate multiple investment scenarios in minutes instead of days. It significantly expands our analytical capacity." (Respondent 5)

"In the future every finance manager will have an AI co-pilot capable of running portfolio simulations and preparing decision alternatives during meetings." (Respondent 21)

"Generative AI frees financial leaders from routine quantitative analysis and enables them to focus on strategy, innovation and stakeholder management." (Respondent 34)

"The greatest benefit is not automation itself but the ability to identify complex market patterns and opportunities that humans might overlook." (Respondent 16)

On the other hand, the interviews revealed deep structural concerns regarding algorithmic bias, model hallucination and the potential institutionalization of flawed historical data. Fiduciary accountability remains a major issue; respondents consistently questioned how corporate responsibility should be assigned when AI-supported investment decisions produce undesirable market outcomes or financial losses. Many feared that excessive reliance on automated algorithms could weaken personal accountability, encourage moral hazard and blur traditional corporate governance boundaries within finance departments.

Interestingly, finance managers rarely identified algorithmic sophistication or mathematical complexity as the primary challenge associated with AI implementation. Instead, financial data quality emerged as the most frequently cited operational obstacle. Fragmented financial databases, inconsistent legacy information structures, incomplete transaction records and poor data governance were consistently described as greater barriers than the algorithms themselves. Many organizations reportedly spend substantial portions of their digital transformation budgets on financial data cleansing, data lineage tracing and architecture redesign. According to several respondents, the sustainable competitive advantage associated with AI in the financial sector increasingly depends on data quality and infrastructure robustness rather than modelling sophistication alone.

To mitigate these systemic risks, finance managers emphasized that future AI adoption will depend not only on predictive performance but also on safeguarding the decision environment against specific vulnerabilities:

"A convincing answer generated by AI is not necessarily a correct financial answer. There is always a danger that managers trust the output too quickly without cross-checking the market data." (Respondent 11)

"If we do not understand how the model reached its quantitative recommendation, it becomes impossible to justify investment decisions to stakeholders and regulators." (Respondent 27)

"Overreliance on AI may gradually weaken managerial judgment and domain expertise, especially among less experienced finance professionals." (Respondent 39)

"Black swan events remain a major concern. AI performs exceptionally well with historical patterns but struggles when facing structural breaks it has never encountered before." (Respondent 8)

"The larger the role of AI in corporate capital allocation, the more important absolute accountability becomes. Someone must remain legally responsible when financial models fail." (Respondent 30)

Consequently, the empirical evidence demonstrates that successful deployment of generative AI within corporate financial decision-making requires a balanced framework where technological predictive capabilities are strictly coupled with human contextual interpretation, explainable risk models and robust information infrastructures.

4.5 Leadership Transformation

Perhaps the most significant finding concerns the transformation of managerial roles. Across all interviews, participants described a profound shift in the competencies and responsibilities expected from future investment leaders.

Traditional managerial identities centred on planning, budgeting, analysis, reporting and control appear to be gradually losing prominence. Respondents repeatedly suggested that AI systems will increasingly assume responsibility for analytical and computational activities previously performed by managers.

At the same time, entirely new competencies are gaining importance. Data literacy emerged as one of the most frequently mentioned capabilities. Managers emphasized that future leaders do not necessarily need to become data scientists, but they must understand analytical logic, question assumptions, recognise misleading conclusions and interpret algorithmic outputs critically.

Adaptability and learning agility were also identified as crucial future competencies. Participants argued that managers must continuously revise assumptions, abandon obsolete practices and integrate emerging technologies into decision-making processes.

Critical thinking and constructive scepticism appeared repeatedly throughout the interviews. Respondents emphasized that effective leaders will need to challenge algorithmic recommendations, identify blind spots and recognise situations where human judgement should override machine-generated outputs.

Table 2
Main Conclusions Emerging from the Interviews

Conclusion	Evidence from the Interviews
Investment management is shifting from planning to adaptation	Continuous budgeting, KPI-based reallocation, real-time monitoring
Data quality is becoming more important than algorithm sophistication	Data fragmentation was mentioned more frequently than AI limitations
The future is neither human-centered nor machine-centered	Managers repeatedly described hybrid decision environments
Trust and explainability are prerequisites for AI adoption	Black-box concerns appeared across industries
Leadership is transforming rather than disappearing	Managers expect to become strategic interpreters and sensemakers
Decision effectiveness increasingly depends on learning capability	Continuous feedback and rapid recalibration emerged as recurring themes
Competitive advantage stems from intelligence orchestration rather than capital allocation alone	Human judgment, analytics and organizational learning increasingly function as an integrated system

Many managers further emphasized the importance of cross-functional collaboration. Future leaders are expected to act as integrators connecting finance, technology, operations, strategy, legal compliance and sustainability functions.

Ethical awareness emerged as another increasingly important capability. Participants frequently highlighted the growing need to evaluate investments not only through financial metrics but also through broader considerations involving privacy, regulation, sustainability and stakeholder impacts.

The future-oriented interviews revealed a strikingly coherent vision of investment organisations in 2035. Respondents imagined flatter organisational structures, decentralised decision authority, continuous budgeting systems, AI-integrated governance processes, automated compliance mechanisms and highly adaptive resource allocation models.

Within this environment, the managerial role shifts fundamentally. Rather than calculating optimal investment decisions, leaders increasingly become interpreters, architects of organisational learning, facilitators of collective intelligence and evaluators of strategic alternatives generated through human-AI collaboration.

Taken together, the findings indicate that the most significant consequence of AI adoption may not be technological but managerial. Investment management is evolving from an activity focused primarily on allocating capital toward a process centred on coordinating intelligence, interpreting complexity (Table 2.) and continuously adapting organisational decision systems. This shift represents a profound

transformation in both the practice of investment management and the nature of managerial leadership itself.

5. Cybernetic Middle Management Decision Model (CMMDM)

Based on the empirical findings and the principles of cybernetic leadership, this study proposes the Cybernetic Middle Management Decision Model (CMMDM) as a practical solution framework for improving investment decision effectiveness in AI-enabled organizational environments.

Table 3
Detailed Empirical Synthesis: How the Findings Lead to the CMMDM Model

Finding Typology	Findings in Details	How & Why?	CMMDM Component
Decision Support	Increasing use of AI, predictive analytics, simulations, dashboards and data-driven evaluation tools	Growing environmental complexity exceeds individual cognitive processing capacity. Managers increasingly rely on AI to collect, process and synthesize information before decisions are made.	Intelligence Acquisition
Information Overload	Continuous growth of available data sources and performance indicators	More data does not automatically create better decisions. The critical challenge shifts from information access to information selection and relevance identification.	Intelligence Acquisition
Human–AI Collaboration	Managers consistently reject both purely human and fully automated decision-making	AI improves analytical capability, but contextual interpretation, ethical reasoning and accountability remain human responsibilities.	Contextual Interpretation
Strategic Uncertainty	AI performs well in stable situations but struggles with unprecedented events, market disruptions and geopolitical uncertainty	Historical data cannot fully explain novel situations. Human experience and judgement become increasingly important when ambiguity increases.	Contextual Interpretation
Adaptive Capital Allocation	Shift from annual budgeting toward continuous allocation, milestone funding and iterative investments	Rapid environmental change reduces the effectiveness of fixed long-term commitments. Organizations require flexibility to reallocate resources dynamically.	Adaptive Decision Commitment
Shorter ROI Expectations	Organizations increasingly expect visible value creation within 12–18 months	Managers are pressured to validate assumptions earlier and reduce uncertainty through phased investment approaches.	Adaptive Decision Commitment
Decision Speed Acceleration	AI-supported simulations, real-time dashboards and automated reporting reduce evaluation time	Markets evolve faster than traditional planning cycles. Faster decisions become possible when governance mechanisms are embedded into decision systems.	Adaptive Decision Commitment

Finding Typology	Findings in Details	How & Why?	CMMDM Component
Decision Velocity Governance	Stage-Gate systems, predefined risk thresholds and conditional approvals become widespread	Organizations seek to increase decision speed without sacrificing control, accountability, or analytical rigor.	Adaptive Decision Commitment
Data Quality Constraints	Fragmented databases and inconsistent information are identified as major obstacles	Investment effectiveness increasingly depends on data quality rather than analytical sophistication. Poor-quality data undermines AI performance.	Intelligence Acquisition
Trust and Explainability Issues	Managers frequently describe AI systems as black boxes	Lack of transparency reduces trust and organizational acceptance. Explainability becomes a prerequisite for responsible adoption.	System-Wide Enabling Conditions
Accountability Concerns	Uncertainty about who is responsible for AI-supported decisions	Decision authority remains human even when analytical support is automated. Effective governance requires clear ownership and responsibility.	System-Wide Enabling Conditions
Organizational Learning	Continuous monitoring through KPIs, dashboards and feedback mechanisms	Organizations increasingly learn through rapid experimentation, performance evaluation and iterative adjustment.	Recursive Learning Feedback
Dynamic Adaptation	Investment priorities are continuously reviewed and adjusted	Effective organizations behave as adaptive systems that learn from outcomes rather than relying solely on forecasts.	Recursive Learning Feedback
Leadership Transformation	Managers evolve from analysts and controllers to interpreters, facilitators and orchestrators	Analytical tasks become increasingly automated, while value creation shifts toward interpretation, strategic judgement and coordination.	Contextual Interpretation & Recursive Learning Feedback
Future Organizational Vision	Decentralized structures, AI-supported governance, continuous budgeting and distributed intelligence	Competitive advantage increasingly depends on learning speed, adaptability and the integration of human and artificial intelligence.	Entire CMMDM Cycle

The analysis of the 42 semi-structured interviews (Table 3.) suggests that future managerial effectiveness is not determined by a single decision event but by the ability to continuously move through four interconnected activities:

Acquire Intelligence → Interpret Context → Commit Adaptively → Learn Recursively

The CMMDM therefore reframes investment decision-making from a linear planning activity into a cybernetic learning cycle in which data, human judgement, adaptation and feedback continuously interact to improve decision quality and organizational responsiveness.

Unlike traditional decision models that focus on a single decision event, the CMMDM conceptualizes decision-making as a continuous cybernetic process. The model assumes that effective managerial decisions emerge through successive cycles of intelligence acquisition, contextual interpretation, adaptive commitment and recursive learning.

The first phase, Intelligence Acquisition, focuses on sensing the environment through data collection, analytics, simulations and predictive insights. The objective is not merely to gather information, but to develop a comprehensive understanding of emerging opportunities and risks.

The second phase, Contextual Interpretation, represents the uniquely human element of the process. At this stage, managers evaluate analytical outputs within their strategic, organizational, market and stakeholder contexts. The purpose of this phase is to transform information into actionable meaning.

The third phase, Adaptive Decision Commitment, replaces traditional one-time decision making with an iterative commitment approach. Managers allocate resources, initiate experiments, establish milestones and continuously adjust investment intensity according to evolving circumstances.

The fourth phase, Recursive Learning Feedback, transforms every decision into a learning opportunity. Outcomes are monitored, assumptions are evaluated, lessons are extracted and future decision parameters are recalibrated. The feedback generated in this phase initiates a new cycle of intelligence acquisition, creating a continuous learning system.

Table 4
High-Level Model Mapping

Findings Theme	CMMDM Component
Data-driven decision support	Intelligence Acquisition
Context-sensitive managerial judgment	Contextual Interpretation
Agile capital allocation and staged investment	Adaptive Decision Commitment
KPI monitoring and organizational learning	Recursive Learning Feedback
Trust, explainability, accountability	System-wide enabling conditions

The model proposes that decision effectiveness no longer depends primarily on analytical precision or managerial intuition alone. Instead, effectiveness emerges from the organization's ability to maintain a continuous cycle of sensing, meaning-making, acting and learning.

In practice, the CMMDM enables organizations to move beyond static investment planning toward adaptive decision systems capable of responding to uncertainty, technological disruption and changing

market conditions.

Three enabling conditions support the successful operation of the model:

- Data Quality
- Trust
- Explainability

These factors function as systemic prerequisites influencing all four phases of the decision cycle (Fig. 2.).

The central proposition of the model is that future middle-management decision effectiveness is determined by the capability to continuously integrate AI-generated intelligence, human interpretation, adaptive action and organizational learning within a trusted decision environment.

Effective future decisions are not the result of choosing correctly once, but of continuously sensing, interpreting, adapting and learning faster than environmental conditions change.

6. Conclusion

The emergence of generative AI extends the role of artificial intelligence beyond prediction and classification toward content generation, scenario construction, synthetic data creation and decision augmentation. Within investment management, these capabilities have the potential to influence capital allocation, risk assessment, strategic forecasting and organizational decision-making. At the same time, increasing reliance on AI-generated outputs raises important governance questions related to explainability, accountability, systemic risk and organizational resilience.

This study explored how middle managers perceive the ongoing transformation of investment management within increasingly digital and AI-enabled organizational environments. Based on 42 semi-structured interviews, the findings reveal that investment management is entering a fundamentally new phase characterized by adaptive decision-making, distributed intelligence, continuous capital allocation and growing collaboration between human and artificial intelligence.

Five interconnected transformation domains emerged from the analysis: Augmented Decision Intelligence, Adaptive Capital Allocation, Decision Velocity Governance, Trust and Explainability and Leadership Transformation. Collectively, these dimensions suggest that investment management is no longer primarily concerned with allocating financial resources according to predefined plans. Instead, it is becoming a continuous process of interpreting information, evaluating alternatives, managing uncertainty and dynamically reallocating resources in response to changing environmental conditions.

The proposed Cybernetic Middle Management Decision Model (CMMDM) integrates these developments into a coherent conceptual framework. The framework demonstrates how data quality, AI-driven analytics, human judgment and continuous feedback mechanisms jointly create adaptive

investment ecosystems. At the same time, trust, explainability and ethical accountability function as critical governance dimensions that determine whether technological capability can be translated into sustainable organizational value.

A particularly important finding concerns the changing nature of managerial work. Rather than replacing managers, artificial intelligence appears to be redefining managerial responsibilities. As computational and analytical activities become increasingly automated, managers are expected to assume new roles as strategic interpreters, ethical evaluators, sensemakers and coordinators of distributed intelligence. The future investment leader is less likely to be a controller of decisions and more likely to become an architect of decision environments.

The findings further indicate that future investment organizations will be more decentralized, more adaptive and more data-intensive than their predecessors. Continuous budgeting, real-time performance monitoring, AI-assisted governance and dynamic resource allocation are likely to replace many of the assumptions that have traditionally defined investment management. However, increased technological sophistication does not diminish the importance of human judgment. On the contrary, the greater the analytical capabilities of organizational systems become, the more valuable the uniquely human capacities for contextual interpretation, ethical reasoning and strategic foresight appear.

Research Questions Revisited

RQ1

The findings indicate that finance middle managers increasingly rely on AI-supported analytics while retaining responsibility for contextual interpretation, ethical evaluation and final decision authority. The dominant approach in financial investment decisions is therefore not automation but human-in-the-loop decision-making.

RQ2

The results reveal a transition from periodic corporate investment planning toward adaptive capital allocation systems within the financial sector, characterized by continuous monitoring, staged investments, milestone-based funding, and dynamic resource reallocation.

RQ3: Participants envision AI as an embedded decision partner rather than a substitute for financial leadership. By 2035, AI is expected to play a central role in financial analytics, forecasting, risk assessment and decision support, while finance managers increasingly focus on interpretation, coordination, learning and strategic sensemaking.

Together, the answers to the three research questions support the central proposition of this study: future financial investment decision effectiveness depends on the continuous integration of artificial intelligence, human judgment, adaptive capital allocation and recursive organizational learning within a cybernetic decision system.

From a broader perspective, the results suggest that investment management is evolving from a discipline focused on capital allocation into one centred on intelligence orchestration. Competitive advantage will increasingly depend not on the ability to predict the future with greater accuracy, but on the ability to continuously learn, adapt and reconfigure decisions as conditions change.

Ultimately, the future of investment management is neither human-centered nor machine-centered. It is characterized by adaptive human-in-the-loop systems in which data, algorithms, managerial judgment and organizational learning interact continuously to generate resilient and informed investment decisions.

The future belongs not to organizations that allocate capital most efficiently, but to those that learn most effectively, adapt most rapidly and integrate human and artificial intelligence into a coherent system of continuous value creation.

Declarations

Participant Consent Statement: Informed consent was obtained from all individual participants included in this study. Participation was voluntary, respondents agreed to the use of their anonymized interview data for research purposes, and no personally identifiable information was collected or reported.

Author Contribution

V.A. conceptualized the study, designed the research framework, collected and analyzed the data, interpreted the findings, prepared the manuscript, and approved the final version for publication.

Data Availability

The data that support the findings of this study are not publicly available because they contain information that could compromise the anonymity of research participants. Aggregated results are presented within the manuscript.

References

1. Annarelli, A., Battistella, C., & Nonino, F. (2021). Competitive advantage implication of different product service system business models: Consequences of non-replicable capabilities. *Journal of Cleaner Production*.
2. Avolio, B. J., Walumbwa, F. O., & Weber, T. J. (2008). Leadership: Current theories, research, and future directions. *Annual Review of Psychology*, 60, 421–449.
3. Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, 3(2), 77–101.

4. Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. W. W. Norton.
5. Bowman, E. H., & Hurry, D. (1993). Strategy through the option lens: An integrated view of resource investments and the incremental-choice process. *Academy of Management Review*, 18(4), 760–782.
6. Davenport, T. H., & Harris, J. G. (2007). *Competing on analytics: The new science of winning*. Harvard Business School Press.
7. Dwivedi, Y. K., Hughes, L., Ismagilova, E., et al. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, 57, 101994.
8. Iñigo, E. A., & Albareda, L. (2019). Sustainability oriented innovation dynamics: Levels of dynamic capabilities and their path-dependent and self-reinforcing logics. *Technological Forecasting and Social Change*, 139, 334–351.
9. Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons*, 61(4), 577–586.
10. Kahneman, D. (2011). *Thinking, fast and slow*. Farrar, Straus and Giroux.
11. Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, 47(2), 263–291.
12. Martín-Rojas, R., Garrido-Moreno, A., & García-Morales, V. J. (2023). Transforming organizations through digital capabilities and organizational learning. *Technological Forecasting and Social Change*, 188, 122459.
13. March, J. G. (1991). Exploration and exploitation in organizational learning. *Organization Science*, 2(1), 71–87.
14. McGrath, R. G. (1997). A real options logic for initiating technology positioning investments. *Academy of Management Review*, 22(4), 974–996.
15. Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation-augmentation paradox. *Academy of Management Review*, 46(1), 192–210.
16. Shrestha, Y. R., Ben-Menahem, S. M., & von Krogh, G. (2019). Organizational decision-making structures in the age of artificial intelligence. *California Management Review*, 61(4), 66–83.
17. Simon, H. A. (1957). *Administrative behavior: A study of decision-making processes in administrative organizations* (2nd ed.). Macmillan.
18. Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of sustainable enterprise performance. *Strategic Management Journal*, 28(13), 1319–1350.
19. Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, 18(7), 509–533.
20. Trigeorgis, L. (1996). *Real options: Managerial flexibility and strategy in resource allocation*. MIT Press.

21. Veitas, V., & Weinbaum, D. (2015). A cybernetic perspective on resilient and adaptive organizations. *Kybernetes*, 44(1), 23–46.
22. Weiser, A. K., Jarzabkowski, P., & Laamanen, T. (2020). Completing the adaptive strategy cycle. *Long Range Planning*, 53(4), 101887.
23. Wilson, H. J., & Daugherty, P. R. (2018). Collaborative intelligence: Humans and AI are joining forces. *Harvard Business Review*, 96(4), 114–123.

Figures

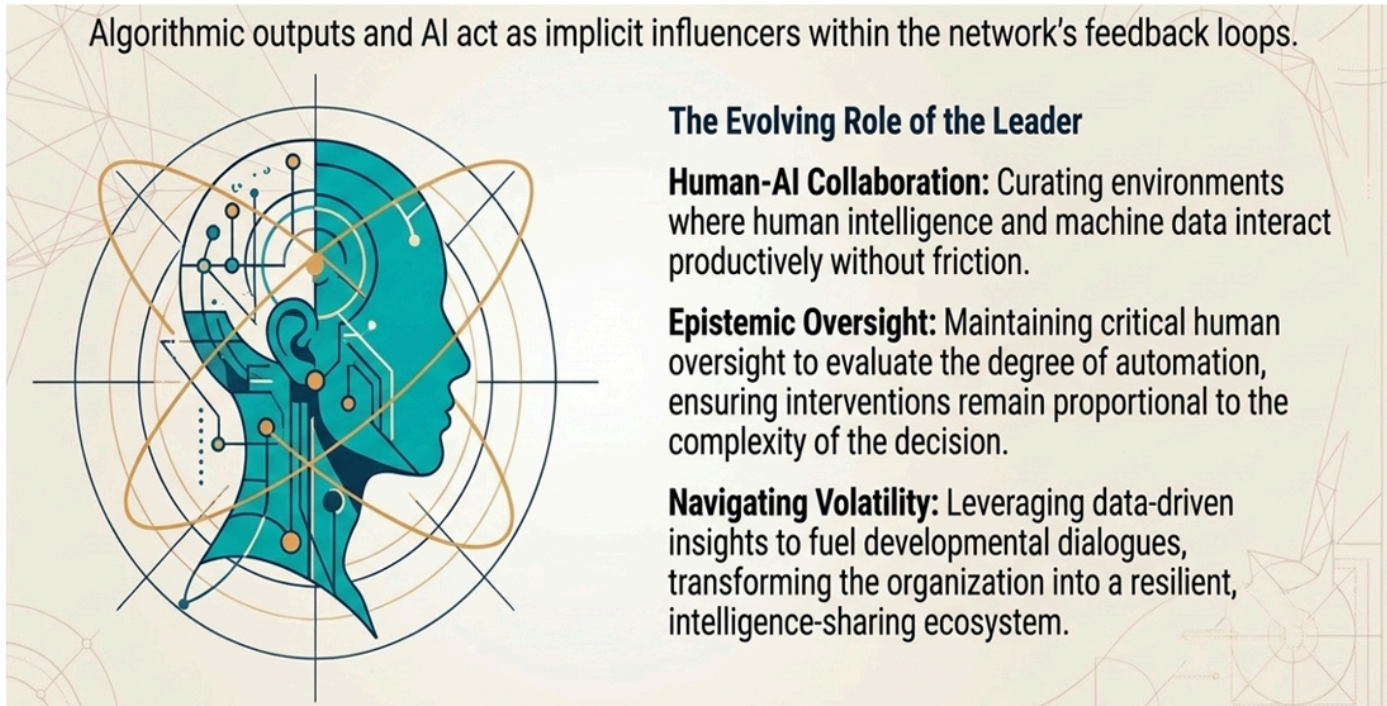


Figure 1

The Future Horizon: Leadership in Socio-Technical Systems

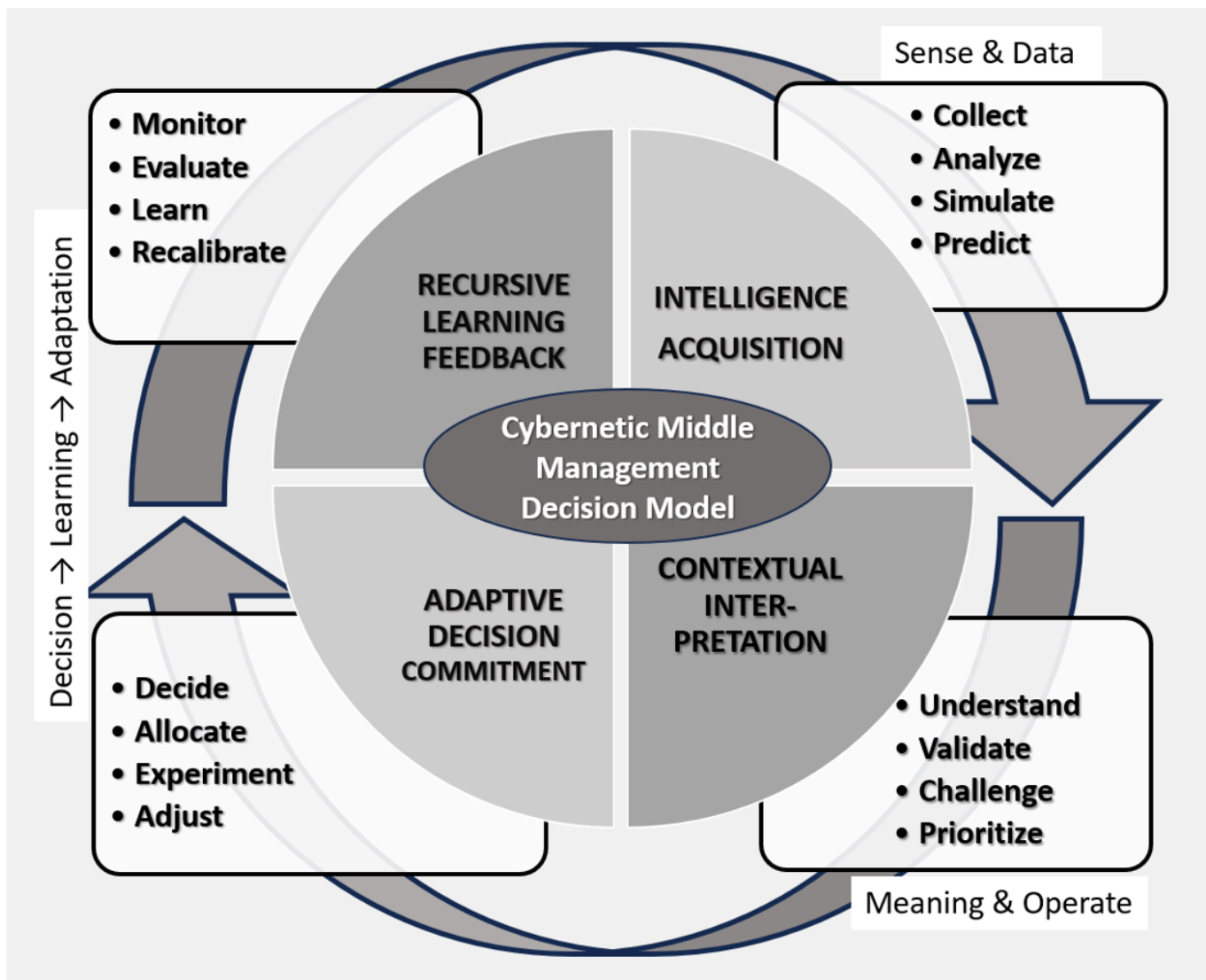


Figure 2

The Cybernetic Middle Management Decision Model (CMMDM)