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Beyond Automation: A Strategic AI Integration Framework for Business Decision-Making

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ABSTRACT

Purpose - This paper develops a Strategic AI Integration Framework (SAIF) explaining how organizations can integrate artificial intelligence (AI) into business decision-making as a strategic capability rather than primarily as an automation tool. **Design/methodology/approach** - This conceptual theory-synthesis study draws on an integrative literature review of 30 purposively selected peer-reviewed articles published between 2015 and 2025 and indexed in Scopus and Web of Science. The corpus was analyzed through thematic synthesis and interpreted through Dynamic Capabilities Theory, bounded rationality, and the Resource-Based View with complementary-assets logic. **Findings** - Four interdependent dimensions form the SAIF: Decision Domain Mapping, AI Capability Alignment, Human-AI Complementarity, and Governance and Accountability Architecture. Six propositions specify how these dimensions are theorized to influence decision quality, organizational trust, and sustainable competitive advantage under appropriate human oversight. **Research limitations/implications** - The framework is theoretically derived from a purposively selected integrative review corpus and requires empirical validation. **Practical implications** - The SAIF provides a conceptual diagnostic framework for prioritizing AI investment, task allocation, and accountability in AI-assisted decisions. **Originality/value** - The study integrates decision-domain characteristics, capability fit, human-AI complementarity, and governance within one strategic model.

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INTRODUCTION

Artificial intelligence has moved from a speculative technological frontier to a core driver of organisational strategy, reshaping how enterprises sense market signals, process information, and make decisions across hierarchical and functional boundaries (Davenport and Ronanki, 2018; Brynjolfsson and McAfee, 2014). The phenomenon is no longer confined to technology firms. The Stanford AI Index reports that 78 per cent of organisations used AI in at least one business function in 2024, up from 55 per cent a year earlier, and that private investment in generative AI reached USD 33.9 billion in the same year (Stanford HAI, 2025). Generative AI has also changed who uses AI in decision-making.

Tools once operated by data scientists are now used directly by managers to draft analyses, test scenarios, and summarise evidence, placing AI inside judgement tasks previously reserved for people (Dwivedi et al., 2021).

Three developments make the integration question urgent. First, the shift from predictive to generative and increasingly agentic systems widens the range of decisions AI can influence and blurs the boundary between recommending and executing (Berente et al., 2021). Second, adoption does not automatically translate into value. Field evidence shows meaningful gains when AI is deployed on well-specified tasks, including the productivity improvements reported for customer-support agents using a generative AI assistant (Brynjolfsson et al., 2025). At the same time, Gartner (2024) forecast that many generative AI projects would be abandoned by the end of 2025 because of poor data quality, escalating costs, unclear business value, or inadequate risk controls. Third, regulatory expectations have intensified. The European Union Artificial Intelligence Act (European Union, 2024) establishes risk-based obligations, including human oversight and documentation requirements for high-risk applications, while comparable governance guidance is emerging in Asia, including Malaysia's National Guidelines on AI Governance and Ethics (MOSTI, 2024). These developments shift the managerial question from whether AI should be adopted to how it should be integrated into decision processes in ways that create value while preserving accountability.

Despite this momentum, a persistent conceptual limitation remains in the literature. AI is still frequently framed in terms of automation, efficiency, or discrete technology adoption, while its strategic role in reshaping managerial cognition, decision rights, organisational capabilities, and accountability is less consistently integrated. Duan et al. (2019) show that AI-enabled decision-making involves more than replacing human cognitive effort; it can change how decisions are framed, how information is weighted, and how outcomes are evaluated. An automation-centric lens alone therefore provides an incomplete basis for explaining strategic AI integration.

The research problem has both theoretical and practical dimensions. Theoretically, research on AI and decision-making remains fragmented across information systems, strategic management, behavioural decision research, and governance. Existing typologies describe what AI can do (Davenport and Ronanki, 2018; Duan et al., 2019), but provide limited guidance on which decisions should be delegated, augmented, or retained by humans, how AI capabilities should be matched to decision characteristics, and how these choices connect to organisational value (Keding, 2021; Raisch and Krakowski, 2021). Governance is also frequently treated as an ethical or compliance issue rather than as part of the strategic logic of integration (Papagiannidis et al., 2025). Practically, managers often lack a structured basis for deciding where AI belongs in the decision portfolio. Opportunistic or imitation-driven adoption can lead to stalled pilots, poorly calibrated trust in algorithmic advice (Burton et al., 2020; Logg et al., 2019), and unclear accountability when AI-assisted decisions fail (Kellogg et al., 2020).

The present paper addresses this gap by advancing a conceptual framework for Strategic AI Integration (SAI) in business decision-making. Recent work increasingly treats AI as an organisational capability that can support innovation, customer value, and competitive positioning, not only operational efficiency (Tio et al., 2026a, 2026b). These 2026 studies are used for contextual framing and are not part of the 2015-2025 analytical review corpus. The proposed framework makes three substantive moves. First, it situates AI integration within Dynamic Capabilities Theory, bounded rationality, and the Resource-Based View supplemented by complementary-assets logic. Second, it classifies decision domains using two explicit characteristics, decision complexity and decision reversibility, to support more disciplined choices about where and how AI should be deployed. Third, it positions human-AI complementarity and governance as integral components of strategic integration rather than as downstream implementation concerns.

Accordingly, this study aims to develop a theoretically grounded framework explaining how to integrate AI strategically into business decision-making. Three objectives guide the study: (1) to synthesise fragmented research on AI-enabled decision-making into a coherent set of integration themes; (2) to translate those themes into a Strategic AI Integration Framework (SAIF) anchored in Dynamic Capabilities Theory, bounded rationality, and the Resource-Based View with complementary assets;

and (3) to derive testable propositions linking the framework dimensions to decision quality, organisational trust, and sustainable competitive advantage.
The contribution lies in the framework's integrative logic. Earlier work has classified AI applications (Davenport and Ronanki, 2018), specified organisational decision structures (Shrestha et al., 2019), or catalogued governance practices (Papagiannidis et al., 2025), but often treats these questions separately. The SAIF connects them in a single sequence that moves from where AI should be used, to which AI capability fits the decision context, to how humans and AI should divide cognitive work, and finally to how AI-enabled decisions should be governed. Governance is therefore treated as a strategic design dimension rather than as a compliance afterthought. The resulting propositions provide an explicit agenda for empirical testing.
The paper is structured as follows. Section 2 reviews the literature on AI decision-making, strategic management, and organisational capabilities. Section 3 sets out the theoretical foundations. Section 4 describes the research method. Section 5 presents the results of the literature synthesis and develops the SAIF with six research propositions. Section 6 discusses the findings in relation to previous studies. Section 7 addresses limitations and future research, and Section 8 concludes the paper.

2. LITERATURE REVIEW

2.1 Artificial Intelligence and Business Decision-Making: An Evolving Discourse

The scholarly engagement with AI in decision-making contexts has evolved across three discernible phases. The first phase, characterised by expert systems and rule-based algorithms in the 1980s and 1990s, largely **focused on automating** structured, programmable decisions (Russell and Norvig, 2020). The second phase, catalysed by the availability of large-scale data infrastructure and advances in machine learning from about 2010 onward, expanded AI applications to semi-structured and pattern-recognition tasks, including demand forecasting, credit scoring, and supply chain optimisation (Makridakis, 2017). The current, third phase is distinguished by the emergence of generative AI and large language models, which introduce qualitatively distinct capabilities in language understanding, scenario reasoning, and knowledge synthesis that challenge existing typologies of AI-enabled decision support.
Duan et al. (2019) provide a comprehensive review of AI applications in decision-making across functional domains and identify three primary roles: decision automation, decision augmentation, and decision interaction. Their taxonomy, while analytically useful, does not address the strategic antecedents that determine which role fits which organisational context. Similarly, Davenport and Ronanki (2018) classify AI applications along dimensions of process automation, cognitive insight, and cognitive engagement, but their framework is largely descriptive and lacks prescriptive logic for integration strategy. This lack of prescriptive grounding significantly limits its use in guiding executive decisions on AI deployment priorities.

2.2 Strategic Management Perspectives on AI as Organisational Resource

The Resource-Based View (RBV) of the firm, as articulated by Barney (1991), posits that sustained competitive advantage derives from resources that are valuable, rare, inimitable, and non-substitutable (the VRIN criteria). Several scholars have applied RBV logic to AI capabilities, arguing that proprietary AI systems and data assets constitute strategic resources when they satisfy these criteria (Lichtenthaler, 2020). However, as Eisenhardt and Martin (2000) note in their critique of static resource-based reasoning, the dynamic and rapidly evolving nature of technological environments demands a capabilities-based perspective that foregrounds reconfiguration and adaptation rather than resource

possession alone. This argument is particularly salient for AI, given the speed at which AI capabilities diffuse across competitive landscapes through open-source proliferation and cloud-based accessibility.

The Dynamic Capabilities framework (Teece et al., 1997) is therefore more analytically appropriate for conceptualising strategic AI integration, as it directs attention to the organisational routines and microfoundations through which enterprises sense AI-relevant opportunities, seize value-creation potential, and reconfigure decision architectures in response to environmental change. Strategic AI integration, in this frame, is not merely a technology adoption decision but an organisational capability-building exercise requiring sustained investment in human capital, data governance, and learning routines.

2.3 Bounded Rationality and the Cognitive Foundations of Decision-Making

Simon's (1960) bounded rationality perspective remains central to understanding why AI augmentation can matter for managerial decision-making. Human decision-makers operate under limits of information, attention, computational capacity, and time. These constraints can produce satisficing rather than fully optimising behaviour. AI can reduce some of these constraints by processing large volumes of information, identifying patterns, and generating analytical alternatives. However, contextual interpretation, value judgements, stakeholder sensitivity, and accountability remain dependent on human judgement, particularly when decisions are ambiguous or consequential.

Kahneman's (2011) dual-process theory provides a complementary lens for thinking about task allocation. Rather than implying that AI itself possesses System 1 or System 2 cognition, the distinction helps identify different classes of decision work. AI is particularly useful for high-volume, pattern-recognition, computational, and retrieval-intensive tasks, while human decision-makers remain central to deliberative interpretation, ethical reasoning, contextual sensemaking, and novel situations. Strategic AI integration therefore requires task allocation based on complementary strengths rather than a simple substitution logic.

2.4 Identified Gaps in the Literature

A critical synthesis of these literature streams identifies three gaps that motivate the present conceptual contribution. First, existing frameworks provide limited integration of decision-domain characteristics, AI capability fit, human-AI complementarity, and governance within a single strategic model. Second, governance and accountability are often discussed separately from strategic value creation, particularly regarding auditability, explainability, decision rights, and ethical boundary conditions. Third, organisational context, including sector risk, firm resources, and leadership orientation, remains underdeveloped as a condition shaping integration effectiveness. The proposed Strategic AI Integration Framework (SAIF) addresses these gaps by linking the four dimensions in a sequential, testable architecture.

3. THEORETICAL FOUNDATIONS

3.1 Dynamic Capabilities Theory

The Dynamic Capabilities framework (Teece et al., 1997; Eisenhardt and Martin, 2000) serves as the primary theoretical anchor for the proposed framework. Dynamic capabilities are defined as the firm's ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments. Applied to the domain of strategic AI integration, dynamic capabilities manifest across three microfoundational processes: (a) sensing, which involves scanning AI landscape developments and identifying decision domains susceptible to AI-enabled enhancement; (b) seizing, which encompasses the design, procurement, and deployment of AI systems aligned with strategic

decision priorities; and (c) reconfiguring, which entails the continuous recalibration of human-AI workflows in response to performance feedback, environmental shifts, and evolving AI capabilities.

3.2 Bounded Rationality and Decision Architecture

Simon's (1960) bounded rationality model provides the microcognitive foundation for understanding why AI integration is strategically imperative, not merely operationally convenient. Human decision-making is subject to cognitive load constraints, informational asymmetries, and temporal pressures that systematically degrade decision quality in complex, data-intensive environments. AI augmentation strategies that are designed with explicit reference to these constraints produce qualitatively different and more effective outcomes than those driven by technological availability or competitive imitation. Accordingly, the SAIF embeds a decision complexity typology informed by bounded rationality logic.

3.3 Resource-Based View and Complementary Assets

Barney's (1991) Resource-Based View (RBV) informs the framework's treatment of AI as a potentially strategic resource whose value depends on organizational complementarities such as data quality, human capital, managerial capability, and governance routines. Teece's (1986) complementary-assets perspective strengthens this logic by explaining why technology alone rarely produces sustained advantage. AI systems create greater strategic value when they are combined with appropriate expertise, redesigned processes, institutional knowledge, and governance mechanisms. In the SAIF, the RBV therefore explains the strategic value of the resource base, while complementary-assets logic explains the organizational conditions required to realize that value.

4. METHOD

4.1 Design of the Research

This paper is a conceptual theory synthesis paper guided by an integrative literature review. It applies the conceptual article approach described in Jaakkola (2020) to integrate ideas and findings from multiple streams of literature in an effort to develop a new explanatory framework. The integrative review design is appropriate for a developing, multidisciplinary subject as it combines theoretical perspectives and provides a unified conceptual model as opposed to pooled effect size estimates (Torraco, 2005; Snyder, 2019). The unit of analysis is published research, not individual respondents or organizations.

4.2 Selection criteria and review corpus

The review corpus consisted of peer-reviewed journal articles on artificial intelligence in organizational or managerial decision-making published in Scopus and Web of Science Core Collection. We used a purposeful, criteria-based selection approach, augmented by backward snowballing of key review reference lists. Articles were eligible if published in English between 2015 and 2025 and related to AI in relation to decision-making, strategy, human-AI interaction, organizational capability, or AI governance. We excluded pure technical studies on algorithm development, conference papers, book chapters and non-peer-reviewed sources. Screening was structured by a PRISMA-informed flow logic (Page et al., 2021) for decisions about identification and eligibility; PRISMA is used here as reporting guidance, not as a claim that the study is a full systematic review. The final analytical corpus was composed of 30 articles purposively selected.

Table 1: Review Protocol and Screening Results

Protocol element	Specification
Review design	Conceptual theory synthesis informed by an integrative literature review
Databases	Scopus; Web of Science Core Collection
Search string	("artificial intelligence" OR "machine learning" OR "generative AI" OR algorithm*) AND ("decision making" OR "decision-making" OR "strategic management" OR "human-AI" OR "AI governance")
Search fields	Title, abstract, and keywords
Publication period	2015 to 2025
Eligibility	English-language, peer-reviewed journal articles examining AI in relation to decision-making, strategy, human-AI interaction, organisational capability, or AI governance
Exclusions	Purely technical algorithm-development studies; conference papers; book chapters; non-peer-reviewed sources
Supplementary identification	Backward snowballing from the reference lists of key reviews
Selection approach	Purposive, criterion-based screening using PRISMA-informed flow logic for reporting transparency
Search timing	2026
Final analytical corpus	30 articles

Source: Authors' review protocol. PRISMA 2020 is used as reporting guidance for screening logic; the review is integrative rather than a full systematic review (Page et al., 2021).

4.3 Search and Data Extraction

Database searches were conducted in Scopus and Web of Science during 2026 using institutional library access. Records were exported with bibliographic data and abstracts into Mendeley for reference management and duplicate screening. Screening proceeded from titles and abstracts to full-text assessment against the stated eligibility criteria. For each included article, a structured extraction sheet recorded the authors, year, journal, research design, decision context, type of AI, principal findings, theoretical lens, and relevance to the emerging SAIF dimensions. Sources published in 2026 that appear elsewhere in the paper are used only for contextual framing and were not included in the 2015-2025 review corpus.

4.4 Thematic Analysis and Supporting Software

The extracted material was analyzed through thematic synthesis using the six-phase logic described by Braun and Clarke (2006): familiarisation, initial coding, theme generation, theme review, theme definition, and reporting. NVivo 14 was used to organize coded material and link codes to source passages, while Microsoft Excel was used to tabulate descriptive characteristics of the selected corpus. VOSviewer (van Eck and Waltman, 2010) was used for supplementary keyword co-occurrence mapping to describe topical relationships in the literature; it was not treated as a validation test for qualitative coding. The coding process was iterative, with candidate themes repeatedly checked against the extraction matrix and representative source evidence. The final themes were then interpreted through the three theoretical lenses in Section 3 to construct the SAIF and derive the research propositions.

5. RESULTS

The framework uses Barney's (1991) resource-based view (RBV) that considers AI as a potentially strategic resource that can be valuable depending on organizational complementarities including data quality, human capital, managerial capability and governance routines. The logic is consistent with the complementary-assets view of Teece (1986) that explains the rarity of sustained advantages through technology alone. When combined with the right expertise, redesigned processes, institutional knowledge, and governance mechanisms, standard artificial intelligence systems are of greater strategic value. In the SAIF, the RBV therefore captures the strategic value of the resource base, while the complementary-assets logic captures the organizational conditions that must be in place to realize that value.

Table 2: Profile of the Reviewed Articles (n = 30)

Category	Sub-category	n	%
Publication period	2015–2018	3	10.0
	2019–2021	18	60.0
	2022–2025	9	30.0
Outlet discipline	Information systems	12	40.0
	Management and strategy	12	40.0
	Behavioural science and economics	4	13.3
	Public administration and ethics	2	6.7
Research design	Conceptual paper or literature review	21	70.0
	Experiment	4	13.3
	Qualitative field study	2	6.7
	Archival or field data analysis	2	6.7
	Survey	1	3.3
Primary theme	Decision domain mapping	6	20.0
	AI capability alignment	7	23.3
	Human–AI complementarity	9	30.0
	Governance and accountability	8	26.7

Source: Authors' analysis of the review corpus.

5.2 Thematic Synthesis of the Literature

The thematic synthesis generated four recurring themes that correspond to the four dimensions of the SAIF. Table 3 reports the dominant thematic classification used for descriptive presentation, representative studies, and the synthesised finding associated with each dimension. The dominant-theme counts in Table 2 characterise the selected corpus, while the qualitative synthesis in Table 3 recognises that the themes are interdependent across studies.

Table 3: Thematic Synthesis and Mapping to SAIF Dimensions

Theme (SAIF dimension)	n	Representative studies	Synthesised finding
Decision domain mapping (Dimension 1)	6	Makridakis (2017); Shrestha et al. (2019); Trunk et al. (2020); Borges et al. (2021); Keding (2021); Fügener et al. (2022)	The appropriate role of AI depends on decision structure, uncertainty, and stakes; delegation must be designed by the organisation rather than left to individuals.
AI capability alignment (Dimension 2)	7	Duan et al. (2019); Haenlein and Kaplan (2019); Collins et al. (2021); Haefner et al. (2021); Mikalef and Gupta (2021); Enholm et al. (2022); Weber et al. (2023)	Value arises from matching the type of AI to the decision context and to complementary resources such as data, skills, and management support.
Human–AI complementarity (Dimension 3)	9	Dietvorst et al. (2015); Jarrahi (2018); Logg et al. (2019); Burton et al. (2020); Fügener et al. (2021); Raisch and Krakowski (2021); Lebovitz et al. (2022); Krakowski et al. (2023); Brynjolfsson et al. (2025)	Human–AI configurations can outperform either party alone when tasks are partitioned by cognitive strengths, but gains depend on calibrated trust and preserved human expertise.

Theme (SAIF dimension)	n	Representative studies	Synthesised finding
Governance and accountability (Dimension 4)	8	Wirtz et al. (2019); Glikson and Woolley (2020); Kellogg et al. (2020); Berente et al. (2021); Dwivedi et al. (2021); Mikalef et al. (2022); Mäntymäki et al. (2022); Papagiannidis et al. (2025)	Transparency, auditability, and clear accountability condition trust and adoption, yet governance is rarely linked to strategic value creation.
Total	30		

Source: Authors' thematic synthesis.

The first theme concerns which decisions AI should make. Shrestha et al. (2019) show that the appropriate decision structure, whether full delegation to AI, sequential human–AI decision-making, or aggregation of human and AI judgements, depends on features such as the specificity of the decision search space, interpretability, and required speed. Trunk et al. (2020) reach a similar conclusion for strategic decisions, finding that AI mainly supports information processing while humans retain responsibility for judgement under uncertainty. Fügener et al. (2022) add a behavioural nuance: people are poor at recognising when to delegate tasks to AI, so organisations need to design delegation rules rather than leave them to individual discretion. This theme underpins Dimension 1, Decision Domain Mapping.

The second theme concerns the fit between AI capabilities and organisational resources. Mikalef and Gupta (2021) conceptualise AI capability as a bundle of tangible, human, and intangible resources and show that it is associated with organisational creativity and firm performance. Enholm et al. (2022) find that the business value of AI depends on enablers such as data quality, skills, and management support, and that process-level effects precede firm-level performance effects. Weber et al. (2023) identify four organisational capabilities needed for AI implementation: AI project planning, co-development of AI systems, data management, and AI model lifecycle management. Across these studies, value arises from matching capability to context rather than from the technology's sophistication, which underpins Dimension 2, AI Capability Alignment.

Human–AI complementarity was the most frequently examined theme, appearing in nine studies. Evidence on how people respond to algorithmic advice is mixed. Dietvorst et al. (2015) found that people abandon algorithms after seeing them err, whereas Logg et al. (2019) found that lay decision-makers often prefer algorithmic to human advice, although experts discount it. Burton et al. (2020) attribute these inconsistencies to factors such as expectations, decision autonomy, and cognitive compatibility. Raisch and Krakowski (2021) argue that automation and augmentation are interdependent, so focusing exclusively on either produces harmful outcomes over time. Field evidence supports complementarity: Brynjolfsson et al. (2025) report that a generative AI assistant raised productivity by 14 per cent on average and by 34 per cent for novice workers, and Krakowski et al. (2023) show that when AI substitutes for human capabilities, competitive advantage shifts towards the ability to combine humans and machines. This theme underpins Dimension 3, Human–AI Complementarity.

Governance and accountability formed the fourth theme, with eight studies. Glikson and Woolley (2020) show that cognitive trust in AI depends on its tangibility, transparency, reliability, and immediacy, and Kellogg et al. (2020) document how algorithmic management reshapes worker control and gives rise to new forms of resistance. Berente et al. (2021) identify autonomy, learning, and inscrutability as the defining challenges of managing AI, each of which complicates assigning responsibility. Mäntymäki et al. (2022) and Papagiannidis et al. (2025) move the debate from principles to practice by defining organisational AI governance and classifying structural, relational, and procedural governance practices. Most governance studies in the corpus, however, treat AI oversight as separate from strategy, which is why Dimension 4 positions governance as a co-determinant of integration effectiveness.

The synthesis also shows that the four themes are interdependent. Studies on complementarity repeatedly point to governance conditions such as transparency and accountability, while studies on capability stress that data and skills determine which decisions can safely be delegated. These

interdependencies motivated the design of the SAIF as an integrated, sequential framework rather than a set of separate checklists. The following subsections set out each dimension and the propositions derived from them.

5.3 Overview of the Strategic AI Integration Framework (SAIF)

The Strategic AI Integration Framework (SAIF) is a four-dimensional conceptual architecture that guides the theoretically informed AI integration in business decision-making. The framework poses four sequential questions, namely: (1) Where to deploy AI? (2) What kind of AI capability fits that context? (1) Decision Domain Mapping defines the decision context; AI Capability Alignment connects system capability with decision characteristics and organizational resources; (3) How to divide decision work between humans and AI? Human-AI Complementarity is about task partitioning and interaction; and (4) How should AI-enabled decisions be regulated? Governance and Accountability Architecture defines oversight, auditability and responsibility. The three theoretical bases address these dimensions: bounded rationality explains why cognitive work may be redistributed, the RBV and complementary-assets perspective explains why organizational resources constrain value creation, and Dynamic Capabilities Theory explains how organizations sense, seize, and reconfigure AI-enabled decision architectures over time

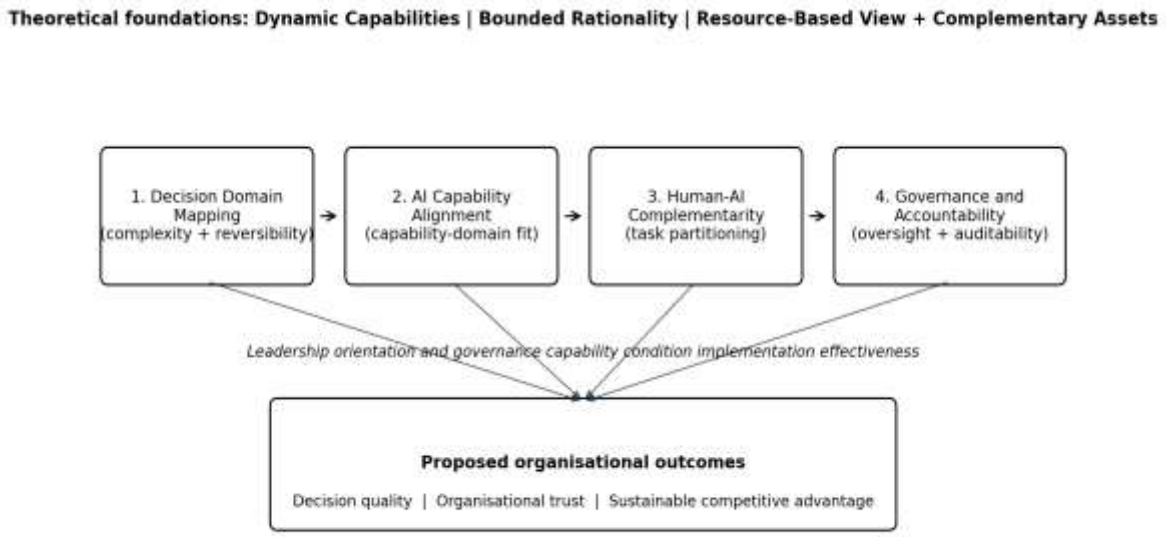

Figure 1. Strategic AI Integration Framework (SAIF)

Note: The framework is conceptual. The arrows indicate the proposed integration sequence and theorised relationships rather than empirically established causal effects.

5.4 Dimension 1: Decision Domain Mapping

Decision Domain Mapping is the foundational analytical step through which organisations classify their decision portfolio along two explicit axes: decision complexity, ranging from structured and rule-based to unstructured and ambiguous, and decision reversibility, ranging from low-stakes, recoverable decisions to high-stakes commitments that are difficult to reverse. The resulting four-quadrant logic distinguishes structured-reversible decisions suited to greater automation, structured-irreversible decisions requiring AI recommendation with human oversight, unstructured-reversible decisions suited to AI-enhanced scenario exploration, and unstructured-irreversible decisions requiring AI-supported

deliberation with primary human accountability. The purpose of the map is not to maximise AI use, but to calibrate AI involvement to the decision's characteristics and consequences.

5.5 Dimension 2: AI Capability Alignment

AI Capability Alignment addresses the fit between the decision domains identified in Dimension 1 and the capabilities of the AI system being considered. For analytical purposes, the framework groups AI capability into three broad orders: analytical capabilities such as prediction, anomaly detection, and optimisation; interactive capabilities such as conversational interfaces, recommendation, and knowledge retrieval; and more autonomous capabilities that can execute actions within defined boundaries. The alignment principle proposes matching AI capability to decision complexity, reversibility, data requirements, organisational resources, and error recoverability. Strategic value therefore depends less on adopting the most sophisticated technology than on achieving an appropriate capability-domain fit.

5.6 Dimension 3: Human-AI Complementarity

Human-AI Complementarity is the SAIF's central task-allocation mechanism. The framework does not assume that AI and humans possess equivalent forms of cognition. Instead, it uses bounded rationality and dual-process theory as organising lenses for identifying complementary task strengths. AI can provide high-speed computation, pattern recognition, retrieval, and option generation, while human decision-makers contribute contextual interpretation, ethical reasoning, stakeholder sensitivity, causal judgement, and accountability in novel or ambiguous situations. Effective integration therefore aims to optimise the division of decision work rather than maximise AI's scope. Practical interaction mechanisms include confidence thresholds, escalation rules, human override, feedback loops, and procedures for maintaining human expertise over time.

5.7 Dimension 4: Governance and Accountability Architecture

The Governance and Accountability Architecture addresses how AI-assisted decisions are controlled, reviewed, and assigned to accountable human actors. Drawing on organisational AI governance scholarship (Wirtz et al., 2019; Mäntymäki et al., 2022; Papagiannidis et al., 2025), the dimension comprises five elements: explainability standards appropriate to decision risk; audit trails documenting relevant inputs, outputs, and decision outcomes; bias and performance monitoring; explicit allocation of human accountability for AI-assisted decisions; and regulatory compliance mapping. Governance is treated as part of strategic integration because it conditions whether AI capability can be used safely, trusted appropriately, and sustained within organisational routines.

5.8 Research Propositions

The SAIF is expressed through six propositions that translate the conceptual architecture into testable relationships. These propositions do not represent empirically established causal effects. Rather, they specify relationships that are theorised from the literature synthesis and provide a structured agenda for future empirical research using survey, longitudinal, experimental, and comparative case designs. Table 4 presents the propositions.

Table 4: Research Propositions of the Strategic AI Integration Framework (SAIF)

Proposition	Statement
P1	Organisations that systematically map decision domains before AI deployment are expected to achieve higher decision quality and lower integration failure than organisations relying primarily on opportunistic or imitation-driven deployment.
P2	AI capability-domain fit strengthens the positive relationship between AI investment and decision performance, such that investments generate greater value when system capabilities match decision complexity, reversibility, and recoverability.
P3	AI integration configurations that allocate tasks according to complementary human and AI strengths are expected to produce higher decision quality than configurations designed primarily to maximise AI task scope.

P4	A stronger Governance and Accountability Architecture strengthens the positive relationship between AI integration depth and organisational trust in AI-enabled decision processes.
P5	Dynamic AI integration capabilities, reflected in sensing, seizing, and reconfiguration routines, mediate the relationship between AI resource investment and sustained competitive advantage in knowledge-intensive organisations.
P6	Executive AI literacy and ethical AI commitment strengthen the positive relationship between Governance and Accountability Architecture and strategic AI integration effectiveness.

6. DISCUSSION

This study synthesized fragmented research on AI-enabled decision-making and translated the synthesis into a strategic integration framework. Four recurring themes emerged from the selected corpus and were organized as interdependent dimensions within the SAIF. The discussion below explains how each dimension confirms, extends, or reframes prior research and clarifies the theoretical logic underlying the six propositions.

The first finding is that the appropriate role of AI depends on the decision's characteristics and consequences, not simply on the available technical capability. This aligns with Shrestha et al. (2019), who link decision structures to the specificity of the decision search space, and with Jarrahi (2018), who distinguishes AI's strengths in complexity from humans' capacity to handle uncertainty and equivocality. The SAIF extends this reasoning by combining decision complexity with reversibility. This distinction separates complex decisions whose consequences can be corrected from high-stakes decisions whose outcomes are difficult to reverse. Because individuals may not consistently recognize when delegation to AI is appropriate (Fügener et al., 2022), Decision Domain Mapping is proposed as an organizational safeguard and strategic design mechanism rather than an administrative checklist. This logic underpins Proposition P1.

The second finding is that AI value depends on capability-domain fit and complementary organizational resources. This is consistent with Mikalef and Gupta (2021) and Enholm et al. (2022), who show that AI-related performance benefits depend on data, skills, and managerial support, and with Teece's (1986) argument that complementary assets shape the returns from technological innovation. The SAIF adds decision-level alignment logic by proposing that analytical, interactive, and more autonomous AI capabilities should match the complexity, reversibility, and recoverability of the decision domain. Proposition P2 therefore focuses on capability-domain fit as a condition strengthening the relationship between AI investment and decision performance.

The third finding is that human-AI complementarity is the most frequently represented primary theme in the selected corpus and provides the framework's central task-allocation logic. This is consistent with Raisch and Krakowski (2021), who argue that automation and augmentation are interdependent, and with Brynjolfsson et al. (2025), who report larger productivity gains among less experienced workers using AI assistance. At the same time, evidence on algorithm aversion (Dietvorst et al., 2015), algorithm appreciation (Logg et al., 2019), and the erosion of human knowledge under sustained AI reliance (Fügener et al., 2021) shows that neither human nor AI control should be treated as the default. Proposition P3 therefore emphasizes allocation according to complementary strengths, supported by confidence thresholds, escalation procedures, and human override.

The fourth finding is that governance is well developed as an ethical and procedural concern but is less consistently integrated into the strategic logic of AI value creation. Papagiannidis et al. (2025) and Mäntymäki et al. (2022) provide detailed accounts of organizational AI governance, while Glikson and

Woolley (2020) show that trust depends on transparency and reliability. The SAIF extends this work by positioning governance as an enabling architecture that conditions whether AI integration can be trusted, audited, and sustained. Proposition P4 links governance to organizational trust in AI-enabled decisions. Proposition P6 narrows the role of leadership by proposing that executive AI literacy and ethical AI commitment strengthen the effectiveness of governance architecture, rather than assuming that leadership moderates every dimension of the SAIF.

Taken together, these findings support three theoretical contributions. First, the SAIF integrates Dynamic Capabilities Theory, bounded rationality, and the Resource-Based View with complementary-assets logic within one explanatory architecture, addressing fragmentation across AI decision-making and strategic management research. Second, the framework gives human-AI complementarity a more precise meaning by grounding task allocation in the characteristics of decision work and in complementary strengths rather than in a generic requirement to keep a human in the loop. Third, it places governance inside the strategic integration process, connecting accountability, trust, and regulatory control to the organizational conditions under which AI resources may create sustained value.

The framework also has practical implications, although these should be interpreted as conceptual guidance pending empirical validation. For executives and chief digital officers, Decision Domain Mapping offers a structured way to identify candidate AI use cases while limiting autonomy in high-stakes, difficult-to-reverse decisions. AI Capability Alignment directs attention to fit between system capability, decision requirements, data quality, and organizational resources. Human-AI Complementarity encourages explicit task-partitioning rules, escalation thresholds, and mechanisms for maintaining human expertise. Governance and Accountability Architecture requires explainability, auditability, bias monitoring, named accountability, and regulatory mapping to be designed alongside technical deployment rather than added after implementation. For policymakers, the framework aligns with risk-tiered oversight approaches such as the EU Artificial Intelligence Act and suggests calibrating governance requirements to decision risk.

7. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

As a conceptual contribution, the SAIF has limitations that empirical research must address. The framework and six propositions are theoretically derived rather than empirically validated, so the proposed relationships should not be interpreted as established causal effects. Human-AI Complementarity, capability-domain fit, governance architecture, and leadership orientation will require clear construct definitions and validated measurement instruments before quantitative hypothesis testing can be undertaken.

The integrative review also has boundaries. It draws on two databases, English-language peer-reviewed journal articles, and a purposively selected corpus of 30 studies. The descriptive frequencies reported in Section 5 therefore characterise the selected analytical corpus rather than the prevalence or publication trajectory of the wider field. Relevant work in other languages, regional journals, conference proceedings, or practitioner sources may have been omitted. Future reviews could use larger systematic or bibliometric designs to examine whether the four SAIF dimensions remain stable across broader evidence bases.

Future research should validate and refine the SAIF through multiple methodological pathways. Comparative case studies can examine how organisations enact Athe four dimensions at different levels of AI maturity. Large-scale survey research can operationalise the constructs and test the proposed direct, moderation, and mediation relationships using structural equation modelling. Longitudinal designs are especially important because learning effects, governance routines, and AI capabilities evolve over time. Experimental work could also test decision-domain and task-partitioning propositions under controlled variations in complexity, reversibility, and human oversight.

The framework also warrants extension in three directions. First, organisational culture should be examined as a contextual condition distinct from leadership orientation. Second, the SAIF may require adaptation for small and medium-sized enterprises, where resource constraints affect data infrastructure, AI expertise, and governance capacity. Third, cross-national research should test whether institutional trust, data regulation, sectoral regulation, and AI governance norms alter the relative importance of the four framework dimensions.

8. CONCLUSION

This paper argues that an automation-centric view alone is insufficient for understanding strategic AI integration in business decision-making. Automation can create efficiency, but sustained organisational value also depends on where AI is deployed, whether its capabilities fit the decision context, how human and AI strengths are combined, and how AI-assisted decisions are governed. The Strategic AI Integration Framework (SAIF) brings these elements together through four dimensions: Decision Domain Mapping, AI Capability Alignment, Human-AI Complementarity, and Governance and Accountability Architecture.

The framework integrates Dynamic Capabilities Theory, bounded rationality, and the Resource-Based View with complementary-assets logic to connect environmental adaptation, organisational resources, and decision-level cognition. Its six propositions convert the conceptual architecture into a testable research agenda concerning decision quality, organisational trust, and sustainable competitive advantage. Because the framework has not yet been empirically validated, its principal contribution is theoretical integration and the specification of relationships that future research can examine across industries, organisational sizes, and national settings.

As organisations expand the use of generative and increasingly autonomous AI, the strategic problem is not simply how much AI to deploy, but how to allocate decision authority, preserve human judgement, and maintain accountability as capabilities evolve. The SAIF provides a structured conceptual basis for addressing that problem. Empirical validation, contextual refinement, and measurement development are therefore the next steps required to determine the framework's explanatory and practical value.

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