INTEGRATING RECOMMENDER SYSTEMS INTO THE STRATEGIC DECISION ARCHITECTURE OF ORGANIZATIONS: A MANAGERIAL PERSPECTIVE ON E-COMMERCE

Bucur Milancovici[*1], Suzana Monica Veress[2], Raluca Simina Bilți[3]
[1)2)3)] *"Aurel Vlaicu" University of Arad, Arad, Romania.*

Abstract
This paper examines the strategic integration of recommender systems within organizational decision-making architectures, with a focus on managerial implications in the e-commerce sector. Anchored in strategic management theory, the study conceptualizes recommender systems as components of organizational intelligence that shape managerial cognition, resource allocation, and long-term competitive positioning. Drawing on established analytical frameworks—including SWOT analysis, Porter's Five Forces, and the Resource-Based View (RBV)—the paper identifies the strategic determinants that condition the adoption and optimization of recommender systems. The analysis develops an integrative conceptual framework linking algorithmic capabilities to strategic choices, competitive dynamics, and value creation. Emphasis is placed on governance mechanisms, ethical alignment, and data-driven leadership as prerequisites for sustainable competitive advantage. By repositioning recommender systems from operational tools to strategic infrastructures, the study contributes to strategic management research on digital transformation and algorithmic decision support.

Keywords
Strategic management; recommender systems; managerial decision-making; e-commerce; organizational intelligence; digital strategy; competitive advantage

JEL Classification
M10, M15, M31, L81

Introduction

The growing ubiquity of data-driven decision-making has reshaped strategic management in contemporary organizations. Within this context, algorithmic recommender systems (RS) have evolved beyond their initial role as operational personalization tools, becoming increasingly embedded in managerial processes that shape competition, resource

[*] Corresponding author, **Bucur Milancovici** – bucur.milancovici@gmail.com

allocation, and long-term positioning in e-commerce. By leveraging advanced data analytics, machine learning, and behavioral modeling, RS enable firms to anticipate consumer preferences, reduce informational complexity, and support adaptive strategic responses in highly dynamic digital markets. As such, recommender systems increasingly function as components of organizational intelligence, translating large-scale data into insights that inform managerial cognition and strategic choice.

1. Review of the scientific literature

Strategic Decision-Making and Organizational Cognition

Strategic decision-making has traditionally been examined through theoretical lenses that emphasize the cognitive limits of managers and the interpretive nature of organizational action. The concept of bounded rationality (Simon, 1979) highlights that decision-makers operate under constraints of limited information, time, and processing capacity, often relying on satisficing rather than optimizing strategies. Complementarily, sense-making theory (Weick, 1995) conceptualizes strategy as a continuous interpretive process through which managers construct meaning in complex and uncertain environments.

In the digital economy, these frameworks acquire renewed relevance. While algorithmic systems dramatically expand the volume and granularity of available information, they also introduce new forms of informational asymmetry (Akerlof, 1970). Managers may gain access to extensive data streams generated by recommender systems, yet lack the analytical capacity to fully interpret their strategic implications. As a result, managerial cognition remains a critical mediating layer between algorithmic output and strategic intent.

Recommender systems thus function as cognitive amplifiers rather than substitutes for managerial judgment. They can mitigate certain biases by grounding decisions in empirical patterns, while simultaneously introducing new risks related to algorithmic opacity, overreliance on automated outputs, and misinterpretation of probabilistic recommendations. Consequently, the strategic value of algorithmic decision support depends not only on technical accuracy but also on how managerial actors integrate algorithmic insights into sense-making and strategic reasoning processes.

Recommender Systems as Strategic Assets

Recommender systems (RS) constitute a class of machine learning technologies designed to filter information and generate personalized suggestions based on user behavior and item characteristics. From a technical standpoint, RS are commonly categorized into content-based, collaborative filtering, and hybrid models, each offering distinct advantages in terms of accuracy, scalability, and adaptability (Burke, 2002; Ricci et al., 2021).

From a strategic management perspective, RS have evolved beyond marketing automation tools into strategic assets embedded within the firm's knowledge infrastructure. Drawing on the Resource-Based View (RBV) (Barney, 1991), recommender systems can represent *valuable, rare, inimitable, and non-substitutable* (VRIN) assets when they leverage proprietary data, advanced algorithms, and continuous learning mechanisms aligned with organizational objectives. They generate sustained competitive advantage through proprietary data accumulation, algorithmic sophistication, and continuous learning loops.

Within the Dynamic Capabilities Framework (Teece et al., 1997), RS enhance a firm's ability to sense market signals, seize opportunities through adaptive recommendations, and reconfigure operations in response to changing environments. Positioned across the value chain, recommender systems influence not only customer-facing activities but also forecasting, inventory management, and innovation processes. As such, they act as a critical interface between data analytics and strategic management, supporting both operational agility and long-term strategic foresight.

Strategic Determinants of Recommender System Adoption

Although the technological foundations of recommender systems are well established, their effective adoption and optimization depend primarily on strategic and organizational determinants. Research on technology adoption and strategic alignment (Tornatzky & Fleischer, 1990; Henderson & Venkatraman, 1993) emphasizes that technological success results from the alignment between technical capabilities and managerial readiness.

Synthesizing this literature, seven interrelated determinants emerge as central to the strategic integration of recommender systems:

1. Leadership and Strategic Vision – Top management commitment is essential for embedding recommender systems within corporate strategy and allocating resources accordingly.
2. Organizational Culture – Cultures that value experimentation and data-driven decision-making facilitate the internal diffusion and acceptance of algorithmic support.
3. Data Governance and Infrastructure – Reliable, interoperable, and ethically managed data infrastructures are prerequisites for strategic reliability and trust in RS outputs.
4. Human Capital and Analytical Capabilities – Analytical literacy enables managers to translate algorithmic outputs into actionable strategic insights.
5. Customer-Centric Orientation – Strategic alignment between personalization objectives, customer value creation, and privacy considerations enhances long-term effectiveness.
6. Resource Allocation and Investment Logic – Sustainable deployment requires strategic evaluation of costs, benefits, and return on investment.
7. Regulatory and Ethical Alignment – Compliance with legal and ethical standards (e.g., transparency, data protection) constitutes a strategic condition rather than a mere compliance requirement.

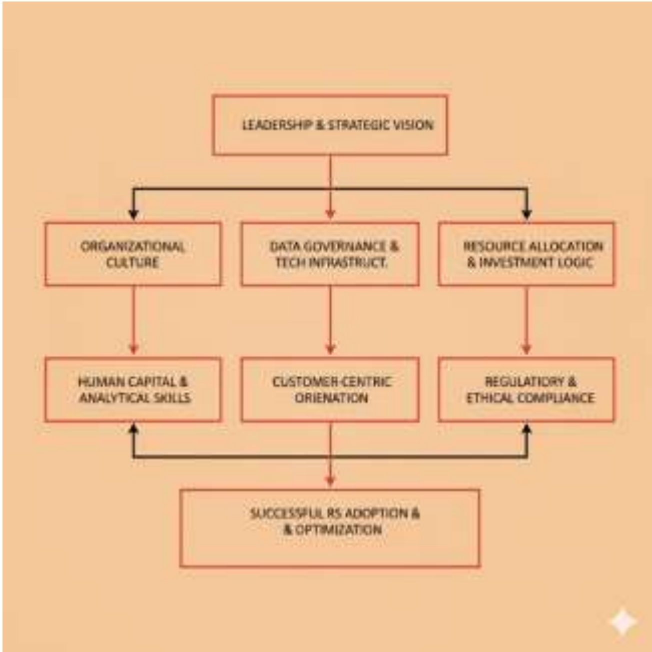

Figure no. 1. Interrelated determinants
Source: Authors' own research

Collectively, these determinants define an organization's **strategic readiness** to transform recommender systems from isolated technological applications into integral components of strategic intelligence. The interaction between leadership, culture, and governance ultimately determines whether recommender systems generate sustained competitive advantage or remain underutilized technological artefacts.

2. Research methodology

Problem Statement

Despite their demonstrated potential to enhance customer engagement, operational efficiency, and competitive differentiation, the strategic integration of recommender systems remains uneven across organizations. Prior research indicates that differences in RS adoption cannot be explained solely by technological capability. Rather, they reflect variation in managerial orientation, organizational governance, decision-making practices, and ethical alignment. In many firms, RS remain confined to tactical marketing applications, while in others, they are embedded within broader decision architectures and strategic foresight processes. This heterogeneity highlights a critical gap in understanding the strategic determinants that enable some organizations to leverage recommender systems as sources of sustainable advantage, while others fail to realize their transformative potential.

Purpose and Research Objective

The purpose of this study is to **identify and systematize the strategic determinants** that influence the adoption and optimization of recommender systems within organizational decision-making. Building on a strategy-oriented perspective, the study conceptualizes these determinants across four interrelated dimensions:

- **Organizational**, encompassing structure, leadership commitment, and governance arrangements supporting algorithmic decision-making;
- **Technological**, referring to data infrastructure, system interoperability, and scalability;
- **Decision-making**, capturing managerial cognition, analytical capabilities, and the integration of algorithmic insights into strategic formulation;
- **Cultural**, including openness to innovation, risk tolerance, and the institutionalization of data-driven thinking.

By examining the interaction among these dimensions, the article advances a **conceptual framework** that clarifies how recommender systems transition from operational tools to integral elements of competitive strategy.

Research Design

This study adopts a **conceptual–exploratory research design**, aimed at developing a theoretically grounded and managerially relevant framework for understanding the strategic determinants that shape the adoption and optimization of recommender systems (RS). The conceptual component synthesizes insights from strategic management, information systems, and artificial intelligence research (Barney, 1991; Porter, 1996; Davenport & Ronanki, 2018), while the exploratory component situates the proposed framework within contemporary e-commerce contexts (2020–2025).

This dual orientation enables the study to bridge abstract strategic theory and organizational practice, consistent with theory-building approaches that emphasize the interaction between conceptual reasoning and contextual observation (Eisenhardt, 1989).

Methodological Approach

The methodological approach combines **qualitative triangulation** and **comparative analysis** to enhance interpretive depth and analytical robustness.

Qualitative triangulation integrates evidence from academic literature, managerial discourse, and corporate documentation, allowing cross-validation of strategic patterns related to RS adoption (Denzin, 1978).

Comparative intersectoral analysis is employed to examine variations across major e-commerce sub-sectors (e.g., retail, digital marketplaces, fashion, consumer electronics), highlighting differences in leadership orientation, data governance, and cultural readiness (Yin, 2018).

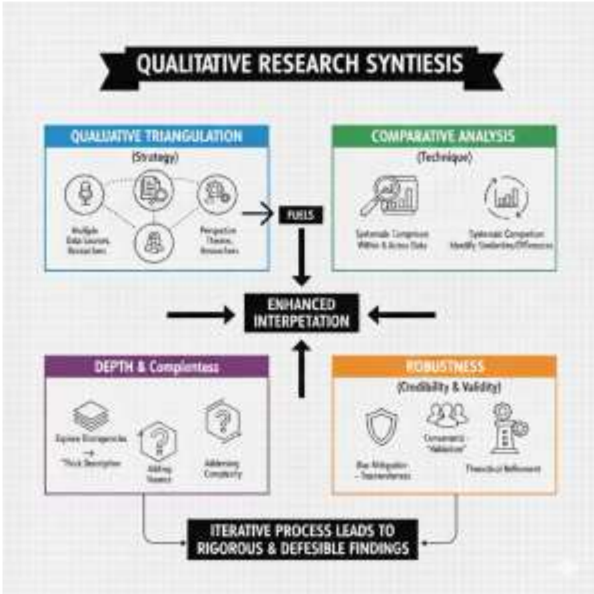

Figure no. 2. Qualitative research syntesis
Source: Authors' own research

Together, these methods enhance analytical generalizability by identifying recurrent strategic configurations rather than statistically representative patterns.

Analytical Framework and Instruments

The core analytical instrument is the **Strategic Determinants Model (SDM)**, a conceptual framework integrating the **Resource-Based View (RBV)** (Barney, 1991) and **Strategic Alignment Theory** (Henderson & Venkatraman, 1993). The SDM identifies seven interrelated dimensions—leadership, organizational culture, data governance, human capital, customer orientation, resource allocation, and ethical compliance—that collectively condition the strategic maturity of RS deployment. Each dimension functions simultaneously as an **enabler and a constraint**, shaping the extent to which RS contribute to strategic decision-making.

To contextualize these determinants, the study employs **SWOT analysis** to assess internal and external conditions influencing RS implementation, and **RBV logic** to evaluate RS as firm-specific strategic assets that may satisfy VRIN criteria when effectively aligned with organizational objectives (Grant, 1996). This combination allows for a structured assessment of how technological capabilities translate into sustained competitive advantage.

Validation Strategy and Data Scope

Empirical grounding is established through **triangulated validation** across three complementary sources:

- **Literature-based evidence**, drawing on peer-reviewed research on recommender systems, AI strategy, and decision support (Ricci et al., 2021; Haenlein & Kaplan, 2020);
- **Managerial perspectives**, synthesized from executive interviews and practitioner reports published by leading consultancies and business outlets (e.g., McKinsey, Deloitte, Harvard Business Review);
- **Sector-level evidence**, based on publicly available data from European e-commerce firms (2020–2025) concerning personalization intensity, conversion outcomes, and algorithmic return on investment.

The analytical focus is placed on **European e-commerce organizations** operating under advanced data governance regimes, allowing observation of RS diffusion during a period of accelerated digital transformation and regulatory consolidation (GDPR).

Analytical Criteria

Evaluation of RS integration is guided by five analytical criteria:

1. **Digital Maturity** – the degree to which RS are embedded within technological and decision-making architectures;
2. **Decision Culture** – managerial reliance on data-driven versus intuition-based reasoning;
3. **Algorithmic Performance** – efficiency indicators such as accuracy, click-through rates, and conversion effects;
4. **Strategic Integration** – alignment between RS outputs and long-term strategic objectives;
5. **Governance and Ethics** – compliance with data protection, transparency, and accountability standards.

These criteria operationalize the SDM dimensions and enable systematic cross-case comparison.

Methodological Coherence

Overall, the methodology reflects an **abductive research logic** (Dubois & Gadde, 2002), combining conceptual model development with contextual validation. By integrating strategic theory (RBV, alignment frameworks), analytical tools (SWOT, SDM), and exploratory evidence from European e-commerce contexts, the study ensures methodological coherence, **analytical transparency, and managerial relevance**. This approach strengthens the contribution of the paper to understanding how recommender systems evolve from technical applications into strategic components of organizational intelligence.

3. Results and Discussion

Determinants Influencing Adoption

The findings indicate that innovation-oriented leadership is the most significant determinant of recommender system (RS) adoption. Organizations whose top management demonstrates a proactive commitment to digital transformation tend to integrate RS earlier and more effectively. This supports the view of Teece et al. (1997) that *dynamic managerial capabilities*—the ability to sense opportunities and reconfigure resources—drive technological assimilation. Leaders who articulate a coherent AI vision and align it with the firm's strategic objectives create organizational legitimacy and resource support for RS deployment.

Organizational culture and **IT infrastructure maturity** further determine the depth and sustainability of adoption. Firms characterized by openness to experimentation and learning—attributes of an *ambidextrous organization* (O'Reilly & Tushman, 2013)—display higher algorithmic utilization rates. These organizations tolerate risk, encourage cross-functional collaboration, and embed algorithmic experimentation within their decision processes. In contrast, firms with rigid hierarchies or siloed data environments experience resistance, leading to partial or symbolic adoption.

Finally, **data quality** and **internal analytical competencies** act as *core enablers* of adoption. High-quality, integrated datasets allow for the training of accurate recommendation models, while teams with advanced analytical literacy transform algorithmic output into actionable strategic insight. This aligns with Davenport and Ronanki's (2018) observation that the real differentiator in AI adoption is not technology per se but the firm's ability to operationalize data-driven learning. Collectively, these determinants confirm that successful RS adoption is as much a managerial and organizational process as it is a technological one.

Determinants Influencing Optimization

Once adopted, the **optimization** of recommender systems depends primarily on the organization's capacity to establish an effective **managerial feedback loop** between decision-makers and algorithmic performance metrics. Firms that institutionalize a structured review of RS outcomes—tracking accuracy, diversity, and conversion rates—achieve more consistent improvements in recommendation quality. This process mirrors the *learning loop* central to Argyris and Schön's (1978) theory of organizational learning, wherein continuous feedback refines both technological parameters and strategic decision logic.

Integration with **Business Intelligence (BI)** systems amplifies optimization effects by embedding RS analytics within broader performance dashboards. When recommendation data are aggregated with operational, financial, and customer metrics, managers gain a holistic view of strategic performance. Such integration enhances **resource efficiency**, allowing firms to adjust marketing investments, inventory levels, and pricing strategies based on real-time behavioral data. The result is an adaptive enterprise capable of aligning micro-level recommendation feedback with macro-level business goals.

Moreover, optimization is markedly higher when recommender systems are conceptualized as part of the **strategic decision architecture** rather than isolated marketing tools. Organizations that treat RS as integral to enterprise planning—linking them to product development, supply chain management, and R&D—achieve stronger synergies across functions. This supports Porter's (1996) argument that competitive advantage arises not from individual technologies but from the fit among interdependent activities. Thus, the highest-performing firms embed RS deeply into their decision infrastructures, transforming them from operational utilities into strategic intelligence systems.

Strategic Outcomes

The strategic consequences of integrating and optimizing recommender systems are evident in how they **reshape planning, segmentation, and innovation processes**. By translating large-scale behavioral data into predictive insights, RS enhance the precision of strategic planning. They enable granular market segmentation based on customer lifetime value, purchase propensities, and psychographic variables, thereby increasing the relevance of strategic choices. As a result, product and service innovation becomes more evidence-driven, guided by customer preference signals rather than managerial intuition alone.

A notable finding concerns the **strategic reconfiguration** of organizational orientation. Firms progress through an evolutionary trajectory from **product-centric** to **customer-centric**, and ultimately to **data-centric** models. This transformation corresponds to the shift described by McAfee and Brynjolfsson (2012), where data becomes the primary driver of competitive strategy. The data-centric firm no longer reacts to customer needs but anticipates them, using RS as the connective tissue between consumer behavior, operational processes, and corporate vision.

Finally, managers increasingly leverage **RS-derived insights** for **strategic positioning and diversification decisions**. Recommender data reveal latent demand clusters, adjacent market opportunities, and underexplored customer segments. In this capacity, RS functions as *strategic sensors*—detecting weak signals and emergent trends that inform long-term positioning. This expands the scope of managerial decision-making from reactive market analysis to predictive and proactive strategy formulation.

Overall, the results demonstrate that the integration of recommender systems reshapes the strategic fabric of organizations. Adoption success depends on leadership and cultural enablers, optimization on feedback and structural integration, and strategic outcomes on the organization's ability to transform data-driven insights into competitive foresight.

Managerial Implications

The findings of this study emphasize that the integration of recommender systems (RS) within organizational strategy is not merely a technological upgrade but a **transformational process** that redefines leadership practices, decision-making structures, and data governance models. The managerial implications derived from this analysis address two critical phases of the RS lifecycle: *adoption* and *optimization*. Each phase requires a distinct yet complementary set of managerial interventions designed to align algorithmic capability with organizational intent.

Recommendations for Adoption

Effective adoption begins with a **strategic and cultural audit** that evaluates the organization's readiness for algorithmic decision-making. Managers should assess the degree to which their corporate culture supports experimentation, data transparency, and cross-functional collaboration. Firms with hierarchical, risk-averse cultures tend to exhibit symbolic adoption—implementing RS superficially without integrating them into strategic processes (O'Reilly & Tushman, 2013). In contrast, organizations that nurture a culture of learning and adaptability demonstrate higher absorption capacity and faster innovation cycles. Conducting a *cultural readiness audit* allows leadership teams to identify behavioral and structural barriers to AI adoption and to develop targeted interventions to overcome them.

A second priority is the formulation of a **comprehensive data strategy**. Recommender systems are only as effective as the data infrastructure supporting them; thus, firms must ensure the quality, governance, and interoperability of data sources. This entails establishing clear ownership protocols, data cleaning processes, and compliance mechanisms consistent with GDPR and ethical AI standards (Haenlein & Kaplan, 2020). A robust data strategy also includes investment in scalable cloud infrastructure and the creation of a centralized data warehouse accessible to both technical and managerial teams. Such integration fosters trust in algorithmic outputs and ensures that decision-makers operate on consistent and validated datasets.

Finally, successful adoption requires **analytical leadership**. Leaders must move beyond a supervisory relationship with data teams to become *data-literate strategists* capable of interpreting and challenging algorithmic results. This aligns with Davenport and Ronanki's (2018) concept of "augmented leadership," in which executives use AI not to replace human judgment but to expand their cognitive horizon. Leadership development programs emphasizing analytical reasoning, scenario modeling, and AI ethics can significantly enhance managerial confidence and reduce resistance to algorithmic decision support.

Recommendations for Optimization

Once recommender systems are operational, the focus must shift toward strategic optimization—ensuring that the technology continuously evolves in tandem with managerial learning and business objectives. The first step is to integrate RS-specific Key Performance Indicators (KPIs) into executive dashboards and performance scorecards. By embedding algorithmic metrics—such as recommendation accuracy, conversion uplift, or engagement rate—within the same reporting environment as financial and operational indicators, firms ensure that RS performance contributes directly to strategic evaluation. This integration facilitates transparency, accountability, and timely adjustments at the leadership level.

A second imperative is decision-oriented training. While data scientists and IT teams manage algorithmic functions, senior and mid-level managers must understand the strategic implications of RS outputs. Regular workshops, scenario simulations, and cross-functional meetings can bridge the cognitive gap between technical and strategic actors, fostering a shared language of data-driven management. Training should focus on interpretation skills rather than coding, emphasizing how algorithmic insights inform pricing strategies, market segmentation, and innovation initiatives.

Third, optimization requires a systematic feedback loop between RS analytics and managerial decision-making. Continuous improvement in recommender systems depends on iterative learning—where human input refines algorithmic models, and algorithmic outputs inform strategic review. Establishing structured communication channels between data teams and executive leadership ensures that performance gaps are detected early, model biases are corrected, and organizational learning is institutionalized. In effect, the RS becomes a dynamic part of the firm's "strategic nervous system," providing ongoing signals for adjustment and adaptation.

Strategic Benefits and Organizational Impact

When effectively adopted and optimized, recommender systems generate measurable strategic and cognitive benefits across the organization.

- Improved decision accuracy: RS provide high-resolution insights into customer behavior, market dynamics, and performance patterns, enabling managers to base strategic decisions on empirical evidence rather than intuition.
- Reduction of cognitive bias: Algorithmic mediation minimizes the influence of human biases—such as overconfidence, recency, or anchoring—thereby enhancing objectivity in managerial judgment (Kahneman, 2011).
- Resource efficiency: The integration of RS analytics with resource allocation models optimizes marketing spend, inventory turnover, and operational efficiency, producing superior return on investment.
- Enhanced strategic agility: Continuous feedback between algorithms and leadership accelerates the firm's capacity to sense environmental change and reconfigure its strategic posture accordingly (Teece, 2018).

Ultimately, the managerial implication is clear: the competitive advantage of recommender systems derives not from the sophistication of the algorithms themselves but from the organization's ability to integrate them into its strategic, cultural, and cognitive fabric. Firms that treat RS as catalysts of organizational learning—rather than as isolated digital tools—are better positioned to sustain long-term differentiation, customer trust, and strategic foresight.

Conclusions

Theoretical Contributions

This study contributes to strategic management and information systems research by articulating an integrated framework that explains how recommender systems (RS) are adopted and optimized as components of organizational decision-making. The main theoretical contribution consists of consolidating key strategic determinants—leadership, organizational culture, data governance, human capital, customer orientation, resource allocation, and ethical compliance—into a coherent explanatory model.

Grounded in the Resource-Based View (Barney, 1991) and Dynamic Capabilities Theory (Teece, 1997), the study conceptualizes RS as strategic resources whose value depends on their alignment with managerial cognition and organizational structures. By extending bounded rationality perspectives, the analysis shows that algorithmic decision support can enhance strategic judgment when embedded within appropriate governance and interpretive mechanisms. This integration extends Simon's (1979) bounded rationality model by showing that algorithms can both mitigate and amplify cognitive limitations, depending on how they are governed and contextualized within managerial structures.

By linking established strategic frameworks (e.g., SWOT, Porter's Five Forces) with algorithmic analytics, the paper bridges strategic decision theory and AI management, offering a unified perspective on how recommender systems evolve from technical tools into instruments of strategic intelligence in digital organizations.

Managerial Contributions

From a managerial perspective, the study provides a structured framework to support the strategic integration of recommender systems. The Strategic Determinants Model (SDM) offers guidance for assessing organizational readiness and for aligning algorithmic capabilities with long-term strategic objectives.

Key managerial implications include:

- the need to evaluate leadership commitment, cultural readiness, and data governance before large-scale RS deployment;
- the importance of governance mechanisms that ensure transparency, ethical alignment, and continuous feedback;
- the integration of RS outputs into business intelligence systems to support strategic planning;
- the development of analytical capabilities that enable managers to interpret and trust algorithmic insights.

Together, these implications translate AI adoption into a deliberate strategic process, enabling organizations to convert recommender systems into sources of sustained competitive advantage.

Future Research Directions

While the study offers a solid conceptual foundation, further research is required to enhance empirical robustness. Future studies should:

- empirically test the Strategic Determinants Model across sectors and over time;
- quantify the impact of recommender systems on strategic performance indicators such as profitability, customer lifetime value, and strategic agility;
- further investigate governance and ethical frameworks that support responsible and resilient use of recommender systems.

Advancing these research trajectories will help bridge the gap between conceptual frameworks and practical applications, ensuring that recommender systems continue to evolve as **integral components of strategic management, organizational intelligence, and ethical digital transformation**.

References

[1] Akerlof, G.A. (1970) ‘The market for “lemons”: quality uncertainty and the market mechanism’, *Quarterly Journal of Economics*, 84(3), pp. 488–500.

[2] Argyris, C. and Schön, D.A. (1978) *Organizational learning: a theory of action perspective*. Reading, MA: Addison-Wesley.

[3] Barney, J. (1991) ‘Firm resources and sustained competitive advantage’, *Journal of Management*, 17(1), pp. 99–120.

[4] Burke, R. (2002) ‘Hybrid recommender systems: survey and experiments’, *User Modeling and User-Adapted Interaction*, 12(4), pp. 331–370.

[5] Davenport, T.H. and Ronanki, R. (2018) ‘Artificial intelligence for the real world’, *Harvard Business Review*, 96(1), pp. 108–116.

[6] Denzin, N.K. (1978). *The research act: a theoretical introduction to sociological methods*. New York: McGraw-Hill.

[7] Dubois, A. and Gadde, L.-E. (2002) ‘Systematic combining: an abductive approach to case research’, *Journal of Business Research*, 55(7), pp. 553–560.
[8] Eisenhardt, K.M. (1989) ‘Building theories from case study research’, *Academy of Management Review*, 14(4), pp. 532–550.
[9] Grant, R.M. (1996) ‘Toward a knowledge-based theory of the firm’, *Strategic Management Journal*, 17(Special Issue), pp. 109–122.
[10] Haenlein, M. and Kaplan, A. (2020) ‘A brief history of artificial intelligence: on the past, present, and future of AI’, *California Management Review*, 61(4), pp. 5–14.
[11] Henderson, J.C. and Venkatraman, N. (1993) ‘Strategic alignment: leveraging information technology for transforming organizations’, *IBM Systems Journal*, 32(1), pp. 4–16.
[12] Kahneman, D. (2011) *Thinking, fast and slow*. New York: Farrar, Straus and Giroux.
[13] McAfee, A. and Brynjolfsson, E. (2012) ‘Big data: the management revolution’, *Harvard Business Review*, 90(10), pp. 60–68.
[14] Mintzberg, H. (1994). *The rise and fall of strategic planning*. New York: Free Press.
[15] O’Reilly, C.A. and Tushman, M.L. (2013) ‘Organizational ambidexterity: past, present, and future’, *Academy of Management Perspectives*, 27(4), pp. 324–338.
[16] Porter, M.E. (1996) ‘What is strategy?’, *Harvard Business Review*, 74(6), pp. 61–78.
[17] Ricci, F., Rokach, L. and Shapira, B. (2021). *Recommender systems handbook*. 3rd edn. Cham: Springer.
[18] Simon, H.A. (1979) ‘Rational decision making in business organizations’, *American Economic Review*, 69(4), pp. 493–513.
[19] Teece, D.J. (2018) ‘Business models and dynamic capabilities’, *Long Range Planning*, 51(1), pp. 40–49.
[20] Teece, D.J., Pisano, G. and Shuen, A. (1997) ‘Dynamic capabilities and strategic management’, *Strategic Management Journal*, 18(7), pp. 509–533.
[21] Tornatzky, L.G. and Fleischer, M. (1990) *The processes of technological innovation*. Lexington, MA: Lexington Books.
[22] Weick, K.E. (1995) *Sensemaking in organizations*. Thousand Oaks, CA: Sage Publications.
[23] Yin, R.K. (2018) *Case study research and applications: design and methods*. 6th edn. Thousand Oaks, CA: Sage Publications.