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# Responsible Artificial Intelligence in Strategic Decision-Making: A Systematic Review and Governance Framework for Socially Sustainable Organisations

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**Abstract**

Artificial intelligence (AI) increasingly shapes strategic decisions that determine how organisations allocate resources, restructure work and treat the people affected by those choices. Yet research has examined the performance benefits and the governance risks of AI largely in isolation, leaving the sustainability implications of delegated algorithmic authority under-theorised. Following PRISMA 2020, this study synthesises 50 studies, identified through four database searches covering 2019–2025 and backward citation tracking, using inductive thematic analysis. Six themes emerge: AI-driven automation and decision support, data-driven strategic decision-making, ethical and governance challenges, data security and privacy, organisational and structural impact, and innovation and competitive advantage. Together, these themes show that performance and governance concerns receive comparable attention (28 and 27 studies) but are rarely addressed together: only five studies span both. Building on these connections, the study develops a governance framework for socially sustainable, AI-enabled strategy. The framework conceptualises responsible AI as a socio-technical capability built on transparency, human–AI complementarity and organisational readiness, and calibrates the degree of algorithmic authority to decision criticality and EU AI Act obligations. The main contribution is therefore an integrative framework that keeps AI-supported strategic decisions both effective and accountable to those they affect, with implications for SDGs 8 and 16.

**Keywords:** algorithmic management; human oversight; decision augmentation; algorithmic bias; organisational legitimacy; decent work; sustainability reporting; resource-based view

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## 1. Introduction

Strategic decisions determine how organisations allocate resources, restructure operations and define their relationships with internal and external stakeholders, and therefore distribute social and governance consequences across employees, suppliers, customers and local communities [1]. As decision authority is increasingly shared with, or delegated to, algorithmic systems, these consequences become harder to trace, question and attribute to identifiable human actors [2,3]. Black-box models and complex data pipelines blur established boundaries of managerial responsibility, creating distinctive challenges for organisational accountability [4]. Such challenges are increasingly addressed through binding regulation rather than voluntary ethical principles alone [5]. The EU Artificial

Intelligence Act [6] imposes risk-management, transparency and human-oversight obligations on high-risk AI systems, including systems used in employment-related decisions; following the 2026 Digital Omnibus amendments, these obligations apply to stand-alone high-risk systems from December 2027 [7]. In parallel, the Corporate Sustainability Reporting Directive [8] and the European Sustainability Reporting Standards [9], notably ESRS S1 (Own Workforce), create disclosure expectations for large undertakings regarding material impacts on their own workforce, although the 2026 Omnibus I Directive has narrowed mandatory reporting to the largest companies [10]. Together, these frameworks indicate that delegating strategic authority to AI is becoming a matter of institutional accountability and social sustainability, not only of managerial efficiency.

The regulatory discussion, including developments after the review period, provides an external legal context for interpreting the synthesis. These legislative sources are distinct from the studies included in the thematic analysis and are not treated as evidence of the framework's effectiveness.

Against this regulatory backdrop, AI has rapidly evolved from a supportive analytical tool into a central component of contemporary strategic decision-making [11]. Organisations increasingly rely on AI-driven systems to process large volumes of data, generate predictive insights and support complex managerial judgments under uncertainty [12]. This shift is reshaping how strategic choices are formulated and executed, positioning AI as a key enabler of organisational agility and competitive advantage [13]. AI-enhanced analytics improve decision accuracy, speed and risk assessment, extending managerial cognition and strategic planning capabilities [14,15]. However, the growing integration of AI into strategic processes also raises significant managerial, ethical and organisational concerns [4,16].

The strategic deployment of AI introduces a fundamental tension. While AI enables firms to automate complex analyses and support evidence-based decision-making at scale, it simultaneously creates risks related to transparency, accountability and organisational readiness [4]. AI-driven decisions may be affected by algorithmic bias, limited explainability and ambiguous responsibility structures, particularly when decision authority is partially delegated to intelligent systems [17,18]. Moreover, successful adoption depends on governance mechanisms, managerial trust and organisational alignment within digitally transforming environments [19]. These tensions suggest that AI's implications extend beyond performance improvements to broader strategic and organisational considerations [2].

Despite rapid growth in the literature, research on AI in business contexts remains fragmented. Existing studies often focus on automation efficiency, predictive analytics or technical implementation, treating AI primarily as a technological capability rather than a strategic managerial phenomenon [20,21]. Consequently, limited attention has been devoted to how organisations integrate performance benefits with governance and ethical requirements in strategic decision-making [4]. Recent review-based research has begun to examine the broader organisational implications of AI adoption. For example, Jobstreibizer et al. [22] provide a bibliometric-systematic review of AI's impact on business models, highlighting themes such as business model innovation, digitalisation, customer engagement and circular economy transformations. However, their analysis primarily conceptualises AI as a driver of business model transformation, whereas the present study focuses on AI-enabled strategic decision-making and the managerial conditions under which AI-supported decisions remain accountable, explainable and strategically aligned.

Against this background, this study develops an integrated and managerially oriented understanding of how AI reshapes strategic decision-making and what conditions enable its responsible use. Specifically, it conducts a systematic literature review of recent research to synthesise insights on AI's strategic role, identify key benefits and risks, and develop a

framework for responsible AI-enabled decision-making. Drawing on the resource-based view and decision theory, the study moves beyond fragmented technical perspectives toward a more holistic conceptualisation of AI in strategic management.

Accordingly, the review addresses three research questions. RQ1: What thematic dimensions characterise research on AI in strategic decision-making? RQ2: Under what organisational and governance conditions does AI-supported strategic decision-making become both effective and accountable? RQ3: What are the implications of these conditions for the social and governance dimensions of organisational sustainability?

This research makes three contributions. First, it consolidates dispersed research into a structured thematic synthesis and compares how studies connect AI's performance contributions with accountability, rights and workforce conditions, identifying existing connections and limitations in their integration. Second, it advances theory by framing responsible AI-enabled strategy as a socio-technical capability and positioning algorithmic governance as the mechanism through which AI-supported strategic decisions remain accountable, explainable and contestable to those affected by them. Third, it links advisory, collaborative and delegated human–AI configurations to the obligations of the EU AI Act, providing managers with a governance-calibration mechanism that connects decision criticality to the social and governance dimensions of sustainability.

To ensure analytical clarity, the scope of this systematic review is deliberately bounded. The study focuses specifically on the social and governance dimensions of organisational sustainability, examining how automated strategic authority influences stakeholder trust, decision transparency and worker agency. Conversely, the environmental footprint of AI infrastructures, such as data centre energy consumption, carbon emissions and hardware lifecycle impacts, falls outside the boundary of this research. This boundary supports focused analysis of accountability and decision authority, but limits our ability to assess interactions between social outcomes, resource use and environmental impacts. It is an analytical trade-off, not an assumption that these dimensions are independent.

## 2. Theoretical Background

The following subsections distinguish strategic-performance and responsible-AI perspectives for analytical clarity, while recognising their overlap. This organisation introduces the perspectives that the subsequent synthesis and framework bring together, rather than assuming that performance and governance are independent domains.

### *2.1. AI in Strategic Decision-Making*

AI has evolved from an operational support tool into a strategic enabler that augments managerial decision-making processes [11,22]. In contemporary organisations, AI systems are increasingly embedded in strategic planning, forecasting and resource allocation, enabling firms to process complex, high-volume data environments more effectively than traditional analytical approaches [23]. This shift reflects a broader transition from task automation to the cognitive augmentation of managerial judgment [24].

A central contribution of AI lies in decision augmentation. Rather than replacing managers, AI-driven systems function as decision-support mechanisms that enhance analytical capacity and reduce cognitive constraints [25]. Machine learning algorithms and predictive analytics enable decision-makers to evaluate multiple strategic scenarios, detect emerging patterns and assess risk with greater precision [15,26]. This capability is particularly valuable in high-uncertainty environments, where data-driven insights enhance strategic responsiveness and support entrepreneurial and opportunity-seeking behaviour [12].

Automation remains a key dimension of AI's strategic role. Intelligent process automation streamlines data-intensive workflows, reduces human error and accelerates decision cycles, enabling managers to focus on higher-order strategic activities [27,28].

AI-driven analytics have expanded data-informed strategic management by integrating structured and unstructured data into real-time insights that support adaptive decision-making, with AI increasingly acting as the intermediary between information and managerial action [12,29].

However, the growing integration of AI into strategic processes raises important managerial challenges. As the boundary between human judgment and algorithmic recommendation becomes increasingly blurred, concerns related to transparency, accountability and governance intensify [13]. These developments highlight the need to understand not only the performance benefits of AI but also the organisational conditions under which AI-supported decision-making remains effective, transparent and aligned with managerial responsibility [30].

### *2.2. Strategic Benefits and Risks*

The strategic adoption of AI offers significant performance-related benefits for organisations, particularly in terms of decision accuracy, operational efficiency and risk management [25]. By leveraging advanced pattern recognition and predictive modelling, AI systems enable firms to identify opportunities and threats earlier than conventional analytical approaches, thereby enhancing strategic agility and improving resource allocation decisions [14,26].

AI reduces uncertainty by continuously updating forecasts based on real-time data, enabling organisations to adapt strategies in volatile environments and strengthen risk management and strategic resilience [29,31,32].

AI adoption also contributes to competitive advantage through improved decision-making, innovation and strategic entrepreneurship, particularly when combined with business intelligence, strategic planning capabilities [12], and business model transformation [22]. Generative AI and advanced analytics facilitate opportunity discovery, product development and customer insight generation, while automation improves operational performance by reducing errors and processing time [14]. From a resource-based perspective, AI can constitute a valuable organisational capability when effectively integrated into strategic processes [12].

However, these benefits are accompanied by significant risks that challenge the effectiveness and legitimacy of AI-enabled decision-making [4,13]. Algorithmic bias remains a central concern, as AI systems may reproduce or amplify existing data biases, leading to unfair or suboptimal outcomes [17]. This is particularly critical in high-stakes domains where biased decisions carry reputational and regulatory consequences.

Transparency and explainability limitations further complicate managerial reliance on AI. Many advanced models operate as "black boxes," making it difficult for decision-makers to understand how recommendations are generated [33,34]. This opacity can undermine trust and create ambiguity in accountability, particularly when AI-supported decisions lead to negative outcomes [24].

In addition, organisational challenges, such as capability gaps, cultural resistance and insufficient governance structures, can limit the effective integration of AI into strategic processes [19]. These issues highlight that successful AI adoption extends beyond technological implementation to include organisational and managerial readiness.

Together, these tensions indicate that AI's strategic value cannot be assessed solely in terms of performance gains [24]. Instead, its effectiveness depends on the ability of organisations to balance analytical capabilities with governance, ethical considerations

and organisational alignment, thereby ensuring the responsible use of AI in strategic decision-making [16].

### *2.3. Responsible AI and Research Gap*

The growing recognition of AI-related risks has stimulated increasing scholarly attention to the concept of responsible AI. Broadly defined, responsible AI refers to the development and deployment of AI systems that are transparent, fair, accountable and aligned with organisational and societal values [35,36]. Within strategic management contexts, responsible AI emphasises the need for governance mechanisms that ensure algorithmic outputs support, and not undermine, managerial judgment and organisational legitimacy [30].

Several streams of research have begun to address components of responsible AI. Ethical frameworks have been proposed to mitigate algorithmic bias and enhance fairness in automated decision systems [37]. Similarly, the development of explainable AI (XAI) techniques seeks to improve transparency by making algorithmic reasoning more interpretable for human decision-makers [26]. Governance-oriented studies also highlight the importance of accountability structures, regular auditing and human oversight in maintaining trust in AI-enabled processes [33]. Related scholarship situates these concerns within the intersection of AI, language and law. Lan and Zhang's [38] bibliometric analysis identifies explainable legal decision support and the ethical regulation of algorithmic governance as developing research directions, alongside limited interdisciplinary integration. This provides a broader context for our framework's attention to explanations, identifiable responsibility and opportunities to challenge AI-supported decisions.

At the organisational level, responsible AI adoption depends not only on technological capability but also on managerial competencies, cross-functional collaboration and change management practices that support human–AI interaction [16,30]. Without these complementary capabilities, firms may struggle to translate AI investments into sustainable strategic value [12].

Despite these emerging insights, the existing literature remains fragmented in several important respects. First, many studies examine technical aspects of AI ethics, such as bias detection or model explainability, without sufficiently connecting these issues to strategic decision-making processes [23,39]. Second, research on AI-driven performance gains often overlooks governance and accountability considerations, treating AI primarily as an efficiency-enhancing tool rather than a socio-technical system embedded in managerial contexts [16,24]. Third, organisational readiness and cultural resistance are frequently analysed in isolation from broader questions of strategic decision quality and long-term competitive outcomes [31].

At the same time, recent review studies have significantly advanced understanding of AI-enabled business model transformation and digitalisation processes [22]. However, these contributions primarily examine AI from the perspective of business model innovation and organisational transformation rather than from the perspective of strategic managerial decision-making itself. As a result, limited integrative understanding exists regarding how AI reshapes managerial judgment, strategic authority, human–AI interaction and algorithmic governance within strategic decision processes.

In particular, it remains unclear how organisations can simultaneously capture the strategic benefits of AI while ensuring responsible managerial oversight [16], and the conditions under which AI-supported strategic decision-making becomes both effective and accountable remain insufficiently theorised [31]. This gap is especially salient for managers who must balance performance pressures with ethical and governance responsibilities in increasingly AI-enabled environments [4].

Accordingly, this study addresses this gap by providing a systematic and managerially oriented synthesis of the literature on AI-enabled strategic decision-making, with the aim of developing an integrated framework that clarifies how organisations can adopt AI responsibly while sustaining strategic performance.

### *2.4. Responsible AI and the Social and Governance Dimensions of Organisational Sustainability*

Responsible AI provides a conceptual bridge between AI-enabled strategic decision-making and the social and governance dimensions of organisational sustainability. Strategic decisions determine how resources, opportunities and risks are distributed across employees and other affected stakeholders. Their sustainability cannot therefore be assessed solely through efficiency, accuracy or competitive performance. It also depends on whether the processes through which those decisions are reached ensure fair treatment, human agency and organisational accountability. Recent research on algorithmic management defines the social sustainability of employment relations in terms of whether consequential decisions remain intelligible, contestable, attributable and open to negotiation by the workers they affect [3]. Applied more broadly to strategic decision-making, intelligibility requires that relevant actors can understand the basis of AI-supported decisions; contestability requires meaningful opportunities to question and correct them; attributability requires identifiable human and organisational responsibility; and negotiability preserves stakeholder voice when algorithmic decisions reshape work and organisational relationships.

Social sustainability requires distinguishing governance inputs, organisational processes and substantive outcomes. Inputs include explanation tools and oversight protocols; processes concern how these are used to involve employees, scrutinise recommendations and resolve disputes; outcomes concern their consequences for worker autonomy, job quality and equitable treatment. The existence of a governance mechanism does not necessarily mean the presence of meaningful social protection. Responsible AI procedures should therefore be assessed through their use and consequences, rather than treated as intrinsic evidence of progress towards the SDGs [33,40,41].

From this perspective, responsible AI-enabled strategy constitutes a socio-technical capability rather than a property of an algorithm alone. It combines technical features, including explainability, traceability and bias mitigation, with organisational arrangements such as decision ownership, audit routines, escalation procedures and accessible mechanisms for review and redress. This interpretation reflects the governance principles expressed in SDG 16.6 [42], which provides a relevant benchmark for effective, accountable and transparent institutions. Because SDG 16.6 primarily addresses public institutions, SDG 12.6, which encourages companies to adopt sustainable practices and integrate sustainability information into their reporting, provides a more direct corporate anchor, while SDG 16.7 on responsive, inclusive and participatory decision-making captures the negotiability dimension discussed above. Explainability contributes to this objective only when it enables substantive scrutiny and responsibility rather than merely producing technical information about model outputs. Algorithmic governance consequently becomes the organisational mechanism through which transparency is translated into accountable decision-making [16,33].

The social dimension is further reflected in SDG 8, particularly its emphasis on decent work and productive employment, and target 8.8 on protecting labour rights and secure working environments, which is directly relevant when AI is used to monitor or evaluate workers. Although AI can augment managerial judgment and relieve employees of repetitive tasks, its introduction may also intensify monitoring, displace roles or reduce workers' practical influence over decisions affecting them. Human–AI complementarity must therefore involve meaningful human control rather than symbolic oversight. This

requires employees and managers to possess the authority, skills and organisational support needed to interpret, challenge and override algorithmic recommendations. Workforce participation, upskilling and responsible job redesign are thus integral components of sustainable AI adoption [25,41].

Finally, SDG 10.3 connects responsible AI to equal opportunity and non-discrimination. Because biased data and model design can reproduce or amplify existing inequalities, fairness requires continuous data governance, bias assessment and post-deployment monitoring rather than a one-off technical intervention [17,37]. Together, these dimensions reposition responsible AI as the organisational capacity to combine technological performance with accountable governance, meaningful human agency and protection against discriminatory outcomes.

## 3. Materials and Methods

### *3.1. Research Design*

This study adopts a systematic literature review (SLR) combined with qualitative thematic analysis to examine how AI reshapes strategic decision-making and the conditions enabling its responsible managerial use. Following established SLR guidance [43] and PRISMA 2020 [44], the review provides a structured, transparent and replicable synthesis of recent research on the strategic, organisational and governance implications of AI adoption in business contexts.

To achieve depth and conceptual rigor, the search strategy was deliberately designed around high-precision criteria targeting strategic-level managerial decision-making, rather than operational AI applications or generic digital tools. While SLR methodologies in broad management fields sometime yield expansive corpora, a tightly bounded corpus of 50 high-quality, peer-reviewed studies was selected following a rigorous multi-stage screening process. This focused sample reflects the deliberate exclusion of peripheral technical or operational papers, ensuring that the reviewed literature directly addresses the intersection of strategic judgment, algorithmic authority and socio-governance accountability. Rather than assuming that a smaller corpus inherently yields greater depth, our search implementation demonstrates that this boundary-based strategy comprehensively captured the primary peer-reviewed literature dedicated, in particular, to strategic AI governance between 2019 and 2025.

### *3.2. Search Strategy and Data Sources*

A multi-database search strategy was employed in order to ensure broad coverage of peer-reviewed research in management, information systems and AI-related domains. The search covered publications from 2019 to 2025, capturing the most recent phase of AI diffusion into strategic management. The review uses 2025 as its final publication year to establish a clearly bounded evidence base and avoid combining previous years with an incomplete 2026 publication year. The literature cited in the background and discussion sections to contextualise the findings is not restricted to this window and does not form part of the review corpus.

The final database searches were conducted on 18 December 2025 in Scopus, Web of Science, ScienceDirect and the ACM Digital Library. The searches yielded 771 records before deduplication: 207 from Scopus, 261 from Web of Science, 231 from ScienceDirect and 72 from the ACM Digital Library. Four search blocks addressed AI and strategic decision-making (385 records), responsible AI and governance (192), human–AI collaboration and organisational transformation (124), and a supplementary combination of AI adoption, generative AI, innovation and governance terms (70).

The searches followed a common conceptual structure, with database-specific implementation of search fields, query expressions and available filters. The four blocks are presented in Appendix A. Eligibility was restricted to English-language, peer-reviewed journal articles and conference papers published during 2019–2025. Criteria not available as database filters were applied during screening. During manuscript revision, Claude Sonnet 5 (Anthropic) was used to support structural and linguistic improvements. All AI-generated suggestions were reviewed and validated by the authors, who retained full responsibility for the manuscript's scientific content and conclusions.

### *3.3. Inclusion and Exclusion Criteria*

To ensure methodological rigor and relevance, explicit inclusion and exclusion criteria were applied. Studies were included if they met the following criteria: (i) peer-reviewed journal articles or conference papers, (ii) published in English, (iii) published between 2019 and 2025, (iv) explicitly examined AI within business, organisational or strategic decision-making contexts, and (v) provided empirical evidence, conceptual development or systematic analysis relevant to managerial decision processes. Studies were excluded if they (i) were non-peer-reviewed sources (e.g., editorials, opinion pieces or blogs), (ii) focused exclusively on technical AI development without managerial or organisational implications, (iii) did not address business or strategic decision-making contexts, or (iv) lacked sufficient methodological transparency. The application of these criteria ensured that the final sample consisted of high-quality and managerially relevant studies aligned with the objectives of the review. Included studies were subsequently grouped according to their primary analytical focus and synthesised through inductive thematic clustering to identify recurrent managerial and organisational patterns across the literature.

Methodological quality was appraised during the review using design-specific criteria. Studies were classified by dominant design and assessed with an adapted CASP/JBI checklist (quantitative), the CASP Qualitative Checklist, an adapted CASP Systematic Review Checklist or, for conceptual papers, for which no CASP tool exists, six conceptual-rigour criteria derived from the JBI Checklist for Text and Opinion Papers and Jaakkola (2020). Each criterion was rated 2/1/0, and studies were classified as High ($\geq$75%), Moderate (50–74%) or Low (<50%) quality. Because study-level scores were not originally tabulated, the appraisal record was compiled from the full texts during revision (Table S1). Appraisal informed the weight given to evidence rather than inclusion: no study that met the eligibility criteria was excluded on the basis of its appraisal rating, and the conclusions in Section 5.1 draw mainly on High-rated empirical studies.

### *3.4. Study Selection and PRISMA Process*

The study selection process followed the four-stage PRISMA framework: identification, screening, eligibility and inclusion (Figure 1). Initially, the database search produced 771 records. After removing 421 duplicates, 350 records remained for screening. Following title and abstract screening, 285 records were excluded. Of the 65 reports sought for retrieval, 3 could not be retrieved, and 62 full-text articles were assessed for eligibility. Full-text articles were excluded for the following reasons: absence of managerial implications relevant to strategic decision-making ($n$ = 5), insufficient methodological transparency ($n$ = 4), lack of strategic-level focus despite discussing AI applications ($n$ = 3), and reports excluded for other reasons ($n$ = 2). In addition, two foundational sources identified through backward citation tracking were included to enrich the theoretical contextualisation: Jarrahi [45], published in 2018, which was outside the primary 2019–2025 timeframe, and Floridi and Cowls [35], an edited book chapter. To maintain absolute methodological consistency and transparency, these theoretical anchors were explicitly differentiated from

the primary SLR corpus. Specifically, these two sources were used only for conceptual grounding in the theoretical background and framework synthesis, and they were strictly excluded from the systematic thematic coding, percentage occurrence calculations, and quantitative corpus analytics. Both studies are reported in the PRISMA flow diagram as records identified through other methods. The systematic evidence base for all thematic frequency analyses thus rests uncompromised on the 50 peer-reviewed articles meeting all formal eligibility criteria.

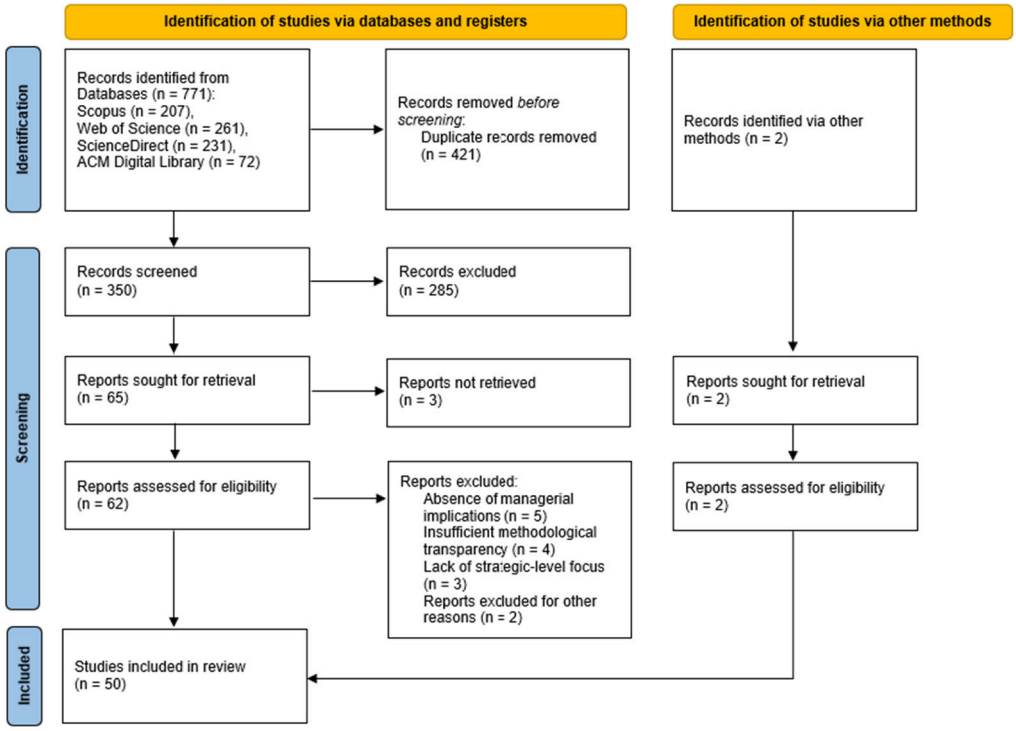


**Figure 1.** PRISMA 2020 flow diagram of study selection.

Following the said removal of 421 duplicates, the remaining 350 unique publications were evaluated as a consolidated corpus. This is because many of the included papers are indexed concurrently across multiple databases, such as Scopus, Web of Science, and ScienceDirect. Consequently, database breakdown is reported strictly at the initial identification stage, in alignment with PRISMA 2020 guidelines. During the screening phase, titles and abstracts were reviewed to assess thematic relevance. Studies that did not address AI in strategic or organisational decision-making contexts were excluded. In the eligibility phase, full-text articles were examined against the predefined inclusion and exclusion criteria, with particular attention to their strategic relevance, managerial implications and consideration of governance issues.

Screening was conducted in two stages by two authors working independently (A.K. and M.S.). Titles and abstracts were initially screened against the inclusion criteria, followed by full-text eligibility assessment of the retained studies. Screening decisions were reviewed iteratively to ensure consistency in interpretation, and disagreements regarding inclusion were resolved through discussion and re-evaluation against the predefined criteria. The review protocol was not prospectively registered.

The final inclusion stage resulted in a refined corpus of studies forming the basis of the thematic analysis. The structured PRISMA approach enhances the transparency, replicability and methodological robustness of the review process.

### *3.5. Data Extraction and Thematic Analysis*

Following study selection, a structured data extraction form was used to record publication details, research design, the AI technologies examined, strategic context, key managerial implications and principal findings. Data extraction was conducted iteratively and cross-checked for consistency to support cross-study comparison and conceptual alignment.

The qualitative synthesis employed thematic analysis following the Braun and Clarke [46] framework. Initial codes were generated inductively from the extracted material and iteratively compared across studies to identify recurring patterns in how the literature conceptualised AI in strategic decision-making. These codes were then consolidated into higher-order thematic categories through repeated comparison, refinement and conceptual abstraction. To enhance analytical rigor, coding and theme development were conducted iteratively through continuous comparison, refinement of code boundaries and revisiting ambiguous classifications.

This process resulted in the identification of six overarching thematic domains: (1) AI-driven automation and decision support, (2) data-driven strategic decision-making, (3) ethical and governance challenges, (4) data security and privacy, (5) organisational and structural impact, and (6) innovation and competitive advantage. These themes capture both the performance-related benefits and the governance complexities associated with AI adoption in strategic contexts. Data extraction and thematic coding were organised using a researcher-developed Microsoft Excel spreadsheet (Microsoft Corporation, Redmond, WA, USA). Thematic analysis was conducted manually, without the use of specialised qualitative data analysis software.

For the higher-order comparison, Themes 1, 2 and 6 were grouped as performance-oriented because they concern analytical efficiency, decision support and innovation. Themes 3, 4 and 5 were grouped as governance- and workforce-oriented because they concern accountability, data protection and organisational roles. Cross-orientation coverage denotes assignment to at least one theme in each group. This grouping summarises thematic coverage rather than imposing mutually exclusive identities on studies: organisational transformation may also concern performance, while performance-focused studies may address ethical issues without receiving a separate governance code. The resulting pattern is therefore sensitive to the search scope and thematic boundaries.

Following completion of the inductive coding and theme-development process, the six themes were mapped to relevant sustainability dimensions and SDG targets as a post-coding interpretive overlay. This mapping did not alter the original codes, theme boundaries, article assignments or occurrence rates.

## 4. Results

The thematic analysis identifies six interrelated dimensions through which AI is reshaping strategic decision-making (Table 1). For the cross-theme comparison, Themes 1, 2 and 6 are grouped as performance-oriented, while Themes 3, 4 and 5 are grouped as governance- and workforce-oriented. These orientations organise the thematic presentation without treating the studies as mutually exclusive groups; their connections and limitations are examined in Section 4.7.

**Table 1.** Thematic analysis overview: occurrence, key studies and sustainability interpretation.

| No. | Topic | Description | Number of Articles | Occurrence Rate (%) | Key Articles | Sustainability Dimension/SDG Link |
|---|---|---|---|---|---|---|
| 1 | AI-Driven Automation | Automation through AI that reduces human error and increases efficiency | 11/50 | 22 | [14,19,26–28,34,47–51] | Economic sustainability—SDG 9: process innovation, technological capability and efficiency-enhancing infrastructure |
| 2 | Data-Driven Strategic Decision-Making | AI for data analysis, trend forecasting, strategic planning and decisions | 16/50 | 32 | [5,11,14,19,20,22,24,26,29,31,32,47,49,52–54] | Economic sustainability—SDG 9: data infrastructure, analytical capability and innovation-led decision-making |
| 3 | Ethical & Governance Challenges | Issues of ethics, bias, transparency and accountability in AI systems | 19/50 | 38 | [2,16–18,22,33–37,40,41,55–61] | Social and governance sustainability—SDGs 16.6, 16.7, 12.6 and 10.3: accountability, transparency, explainability and non-discrimination |
| 4 | Data Security & Privacy | Integrity, protection and management of sensitive data in an AI environment | 5/50 | 10 | [2,18,61–63] | Social and governance sustainability—SDGs 16.10 and 16.6: privacy as a fundamental freedom, data rights and accountable data governance |
| 5 | Organisational & Structural Impact | Changes in structure, roles and administrative decision-making due to AI | 9/50 | 18 | [2,19–22,34,45,49,64] | Social sustainability—SDG 8 (target 8.8): decent work, workforce capabilities, meaningful human control and human–AI complementarity |
| 6 | Innovation & Competitive Advantage | The contribution of AI to strategic innovation and the creation of competitive advantage | 9/50 | 18 | [14,15,25,26,29,65–68] | Economic sustainability—SDG 9: organisational innovation, technological development and sustainable competitive capacity |

Note: The sustainability and SDG links represent the authors' post-coding interpretation of thematic relevance, not measured contributions to SDG targets or relationships established across the included studies. Occurrence rates use the complete 50-source corpus, including the two eligibility exceptions [35,45]. A calculation excluding these sources from the assignments reported in Table 1 reduces Theme 3 from 19 to 18 studies and Theme 5 from nine to eight. With a denominator of 48, their occurrence rates become 37.5% and 16.7%, respectively, compared with 38% and 18% in the full corpus. All six themes remain represented, and Theme 3 remains the most frequent; this check concerns numerical sensitivity rather than a separate thematic recoding. The PRISMA 2020 checklist and Table S1. Design-specific methodological quality appraisal of the 50 included studies can be found in the Supplementary Materials provided.

### *4.1. AI-Driven Automation and Decision Support*

A dominant pattern concerns AI's role in automating analytical tasks and augmenting managerial decision processes [14]. AI-enabled systems streamline data processing, forecasting and routine decision workflows, reducing manual effort, minimising errors and accelerating decision cycles [27,28].

Beyond efficiency gains, AI functions as a cognitive support tool that enhances managerial judgment [48]. Predictive analytics and decision-support systems enable executives to evaluate multiple scenarios and detect weak signals in complex environments [15], particularly under conditions of time pressure and information overload [47].

However, the benefits depend on how AI outputs are produced and used. In entrepreneurial settings, Csaszar et al. [19] find that LLMs can generate and evaluate strategies at levels comparable to human participants. Doshi et al. [14] qualify this potential: individual AI evaluations of business models are often inconsistent and biased, whereas aggregated evaluations more closely resemble expert rankings. These findings support structured analytical assistance rather than unrestricted reliance. Moreover, Bankins' conceptual HR framework [40] identifies automation bias as a reason why formally retaining human authority may fail to preserve critical judgment.

Implication: AI strengthens decision capacity through efficiency and augmentation, but its value depends on maintaining appropriate human oversight.

### *4.2. Data-Driven Strategic Decision-Making*

A second theme highlights AI's role in enabling data-centric strategic management [31]. AI technologies expand organisations' ability to transform large volumes of structured and unstructured data into actionable insights, supporting more precise forecasting and competitive positioning [26,29].

AI-driven predictive models allow organisations to continuously update strategic decisions based on real-time data, enhancing adaptability in volatile environments [32]. As a result, AI is increasingly embedded in scenario planning, risk modelling and resource allocation processes [24].

At the same time, effective implementation depends on data quality and governance. Weak data integration or poor data management can undermine AI outputs and lead to misleading strategic insights [14].

Implication: AI enhances data-driven strategic decision-making, but its effectiveness relies on robust data governance and analytical maturity.

### *4.3. Ethical and Governance Challenges*

A central theme concerns the ethical and governance risks associated with AI-enabled decision-making. Algorithmic bias emerges as a key concern, as AI systems may reproduce or amplify existing data biases, leading to discriminatory or suboptimal outcomes [17,37].

Transparency and explainability limitations further complicate managerial reliance on AI, but the studies distinguish technical intelligibility from organisational accountability. McDermid et al. [34] argue that explanations must address stakeholder purposes and be situated within wider accountability arrangements. Ayling and Chapman's assessment of practical ethics tools [33] identifies gaps in stakeholder participation, external verification and lifecycle coverage. Similarly, Jobin et al. [36] find convergence around ethical principles alongside divergence in their interpretation and implementation. Agreement on transparency and oversight therefore provides stronger support for their importance as governance requirements than for their consistently demonstrated effectiveness.

Importantly, these findings indicate that responsible AI is a socio-technical challenge requiring governance structures, managerial accountability and continuous monitoring [57].

Implication: Without robust governance and transparency, AI's strategic benefits may be offset by legitimacy and accountability risks.

### *4.4. Data Security and Privacy*

The literature emphasises that the value of AI-enabled decision-making depends on the integrity and protection of organisational data [18]. Because AI systems rely on large-scale data processing, including sensitive information, data security and privacy are foundational concerns [62].

AI adoption expands organisational vulnerability to cyber risks, including data breaches and unauthorised access, particularly when systems are widely integrated across

digital infrastructures [62]. Weak data protection can compromise decision reliability and undermine trust.

Moreover, compromised or low-quality data complicates accountability and traceability, weakening managerial oversight [18,34].

Implication: Secure and well-governed data is a prerequisite for reliable and accountable AI-supported strategic decision-making.

### *4.5. Organisational and Structural Impact*

AI adoption is associated with significant organisational transformation. Successful integration requires changes in structures, roles and capabilities, particularly in relation to human–AI collaboration [64].

Most organisations adopt hybrid decision models, where AI generates recommendations and managers retain final authority. This shift increases the importance of managerial skills such as data literacy and critical evaluation of AI outputs [19].

Cultural readiness also plays a key role. Resistance to AI adoption, driven by mistrust or concerns about job displacement, can limit its effectiveness, whereas organisations investing in training and change management are more successful in embedding AI into decision processes [21].

Implication: Organisational readiness and human–AI collaboration capabilities are critical for translating AI adoption into strategic value.

### *4.6. Innovation and Competitive Advantage*

The final theme concerns AI's contribution to innovation and competitive advantage, although gains vary by outcome and context. In a creative problem-solving experiment, Boussioux et al. [48] find that human–AI solutions outperform crowd-generated solutions in strategic viability and overall quality, whereas human solutions exhibit greater novelty. At the firm level, Liu et al.'s study of 246 Australasian B2B firms [66] links AI-enabled systems to innovation through decision-making performance, with the contribution of strategic agility plateauing at excessive levels. These findings qualify broad expectations of improvement: solution viability, novelty and firm-level innovation are distinct outcomes rather than interchangeable indicators of strategic success.

From a resource-based perspective, AI can generate competitive advantage when combined with complementary assets such as proprietary data and organisational capabilities. However, as AI technologies become increasingly commoditised, advantages depend less on adoption and more on effective integration into strategic processes [67].

Firms achieving the greatest performance gains are those that align AI deployment with broader strategic objectives rather than treating it as a standalone initiative [68].

Implication: AI can drive innovation and competitive advantage, but sustained value depends on strategic alignment and organisational integration.

### *4.7. Sustainability Interpretation of the Thematic Structure*

The thematic structure gives comparable prominence to performance and governance concerns. Themes 3, 4 and 5 account for 33 of the 69 article–theme assignments (48%), while Themes 1, 2 and 6 account for 36 (52%). In total, 28 studies address at least one performance-oriented theme and 27 at least one governance- or workforce-oriented theme; five span both. However, cross-orientation coverage should be interpreted as a feature of this thematic mapping, not proof of a fundamental division in the wider literature. Search terms, eligibility criteria and the grouping of organisational transformation with governance influence the observed pattern. The findings therefore identify different analytical emphases within the selected corpus rather than establish two mutually exclusive research streams.

The studies spanning both theme groups connect them in different ways. Csaszar et al. [19] examine strategic capabilities and their organisational implications; Trunk et al. [20] connect decision support with task allocation, responsibility and implementation conditions; and Kitsios and Kamariotou [49] relate value creation to strategic alignment and organisational integration. Jobstreibizer et al. [22] address business-model transformation, whereas McDermid et al. [34] connect technical explanation methods to stakeholder purposes and accountability. These contributions differ in analytical scope and do not constitute a single integrated research approach. Conversely, Rana et al. [60] explicitly connect ethical principles, GenAI adoption and organisational performance despite appearing only under Theme 3 in Table 1. Theme membership thus does not exhaust substantive connections between the orientations. The framework builds on these existing connections to examine how strategic benefits and accountable decision authority can be considered together.

This interpretation is reinforced by the prominence of Theme 3. Ethical and Regulatory Challenges is the largest individual theme, appearing in 19 of the 50 studies (38%). Its emphasis on algorithmic bias, explainability, accountability and organisational oversight positions governance as a central condition of responsible AI adoption rather than a secondary constraint on technological performance. We interpret these concerns as relevant to the objectives of institutional transparency and accountability under SDG 16.6 and non-discrimination under SDG 10.3; this conceptual correspondence does not demonstrate progress towards those targets.

Although Theme 4, Data Security and Privacy, appears in only five studies (10%), its significance becomes clearer when data protection is understood as a social sustainability concern rather than solely a technical requirement. Privacy, control over personal information and protection against inappropriate data use affect the autonomy and rights of employees, customers and other stakeholders subject to AI-supported decisions. Theme 5 similarly connects organisational transformation with SDG 8 through its focus on changing roles, workforce capabilities and human–AI collaboration. The thematic findings therefore support repositioning responsible AI as a socio-technical capability through which organisations combine strategic performance with accountable governance, data rights and meaningful human participation.

## 5. Discussion

Section 4 presents the thematic findings and their limitations; the following discussion develops our conceptual interpretation of their relationships and translates it into managerial guidance. This study develops an integrated managerial understanding of how AI reshapes strategic decision-making and when its adoption can be considered responsible and effective. The findings reveal a central duality: AI potentially fosters analytical capacity and strategic agility while introducing governance and accountability challenges that can undermine decision quality and legitimacy. It therefore reframes AI as a socio-technical strategic capability whose value depends on alignment between technological performance, governance and organisational readiness. The review further identifies different emphases and existing connections between performance and governance research (Section 4.7), which the framework developed below brings into a common account of strategic decision authority. Whereas prior review-based studies have primarily examined AI in relation to business model innovation and digital transformation [22], the present study extends the conversation toward the governance and managerial dimensions of AI-supported strategic decision-making.

### *5.1. Reframing AI in Managerial Decision-Making*

The evidence suggests that AI is best understood not merely as an automation technology but as a transformative cognitive infrastructure within contemporary organisations [13]. While early discussions of AI in management often emphasised efficiency gains through automation, the reviewed literature indicates a more nuanced evolution toward decision augmentation and hybrid human–AI judgment systems [30]. This shift reframes AI from a tool that replaces managerial work to one that reconfigures how strategic cognition is distributed within firms [30].

From a decision theory perspective, AI expands the informational bandwidth available to managers, enabling more data-intensive and probabilistic forms of strategic reasoning [24]. Predictive analytics, scenario modelling and real-time data processing reduce bounded rationality constraints by allowing decision-makers to evaluate a wider range of alternatives under uncertainty [25]. However, the findings also indicate that the reduction of cognitive constraints does not eliminate the need for managerial judgment [30]; rather, it changes its locus [31]. Managers increasingly move from primary decision producers to evaluators, interpreters and governors of algorithmic outputs [14].

This extends the resource-based view by showing that AI capabilities become strategically valuable only when embedded within complementary organisational processes, governance structures and managerial competencies [12,30].

At the same time, the literature highlights a growing risk of algorithmic overreliance [26]. As AI systems become more accurate and embedded in decision workflows, managers may exhibit automation bias, over-trusting algorithmic recommendations even when contextual judgment is required [57]. Consequently, the role of managerial oversight becomes more (not less) critical in AI-enabled environments [4].

The evidence supports task-specific benefits more directly than durable organisational gains: aggregated AI evaluations can approximate expert rankings [14], and human–AI solutions can improve selected quality dimensions while sacrificing novelty relative to human solutions [48]. Firm-level innovation relationships remain conditional [66], while governance analyses identify implementation gaps rather than consistently effective safeguards [33,36]. The central synthesis is therefore that analytical capability and accountable use require distinct, complementary arrangements. This interpretation motivates the three-pillar framework developed below; it does not establish that adopting its components necessarily improves performance or legitimacy.

### *5.2. Toward Responsible AI-Enabled Strategy*

Building on these insights, this study advances a central conceptual contribution: the effectiveness of AI in strategic decision-making is contingent on the development of responsible AI-enabled strategy [16]. The thematic synthesis indicates that performance gains and governance risks are deeply intertwined rather than independent phenomena [24]. Organisations that pursue AI adoption purely for efficiency improvements without parallel investment in governance and organisational readiness expose themselves to legitimacy, accountability and trust vulnerabilities [30]. If left unaddressed, these conditions are likely to intensify over time, increasing automation bias, diffusing accountability and exposing firms to avoidable regulatory and reputational risk.

First, algorithmic transparency and explainability are foundational [23,39]. The literature consistently demonstrates that black-box AI systems undermine managerial trust and complicate accountability structures [25]. XAI mechanisms therefore function not only as technical tools but as governance enablers that allow managers to interrogate, validate and appropriately contextualise algorithmic recommendations [26]. Beyond technical interpretability, transparency may support the accountability objectives associated

with SDG 16.6 when explanations enable affected stakeholders to scrutinise and contest decisions [33,34].

Second, human–AI complementarity emerges as a critical design principle [48]. Rather than pursuing full automation, the most effective implementations maintain structured human-in-the-loop or human-on-the-loop arrangements [31]. These configurations preserve managerial judgment while still leveraging AI's analytical strengths [14]. The findings suggest that the optimal balance is context-dependent, varying according to decision criticality, data reliability and regulatory exposure [57]. In relation to SDG 8, this complementarity may support decent work when human involvement preserves practical influence over decisions and is accompanied by attention to job quality and workforce consequences [25,41]. Furthermore, human involvement should not be considered as a foolproof safeguard against algorithmic risks. Just because someone has responsibility in a company does not mean that there is proper control over process. Human reviewers may lack the necessary skills and understanding needed to fulfil tasks or they may face excessive pressure from people at work and rely too heavily on machines and automated processes, making supervision of the processes ineffective.

Third, organisational readiness and capability development condition whether AI adoption translates into sustained strategic value [12]. The review highlights that firms achieving superior outcomes invest not only in technical infrastructure but also in data governance, cross-functional collaboration and managerial upskilling [16]. Responsible AI, therefore, should be conceptualised as a socio-technical capability embedded in organisational routines rather than a purely technological attribute [30]. This positions readiness as a broader social capability that prioritises continuous workforce upskilling and participatory change over rigid technical implementation. Recent research outside the review period strengthens this contextual interpretation. Extending the technology–organisation–environment perspective, Zhou [69] identifies different configurations of AI adoption in Chinese environmental governance and distinguishes compliance-driven implementation from deeper organisational integration. The study's discussion highlights risks of token compliance under hierarchical pressure and automation bias where advanced technology encourages uncritical reliance. These observations connect organisational readiness with human–AI complementarity: infrastructure and adoption incentives need to be considered alongside critical capacity and accountability arrangements, although their effectiveness in strategic business decisions requires separate investigation. Together, these three dimensions form the three-pillar framework of responsible AI-enabled strategy presented in Figure 2.

Our conceptual contribution concerns the relationships between these established dimensions. We propose that transparency supplies information for human scrutiny [34], human–AI complementarity determines how that information informs judgment and intervention [40], and organisational readiness provides the skills and responsibilities needed to sustain both [20]. Monitoring and review can, in turn, identify changes needed in explanations, training and oversight [33]. These proposed relationships require empirical validation. This interpretation builds on existing accounts of human–AI decision structures [2], ethical task–technology fit [40] and organisational adoption conditions [53] by considering their joint implications for accountable strategic decision authority. The pillars are treated as mutually reinforcing dimensions, not successive implementation stages. Organisational readiness supports explanation and human intervention throughout implementation, while difficulties encountered during human evaluation can reveal changes needed in explanations, skills and decision boundaries. The proposed contribution therefore concerns how these dimensions interact: explainability may contribute little to

accountability without authority to intervene, and formal human approval may remain ineffective without adequate organisational support.

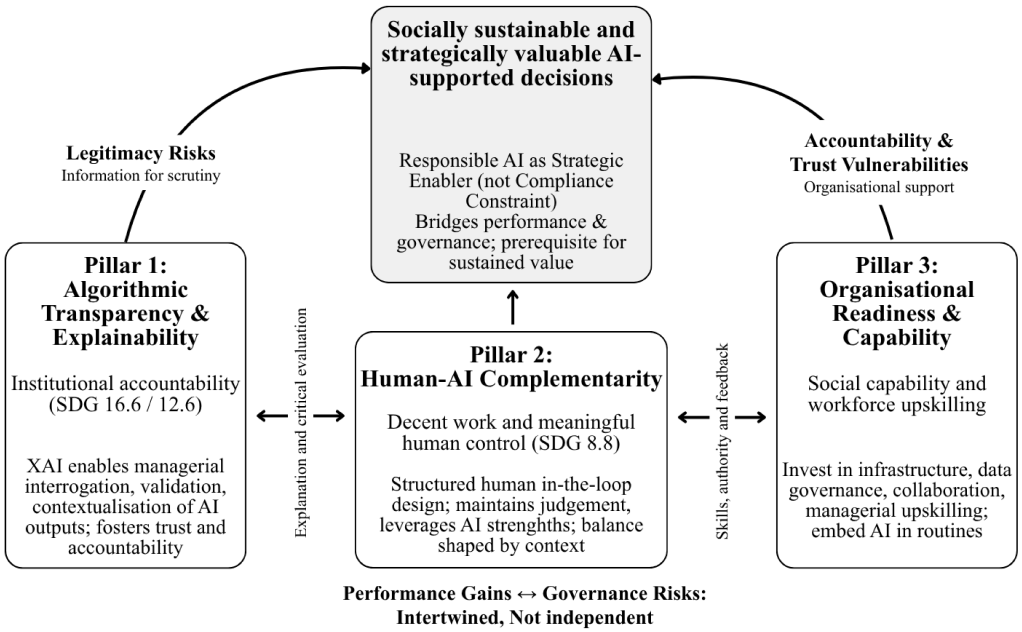


**Figure 2.** The three pillars of responsible AI-enabled strategy. Note: The arrows depict proposed relationships between the pillars and intended outcomes rather than empirically established causal effects.

Building on this framework and its alignment with social sustainability imperatives, we formulate three orienting conceptual propositions, specifying proposed organisational mechanisms and boundary conditions. These are not fully specified hypotheses or effects established by the review; empirical testing will require context-specific operationalisation of the constructs, outcomes and boundary conditions. First, the institutional accountability and legitimacy of AI-supported strategic decisions toward affected stakeholders are likely to increase when algorithmic governance structures are formalised and calibrated to decision criticality. The underlying mechanism relies on reducing information asymmetries and providing clear audit trails; however, this relationship is bound by organisational context, holding primarily in firms with sufficient compliance maturity, whereas in low-maturity or resource-constrained settings, formalisation may degrade into symbolic compliance. Second, the accountability, explainability and contestability of AI-augmented strategic decisions are likely to be greatest in collaborative human–AI configurations that preserve meaningful human control and worker agency rather than in fully delegated arrangements. The mechanism here is the active distribution of cognitive workload and mutual error-correction; nevertheless, this effect depends heavily on whether workers possess the psychological safety and structural authority to override recommendations without facing negative career repercussions. Third, the long-term social legitimacy and organisational sustainability of AI-supported strategic decisions are likely to depend on the joint maturity of explainability mechanisms, data governance standards and accessible procedures for review and redress available to affected stakeholders. The underlying dynamic is the systemic alignment between technical transparency and institutional recourse; yet, this condition fails to hold if redress channels are mainly nominal and decoupled from operational decision-making power. Together, these propositions provide directions for investigating relationships between governance design, human–AI role configuration and the accountability of strategic decision outcomes.

The framework's contribution to social sustainability is therefore a proposition to be evaluated rather than an established outcome of adopting its pillars. Evaluation should ex-

amine whether employee input changes decisions, whether challenges lead to correction or remedy, and how changes in workload, autonomy, job security and access to opportunities are distributed across employee groups. These proposed assessment criteria extend the framework beyond procedural compliance; they are not outcomes demonstrated by this review [33,40,41].

### *5.3. Managerial Implications*

The findings generate several actionable implications for managers seeking to leverage AI in strategic decision-making. First, organisations should avoid full decision automation in high-stakes strategic contexts [25]. While AI can substantially improve analytical speed and accuracy, the evidence indicates that maintaining human oversight remains essential for managing contextual complexity and ethical risk [30]. Drawing on decision contingencies and ethical task–technology fit [2,40], we propose assessing decision criticality, uncertainty, data quality, stakeholder harm, reversibility and organisational capability before allocating AI authority. High-impact or difficult-to-reverse decisions favour advisory support or collaboration with explicit human approval. Collaboration is appropriate where iterative comparison of algorithmic analysis and contextual judgment is feasible [20]. Delegation should be restricted to bounded, reversible decisions with reliable data, validated operating conditions and effective monitoring. Inadequate data or insufficient capacity to evaluate and override outputs should prompt narrower use or postponement rather than greater delegation.

A practical way to operationalise these governance choices is to distinguish between advisory, collaborative and delegated human–AI configurations. In advisory configurations, AI informs managerial judgment while decision authority remains human [70]; in collaborative configurations, AI and managers jointly shape decision outputs [71]; in delegated configurations, AI operates within predefined parameters with escalation and override thresholds [2]. Illustratively, advisory AI could compare workforce-restructuring options while executives retain responsibility for evaluating their human consequences. A collaborative market-entry process could involve managers challenging assumptions and requesting revised AI scenarios before approving a strategy. Within an approved marketing strategy, delegated AI could adjust campaign expenditures within predefined budget and performance limits, subject to monitoring and override. These hypothetical applications illustrate configuration choices rather than empirically validated prescriptions; the appropriate arrangement depends on the assessment above.

Second, firms should invest early in explainability and governance mechanisms [16]. Rather than treating responsible AI as a downstream compliance exercise, organisations should embed transparency, auditability and accountability structures at the design stage of AI deployment [57]. To operationalise accountability and stakeholder scrutiny [33,34,40], we propose assigning a named decision owner who retains final approval in advisory and collaborative configurations and responsibility for monitoring delegated decisions. Automated execution should pause for human review when predefined limits are exceeded, data-quality checks fail or credible stakeholder harm is identified. A proportionate decision record should capture the model version, relevant inputs and assumptions, recommendation, human response and reasons for the final action. Disputed recommendations should enter an accessible review channel, with implementation paused where feasible, assessment by a reviewer not involved in the initial decision, and a documented explanation and corrective action where warranted.

Third, managerial capability development must accompany technological adoption [12]. The shift toward AI-augmented decision-making requires new skill profiles, including data literacy, algorithmic awareness and critical evaluation of model outputs [14].

Training programs and role redesign should therefore be integral components of AI strategy rather than afterthoughts [68].

Fourth, data governance should be treated as a strategic priority. The effectiveness of AI systems is highly sensitive to data quality, integration and accessibility [18]. Managers should prioritise investments in data infrastructure, standardisation and lifecycle management to ensure that AI-generated insights remain reliable and decision-relevant [26,72].

Fifth, AI initiatives should be tightly aligned with broader strategic objectives [13]. The literature shows that organisations deriving the greatest value from AI are those that embed it within clearly articulated strategic priorities rather than pursuing isolated pilot projects [19]. Strategic alignment helps prevent technology-driven adoption that lacks measurable business impact [67].

Overall, the managerial challenge is not whether to adopt AI, but how to govern and integrate it in ways that enhance strategic decision quality while preserving accountability and organisational trust [14].

### *5.4. Implications for Social and Governance Sustainability*

The advisory, collaborative and delegated configurations identified in Section 5.3 build on research showing that AI changes organisational decision-making by redistributing cognitive tasks and decision authority between humans and algorithms [2,20]. This distribution cannot be understood as a simple progression from human control to automation. Automation and augmentation remain interdependent: systems designed to support human judgment may influence it substantially, while apparently automated decisions continue to depend on human choices concerning objectives, data and decision boundaries [73]. The following mapping to the EU AI Act is our interpretation of the configurations' regulatory implications, rather than a finding extracted from the reviewed studies or a validation of the proposed framework.

Two clarifications about regulatory scope are necessary. First, the AI Act classifies systems according to their intended purpose and the conditions in Article 6, rather than by the strategic importance of the decision they support. Many strategic applications, such as AI support for capital allocation, market entry or portfolio decisions, are not listed as such in Annex III. Their governance may nevertheless remain subject to other applicable legal duties, alongside voluntary instruments such as ISO/IEC 42001 [74] and the NIST AI Risk Management Framework [75]. By contrast, Annex III, point 4, expressly addresses specified employment applications, including recruitment, promotion, termination, certain forms of task allocation, and worker monitoring or evaluation, subject to the classification conditions in Article 6(2)–(3) [6]. These provisions are particularly relevant to the social dimension of sustainability because they address decisions affecting employment and working conditions.

Second, organisations using these systems under their authority generally act as deployers, although their legal role must be assessed for the particular activity. Where applicable, Article 26 requires deployers to assign human oversight to persons with appropriate competence, training, authority and support, retain automatically generated logs under their control and, when acting as employers, inform workers' representatives and affected workers before workplace deployment. Article 86 separately establishes a conditional right to explanations concerning legally or similarly significant decisions based on specified Annex III high-risk systems, subject to its exclusions and limitations. Following the Digital Omnibus amendment, the Chapter III, Sections 1–3 provisions, including Article 26 but excluding Article 6(5), apply to Article 6(2)/Annex III high-risk systems from 2 December 2027, subject to Article 111's transitional provisions. This postponement does not extend to Article 86 itself [7]. Furthermore, these legal obligations must not be

misconstrued as universally applicable organisational governance principles. Their legal relevance and operational applicability strictly depend on the system's intended purpose, its formal risk classification under the regulation, the organisation's specific legal role (e.g., deployer versus provider), and the relevant jurisdiction.

In advisory configurations, AI produces analyses or recommendations while formal decision authority remains human. This model corresponds to the augmentation logic emphasised in research on human–AI complementarity, which combines algorithmic processing capacity with contextual human judgment [20,25]. However, retaining a human decision-maker does not necessarily ensure meaningful oversight. Managers may defer to apparently objective recommendations, particularly when algorithmic processes are difficult to interpret [2,57]. Nor does an advisory configuration automatically fall outside the AI Act's high-risk category: an AI system used in an Annex III context may remain high-risk where its output materially influences decisions concerning employment, education or access to essential services. Effective oversight therefore depends on reviewers having relevant information, competence, time and authority, alongside organisational incentives that support justified disagreement. To operationalise these conditions, the framework proposes that reviewers document reasons for accepting or overriding consequential recommendations and can escalate unresolved concerns to a reviewer with sufficient independence and corrective authority. Formal human approval alone should not be treated as evidence of accountability.

Collaborative configurations involve humans and AI systems jointly producing decision outcomes. Research identifies such arrangements as potentially valuable under uncertainty because they combine complementary analytical and interpretive capabilities [20,45]. Nevertheless, collaboration can obscure responsibility when the respective contributions of the manager and the system are not documented. This creates an accountability gap in which human actors can attribute problematic outcomes to the algorithm, while system complexity makes organisational responsibility difficult to establish [40,76]. For high-risk systems, the AI Act's requirements concerning documentation, logging, transparency and human oversight provide mechanisms for addressing this problem. As an organisational recommendation, the framework calls for defined decision ownership, documentation of how AI outputs shaped the final judgment, and accessible explanation, review and redress procedures; the corresponding legal duties depend on the applicable provisions. However, providing formal explanation and review channels is only a governance input; its conversion into meaningful sustainability outcomes depends on the actual power dynamics within the organisation. Across all three configurations, employee participation should include opportunities to influence decision criteria and implementation, directly or through representatives. Review arrangements should protect employees against retaliation, provide access to a reviewer with sufficient independence and authority to correct decisions, and communicate the remedy and its implementation. These arrangements are proposed safeguards against unequal decision authority, whose effectiveness requires evaluation [33,40,41].

Delegated configurations grant AI systems authority to make or implement decisions within predetermined parameters. Shrestha et al. [2] argue that full delegation is most defensible when the decision space is specific, outcomes are measurable and the process can be reliably replicated. Delegation becomes more problematic when decisions involve ambiguity, contested values or significant consequences for individuals. Although delegation does not itself determine legal risk under the AI Act, greater autonomy increases the danger of diffused accountability and ineffective human intervention. End-to-end auditing, continuous monitoring, escalation thresholds and effective override mechanisms are consequently necessary to preserve organisational accountability [76]. Decisions affecting

employment, livelihoods or access to opportunities must also remain intelligible, contestable and attributable to an identifiable organisational actor [3]. Figure 3 synthesises this two-dimensional logic by mapping advisory, collaborative and delegated human–AI configurations against regulatory context, illustrating how increasing algorithmic authority and stronger regulatory obligations jointly intensify requirements for oversight, documentation, auditing and redress.

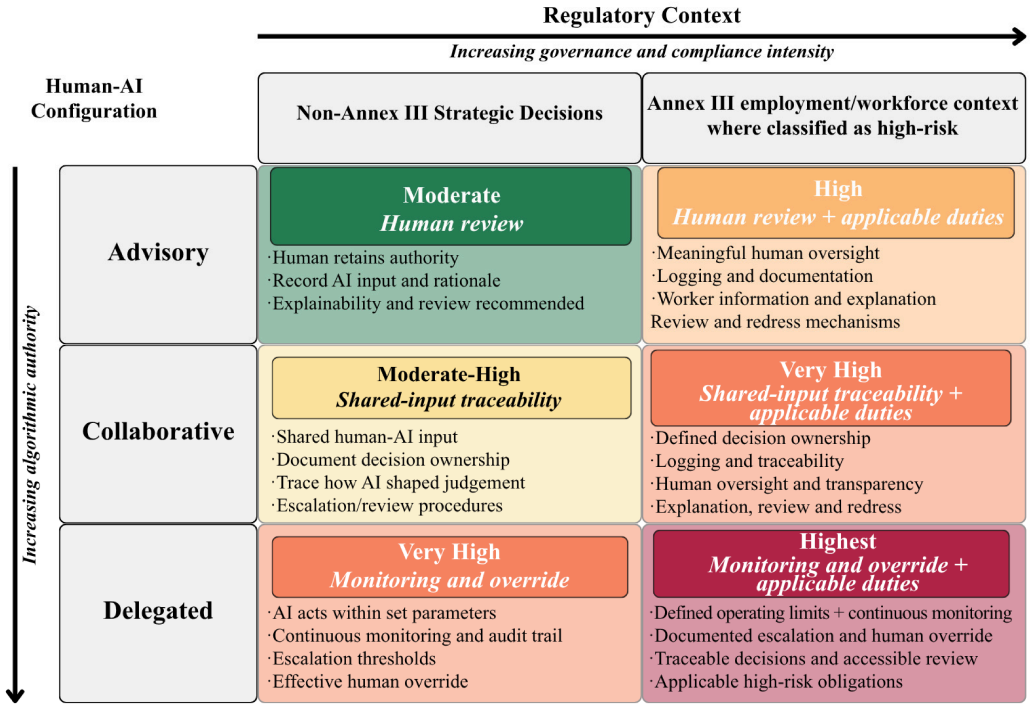


**Figure 3.** Governance calibration of human–AI decision configurations across regulatory contexts. Note: Regulatory context determines whether AI Act high-risk obligations apply; human–AI configuration informs the organisation of oversight, documentation, auditing and redress. The governance arrangements are illustrative rather than empirically validated prescriptions. Human review concerns the evaluation and approval of recommendations; shared-input traceability records decision ownership and how AI influenced judgment; monitoring and override concern delegated execution within defined limits. These emphases are not exclusive: all configurations require proportionate documentation and accessible review. Section 5.3 explains the selection criteria, decision responsibilities and review procedures through which the framework can be applied.

The resulting framework is therefore two-dimensional: the organisational typology specifies how authority is allocated, while the AI Act determines the regulatory obligations arising from the system's intended purpose and context. As algorithmic authority, stakeholder impact and legal risk increase, organisations must intensify documentation, auditing, human oversight and access to redress. This transforms the typology into a governance-calibration mechanism linking human–AI configuration choices to accountable institutions, meaningful human control and the social sustainability of AI-supported strategic decisions.

## 6. Conclusions

Building on prior syntheses of AI and business model transformation [22], this study synthesises fragmented research on AI in strategic decision-making and develops an integrated governance framework for socially sustainable, AI-enabled strategy. The review addresses RQ1 through the six-theme synthesis presented in Section 4, RQ2 through the organisational and governance conditions developed in Sections 5.1–5.3, and RQ3

through the sustainability interpretation and governance-calibration analysis presented in Sections 4.7 and 5.4. It makes three contributions: it identifies different emphases and limitations in how the selected literature connects AI's performance benefits with governance and workforce implications; it reframes responsible AI as a socio-technical capability and positions algorithmic governance as the mechanism that keeps AI-supported strategic decisions accountable, explainable and contestable; and it links human–AI decision configurations to EU AI Act obligations, offering a calibration mechanism aligned with SDGs 8 and 16.

For practitioners, the central challenge is not whether to adopt AI but how to govern and integrate it effectively. Firms that treat AI as a purely technical upgrade risk underperformance and legitimacy concerns, whereas those embedding it within robust governance and organisational frameworks are better positioned to realise sustained strategic value [26,48].

As with any systematic literature review, this study is subject to several limitations. First, the analysis is restricted to peer-reviewed publications in English, which may exclude relevant insights from practitioner reports or non-English scholarship. Second, the review focuses primarily on the 2019–2025 period to capture recent developments in AI adoption; while appropriate for examining contemporary dynamics, this temporal boundary may overlook earlier foundational contributions. Third, although the thematic synthesis provides integrative insights, it does not offer direct empirical testing of the proposed relationships, which limits causal inference. Fourth, the review addresses the social and governance dimensions of organisational sustainability, whereas the environmental footprint of AI systems, including data-centre energy demand, hardware lifecycle impacts and cooling water usage, lies outside the review boundary and constitutes a critical priority for future research. Complementary research illustrates these connections: Bundele and Devaerakkam [77] examine AI applications in urban organic waste management alongside policy, infrastructure and community participation. Such settings offer opportunities to investigate whether the proposed governance arrangements can address social and environmental objectives jointly while also accounting for AI's own resource demands. In addition, although the review followed a structured and transparent protocol, elements of study selection and thematic interpretation necessarily involved reviewer judgment, which may introduce interpretive subjectivity despite iterative cross-checking procedures. Finally, the rapidly evolving nature of AI technologies means that some findings may require continuous updating as new applications and governance frameworks emerge.

Future research should build on this work in several directions. Empirical studies are needed to test the proposed relationships between AI adoption, governance maturity and strategic performance across different industries and organisational contexts [19]. Longitudinal research could further illuminate how human–AI decision configurations evolve over time and under varying environmental conditions [14]. Additionally, more fine-grained investigation of sector-specific regulatory pressures and ethical risk profiles would deepen understanding of responsible AI implementation [26]. In addition, interdisciplinary work bridging strategic management, information systems and AI ethics could help develop more operationalisable frameworks for responsible AI-enabled strategy [68]. Finally, future research should examine how worker representatives and affected stakeholders participate in governing AI-supported strategic decisions, how firms disclose AI-related workforce impacts under ESRS S1, and how the environmental footprint of AI can be integrated with the social and governance perspective adopted here.

In conclusion, AI is poised to remain a central force in the evolution of strategic management. Organisations that approach AI adoption through an integrated lens, balancing analytical power with robust governance, human capability and strategic alignment,

are most likely to convert technological potential into managerial value that is not only sustained over time but also explicitly accountable to the people whom those strategic decisions affect.

**Supplementary Materials:** The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su182110797/s1, Table S1: Design-specific methodological quality appraisal of the 50 included studies; PRISMA 2020 Checklist.

**Author Contributions:** Conceptualization, S.T. and F.A.; methodology, S.T. and F.A.; validation, S.T., A.K. and M.S.; formal analysis, S.T. and A.K.; investigation, S.T., A.K. and M.S.; resources S.T., A.K. and M.S.; data curation, S.T., A.K. and M.S.; writing—original draft preparation, S.T.; writing—review and editing, F.A., S.T., A.K. and M.S.; visualization, A.K. and M.S.; supervision, F.A. All authors have read and agreed to the published version of the manuscript.

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## Abbreviations

The following abbreviations are used in this manuscript:

| | |
|---|---|
| ACM | Association for Computing Machinery |
| AI | Artificial Intelligence |
| CASP | Critical Appraisal Skills Programme |
| CSRD | Corporate Sustainability Reporting Directive |
| ESRS | European Sustainability Reporting Standards |
| EU | European Union |
| GenAI | Generative Artificial Intelligence |
| PRISMA | Preferred Reporting Items for Systematic Reviews and Meta-Analyses |
| RQ | Research Question |
| SDG | Sustainable Development Goal |
| SLR | Systematic Literature Review |
| UN | United Nations |
| XAI | Explainable Artificial Intelligence |

## Appendix A. Search Strategy

The search strategy comprised four conceptual blocks, presented below. These blocks describe the scope and structure of the search.

Search Block 1: AI and strategic decision-making: ("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning") AND ("Strategic Decision Making" OR "Business Strategy" OR "Corporate Decision Making")

Search Block 2: Responsible AI, governance and trust: ("Responsible AI" OR "Explainable AI" OR "Ethical AI") AND ("Organisational Strategy" OR "Decision-Making" OR "Business Ethics") AND ("AI Ethics" OR "Digital Ethics")

Search Block 3: Human–AI collaboration and organisational transformation: ("Human-AI Collaboration" OR "AI Integration") AND ("Management Decision Making" OR "Strategic Planning" OR "Business Transformation")

Search Block 4: AI adoption, impact and implementation challenges: ("AI Adoption" OR "AI Challenges" OR "AI Benefits") AND ("Strategic Decision Making" OR "Organisational Impact") AND ("Generative Artificial Intelligence" OR "GenAI") AND ("Innovation Management" OR "Innovation Process") AND ("Organisational Values" OR "Efficiency") AND ("Transparency" OR "Data Privacy")

The fourth search block represented a focused refinement search intended to increase conceptual specificity rather than serve as the primary retrieval mechanism. As expected, combining all six conceptual clusters substantially reduced the number of returned records. Therefore, this search was supplementary to the broader core search strategy in order to identify highly relevant studies addressing governance, accountability and strategic decision-making dimensions simultaneously.

The same eligibility-related limits were applied across the four database searches: English-language publications, publication years 2019–2025, and peer-reviewed journal articles or conference papers. Where a database interface did not provide an equivalent document-type filter, the relevant criterion was applied manually during screening rather than by altering the Boolean search string.

Database-specific search implementation:

Scopus: TITLE-ABS-KEY(("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning") AND ("Strategic Decision Making" OR "Business Strategy" OR "Corporate Decision Making"))

Web of Science: TS=(("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning") AND ("Strategic Decision Making" OR "Business Strategy" OR "Corporate Decision Making"))

ScienceDirect: Title, abstract, keywords: ("Artificial Intelligence" OR "Machine Learning") AND ("Strategic Decision Making" OR "Business Strategy"), adapted for term-limit restrictions.

ACM Digital Library: [[Abstract: "artificial intelligence"] OR [Abstract: "machine learning"]] AND [[Abstract: "strategic decision making"] OR [Abstract: "business strategy"]]

Across all four search blocks, database search limits were set strictly to publication years 2019–2025 and document types Article, Conference Paper, or Review.

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