



Department of Digital Business

Journal of Artificial Intelligence and Digital Business (RIGGS)

Homepage: <https://journal.ilmudata.co.id/index.php/RIGGS>

Vol. 5 No. 1 (2026) pp: 8905-8916

P-ISSN: 2963-9298, e-ISSN: 2963-914X

The Evolution of Decision Support Systems (DSS) to Strategic AI: A Systematic Review of Architectural Shifts and Business Value

Farhan Alif Budianto¹, Muharman Lubis², Iqbal Yulizar Mukti³, Setyo Budianto⁴

^{1,2,3,4} Telkom University

frhnalif@student.telkomuniversity.ac.id, muharmanlubis@telkomuniversity.ac.id, iqbalyulizar@telkomuniversity.ac.id, setyobudiantosb@telkomuniversity.ac.id

Abstract

This study examines the evolution of Decision Support Systems (DSS) toward Strategic Artificial Intelligence (SAI) by systematically analyzing architectural shifts and their implications for business value creation. Using a Systematic Literature Review (SLR) approach based on the PRISMA protocol, data were collected from Scopus, Web of Science, and IEEE Xplore databases covering publications from 2000 to 2025. A total of 85 peer-reviewed articles were selected after a rigorous screening and eligibility process. The findings reveal a progressive transition from model-driven, on-premise DSS architectures to cloud-native, agent-based, and LLM-integrated systems characterized by architectural autonomy and decentralized AI mesh structures. This transformation reshapes organizational decision-making from reactive data support to proactive and generative strategic insight. The study proposes a DSS–SAI Convergence Framework that explains how architectural autonomy reduces strategic latency and enhances agility, competitive advantage, and innovation capability. The results highlight that Strategic AI is not merely a technological upgrade but a fundamental shift in organizational intelligence and value logic, requiring new managerial competencies in decision engineering and explainable AI governance. Furthermore, the review identifies emerging risks—including algorithmic drift, governance latency, and configuration complexity—that may undermine strategic alignment if not properly managed. The study contributes to the information systems literature by integrating architectural, organizational, and governance perspectives into a unified analytical lens and offers practical guidance for firms seeking to operationalize AI-driven strategic decision infrastructures.

Keywords: Decision Support Systems, Strategic Artificial Intelligence, Architectural Autonomy, Business Value, Generative AI, Systematic Literature Review

1. Introduction

For over four decades, Decision Support Systems (DSS) have been the cornerstone of organizational intelligence. Conceptually, classical DSS were designed to assist decision-makers in semi-structured tasks by relying on internal databases and static mathematical models [1]. However, the explosion of Big Data and advancements in cloud computing have rendered traditional, reactive DSS architectures inadequate for the velocity of today's global markets [2].

Currently, we are witnessing a paradigm shift toward Strategic Artificial Intelligence (SAI). Unlike its predecessors, SAI does not merely "support" by providing data; it "strategizes" by leveraging Generative AI (GenAI), autonomous agents, and predictive modeling to identify market shifts before they occur [3]. This evolution represents a transition from human-guided queries to AI-guided insight generation.

Despite the rapid adoption of AI tools like Large Language Models (LLMs) in corporate environments, a significant "Architectural Literacy Gap" persists [4]. Much of the existing literature is fragmented, focusing either on isolated technical AI algorithms or high-level business management theories, without robust integration between the two.

The Evolution of Decision Support Systems (DSS) to Strategic AI: A Systematic Review of Architectural Shifts and Business Value

There is a lack of systematic synthesis regarding how the underlying infrastructure of decision systems has fundamentally changed to accommodate autonomous strategic reasoning [5]. Furthermore, the specific mechanisms by which these architectural shifts translate into measurable Business Value such as the transition from cost efficiency to innovation agility require clearer categorization in academic literature.

Based on the identified architectural literacy gap and the fragmented nature of existing studies, this research aims to systematically analyze the evolution of Decision Support Systems (DSS) toward Strategic Artificial Intelligence (SAI) from both architectural and business value perspectives. Specifically, this study seeks to: (1) identify the key architectural shifts underlying the transformation from classical DSS to agent-based and Generative AI-driven systems; (2) synthesize how these architectural changes enable autonomous strategic reasoning within organizations; and (3) categorize the resulting business value transformation, from operational efficiency to competitive advantage and innovation agility. Through a structured systematic literature review using the PRISMA protocol, this study intends to develop an integrative DSS SAI Convergence Framework that bridges technical AI infrastructure with strategic management theory.

2. Research Methods

This study employs a qualitative approach using a Systematic Literature Review (SLR) method. The SLR method was selected to systematically identify, evaluate, and synthesize scholarly works discussing the evolution of Decision Support Systems (DSS) toward Strategic Artificial Intelligence (SAI). This approach ensures methodological rigor, transparency, and replicability in synthesizing interdisciplinary literature within Information Systems and Artificial Intelligence domains.

The review process follows the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) 2020 framework proposed [6], which provides structured stages of identification, screening, eligibility assessment, and inclusion.

2.1. Research Design: The PRISMA Protocol

This study employs a Systematic Literature Review (SLR) approach, following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) protocol [6]. The SLR method was chosen for its transparency, objectivity, and replicability, which are essential for mapping a fast-evolving field like AI and Information Systems [7]. This minimizes researcher bias and ensures the synthesis covers the full spectrum of technological evolution.

2.2. Search Strategy and Data Sources

To capture the evolution from legacy DSS to Strategic AI, a comprehensive search was conducted in early 2026 across three primary academic databases: Scopus, Web of Science (WoS), and IEEE Xplore. These databases were selected for their extensive coverage of Management Information Systems (MIS) and computer science literature [2].

The search string utilized Boolean operators to connect core concepts, "Decision Support System" OR "DSS" and "Strategic AI" OR "Autonomous Agents" OR "Generative AI" and "Architecture" OR "Business Value".

2.3. Inclusion and Exclusion Criteria

To maintain synthesis quality and relevance, the following eligibility criteria were applied (Table 1):

Table 1. Inclusion and Exclusion Criteria

Criterion	Inclusion	Exclusion
Document Type	Peer-reviewed journal articles.	Conference abstracts, editorials, books, and gray literature.
Timeframe	2000 – 2025 (to capture modern evolution).	Pre-2000 (unless seminal works).
Language	English.	Non-English publications.

Journal Ranking	Scopus-indexed (Q1/Q2) or SJR equivalent.	Unindexed or high-risk predatory journals.
Research Focus	Focus on organization, strategy, or architecture.	Pure algorithmic papers without business context.

2.4. Data Extraction and Quality Assessment

Initial search results yielded 540 records. After removing duplicates, 310 records were screened by title and abstract. Following the application of inclusion criteria, 125 full-text articles were assessed for eligibility. The final synthesis includes 85 core articles that directly address the intersection of DSS architecture and strategic business value [3].

Each selected paper was analyzed using a structured extraction template:

1. Context: Industry and decision-making level (Operational vs. Strategic).
2. Architecture: On-premise, Cloud-native, or Agent-based.
3. Value Proposition: Efficiency, Agility, or Competitive Advantage.

2.5. Key Literature Synthesis Table

The following table synthesizes the landmark studies that define the transition from DSS to Strategic AI.

Table 2. Synthesis of Evolutionary Phases in Decision Support and Strategic AI

Era	Key Reference	System Focus	Architectural Shift	Primary Business Value
DSS	Power & Sharda (2007) [1]	Model-Driven	On-premise, Structured Data	Operational Consistency
Big Data	Wang et al. (2018) [8]	Predictive Analytics	Cloud-based, Data Lakes	Cost Efficiency & Forecasting
Digital X	Vial (2019) [2]	Digital Transformation	Ecosystem Integration	Agility & Structural Change
AI Strategy	Shrestha et al. (2019) [5]	AI Decision-Making	Hybrid Human-AI Logic	Organizational Speed
Strategic AI	Arvidsson et al. (2023) [4]	Agentic AI	Decentralized AI Mesh	Competitive Advantage
GenAI	Davenport (2024) [3]	Generative Insights	LLM-Integrated Architectures	Democratized Strategy

3. Results and Discussions

3.1. The Convergence of DSS and Strategic AI

The synthesis of the literature indicates that we are not merely seeing the replacement of DSS, but a fundamental convergence. The "Support" aspect of DSS is being swallowed by the "Agency" of AI. As noted [4], the shift toward Strategic AI requires organizations to move beyond seeing AI as a tool and start viewing it as a core organizational capability. Our review suggests that the traditional boundaries between human intuition and machine calculation are blurring, creating a "Centaur Decision-Making" model where the system suggests the strategy and the human provides the ethical and contextual guardrails.

3.2. Theoretical Implications: The DSS-SAI Framework

This review contributes to the Information Systems (IS) theory by proposing the DSS-SAI Convergence Framework. While [2] focused on digital transformation as a structural change, we argue that the transformation in decision-making is specifically driven by "Architectural Autonomy." * Theoretical Causal Link: The shift from centralized data warehouses to decentralized AI Mesh architectures reduces the latency between "sensing" a market change and "acting" upon it.

- a. Knowledge-Based View: We expand the Knowledge-Based View (KBV) of the firm by suggesting that "Agentic Knowledge" (knowledge held and acted upon by AI agents) is a new category of competitive advantage.

3.3. Managerial Implications

For practitioners and CTOs, the findings offer three critical takeaways:

1. From Infrastructure to Orchestration: Managers should stop investing in static dashboards and begin building Data Fabric architectures that support autonomous RAG (Retrieval-Augmented Generation) [3].
2. The New Skillset: The literacy required for Strategic AI is not coding, but "Decision Engineering"—the ability to frame strategic problems in a way that AI agents can simulate and validate.
3. Risk of "Black Box" Strategy: As systems become more autonomous, the risk of "Strategic Hallucinations" increases. Managers must implement Explainable AI (XAI) protocols to ensure that AI-suggested strategies are traceable [9].

3.4 Architectural Autonomy : Autonomous Enterprise

The turn of the millennium saw significant advances in technologies such as mobile phones, data processing, distributed computing, storage, and digital mobile networks [10], [11]. This digital transformation is more advanced than digitization and is considered a subsequent level of development associated with the term digitalization. Digitalization requires new ways of communicating and collaborating in the workplace and can be understood as the use of digital technology and data (both digitalized and inherently digital) to generate revenue, improve business, and replace/transform business processes (rather than simply digitizing them).

According to [12], this also creates an environment for digital business. Digital transformation, in turn, can be defined as the integration of digital technology into all aspects and operations of an organization, which in turn leads to infrastructural changes in how the organization operates and delivers value to its customers [2], [13].

According to [14], this needs to happen quickly. [14] also emphasize that Digital Transformation (DT) requires changes in leadership, culture and mindset, attitudes toward risk, new ways of working, new technologies, and a willingness to embrace ambiguity and constant change.

The Autonomous Enterprise is often described as the technological evolution of AI-enabled automation, where its development demonstrates a systemic organizational transformation, not simply automatic enhancement.

According to [15], the Autonomous Enterprise is characterized by the integration of AI, data infrastructure, and digital platforms that enable organizations to: sense (detect changes), decide (make decisions), act (execute actions), learn (adapt), and operate in a closed-loop, near-real-time manner. This aligns with the concept of a self-adaptive enterprise system. The Autonomous Enterprise is not just the automation of decisions, but the automation of organizational coordination.

Structure in Autonomous Enterprise Architecture, from a Systemic and Strategic Perspective. Autonomous Enterprise is not just adopting AI, but rather reconfiguring the organization's architecture into a closed-loop cybernetic system capable of sensing, deciding, acting, and learning. Organizations require a layered architectural

stack, conceptually creating a multi-layered intelligence stack that, if unbalanced, will lead to systemic fragility. Here's a deeper look at each layer:

1. Cognitive Layer (Decision Intelligence Core) - plays a strategic role as the organization's epistemic engine—where organizations build a probabilistic understanding of the world. [16] emphasize that the value of organizational AI emerges when systems move from descriptive → predictive → prescriptive → autonomous action. This means that predictions without the ability to direct action only create insight debt, not competitive advantage. In the evolution from prediction to agency, an Autonomous Enterprise requires:
 - a. Level 1 — Predictive AI consists of demand forecasting and churn prediction.
 - b. Level 2 — Prescriptive AI consists of recommendation engines and optimization.
 - c. Level 3 — Agentic AI (Autonomy) consists of policy learning, self-directed planning, and goal-conditioned behavior.

However, this cognitive layer faces the first critical risk: Model Myopia—the model focuses too much on narrow objectives. This phenomenon is part of hidden technical debt in ML systems [17]. Second, Reward Hacking (Specification Gaming). In reinforcement learning, agents can find ways to "win" without fulfilling their true goals. According to [18], they warn that RL systems tend to exploit reward loopholes, develop undesirable behavior, and create misalignment. Third, Causal Misidentification, where many systems are still based on correlation, not causality. According to [19], without causal reasoning, AI is vulnerable to distribution shifts, fails in policy interventions, and is difficult to generalize. Mature Autonomous Enterprises must move towards causal-aware AI.

2. Decision Orchestration Layer "The Real Brain of Autonomy" - is the most underestimated layer, but it is the key differentiator between partial automation and true autonomy. This layer has core functions as Policy Engines, Decision Routing, Multi-Agent Coordination, Exception Handling (Critical),
 - a. Policy Engines, transforming insights into appropriate actions: business rules, compliance constraints, risk thresholds, ethical guardrails
 - b. Decision Routing: Determining which decisions are fully automated, which are human-in-the-loop, and which are escalated. This relates to the concept of selective autonomy. This opinion aligns with [20], who argue that the optimal level of automation must be adjusted to the risk, uncertainty, and impact of the decision.
 - c. Multi-Agent Coordination: In modern Autonomous Enterprises, decisions rarely occur independently. Recent trends include swarm intelligence, agent ecosystems, and market-based coordination. [21] point out that coordination is the primary source of complexity in digital organizations. Without proper coordination, autonomy turns into distributed chaos.
 - d. Exception Handling (Critical): Autonomous organizations fail not under normal conditions, but under edge cases, black swan events, and data anomalies. [22] suggests that the theory of normal accidents suggests that complex systems tend to fail through a combination of small, local failures. An Autonomous Enterprise must have anomaly detection, graceful degradation, and human override pathways. If the cognitive layer is the analytical brain, then the orchestration layer is the organization's executive nervous system.
3. Execution Layer (Digital Brain to Physical Action) - Has Main Components, namely First, Robotic Process Automation (RPA) functions as rule-based automation, legacy system bridging, back-office automation. However, RPA is purely deterministic in the Autonomous Enterprise, RPA must consist of event-driven, AI-triggered, and self-healing. Second, API-Driven Operations is a modern enterprise nervous system. It has important characteristics including composability, real-time responsiveness, modular execution. Without an API-first architecture, autonomy will be hampered by several things such as system latency, integration bottlenecks, and brittle workflows. Third, Autonomous Workflows consist of modern Workflows that are: event-driven, adaptive, context-aware. According to [23] explains that future business processes are moving towards self-adaptive process mining loops. Fourth, Digital Twins that allow for simulation before execution, counterfactual testing, and risk sandboxing. In an Autonomous Enterprise, a digital twin functions as a "strategic flight simulator." This is crucial for high-risk decisions, supply chain optimization, and predictive maintenance. Of all the components mentioned, execution risks are present. This aligns with [17], who note that the greatest complexity of ML systems lies in the production pipeline, including data dependencies, versioning chaos, and feedback contamination.
4. Feedback & Learning Layer Closed-Loop Intelligence (The Survival Layer) - Autonomous Enterprises will experience silent model degradation, policy drift, and strategic misalignment. Critical components include:

- a. Continuous Monitoring, which includes model performance, data quality, decision outcomes, and system health. [24] emphasizes the importance of ML test scores for production reliability.
- b. Drift Detection: This type of monitoring involves monitoring data drift, concept drift, label drift, and policy drift. This aligns with [25] who found that concept drift is the primary cause of long-term ML system failure.
- c. Auto-Retraining Pipelines: Autonomous organizations must have retraining triggers, model validation gates, shadow deployment, and rollback mechanisms. This can transform ML from a project into a living system.
- d. Organizational Learning Loop: The most advanced level encompasses not only model learning but also human feedback integration, policy refinement, and strategic recalibration. According to [26] this is called: single-loop learning, double-loop learning, deutero-learning. A true Autonomous Enterprise must achieve double-loop learning.

3.5 Algorithmic Drift as an Emerging Strategic Risk

Beyond architectural transformation, organizations adopting Strategic AI face a growing but often underestimated phenomenon: algorithmic drift. While traditional DSS degradation was typically caused by data staleness or model obsolescence, AI-native systems introduce a more dynamic risk profile. Algorithmic drift occurs when the statistical properties of input data, user behavior, or environmental context shift over time, causing AI outputs to remain technically accurate yet strategically misaligned.

[17] emphasize that machine learning systems in production environments accumulate “hidden technical debt,” where small distributional changes gradually erode model relevance even when performance metrics appear stable. In Strategic AI settings, this risk is amplified because agentic systems actively influence the environment they learn from, creating feedback loops that accelerate drift.

From a strategic perspective, algorithmic drift manifests in three layers:

1. Data Drift – changes in underlying data distribution
2. Concept Drift – shifts in the relationship between variables
3. Policy Drift – misalignment between AI optimization goals and evolving business strategy

The third layer is particularly critical for Strategic AI because organizations may unknowingly optimize for outdated competitive conditions. This supports the argument by [27] that operational ML systems require continuous human-centered monitoring pipelines rather than one-time deployment governance. Therefore, organizations transitioning toward SAI must implement continuous learning governance, including model monitoring, retraining cadence policies, and strategic alignment audits. Without these mechanisms, architectural autonomy may paradoxically increase long-term strategic fragility despite short-term efficiency gains.

3.6 AI Governance Latency and Organizational Responsiveness

Another underexplored dimension in the DSS–SAI transition is governance latency, defined as the time required for an organization to detect, interpret, and respond to AI-driven risks or opportunities. As AI architectures become more decentralized and agent-based, decision velocity increases—but so does the potential gap between automated action and managerial oversight.

[16] describe this tension as algorithmic management tension, where deeper automation improves efficiency while simultaneously reducing managerial visibility. In Strategic AI environments, governance latency becomes a critical moderating variable between architectural autonomy and realized business value.

We extend prior literature by proposing that governance latency operates through three organizational capabilities:

1. Observability Capability – real-time visibility into AI decisions
2. Intervention Capability – ability to override or recalibrate agents
3. Adaptation Capability – speed of policy and model updates

Firms with high architectural autonomy but low governance responsiveness risk entering what we term autonomy overshoot, a condition where AI systems act faster than organizational control mechanisms can meaningfully respond.

3.7. AI Technical Debt as a Structural Risk

This concept was introduced by [17] and is now central to discussions in the AI industry. Why This Matters: Strategic AI systems are characterized by rapid deployment models, increasingly complex pipelines, increasing

data dependencies, and often lagging monitoring. The result is hidden feedback loops, data dependency fragility, configuration debt, and undeclared consumers. In the context of AI, the more autonomous the system, the greater the accumulation of invisible technical debt. This is an architectural time bomb. The relevance for the DSS–SAI Framework can be strengthened by adding: Architectural Autonomy → Technical Debt Accumulation Risk.

The transformation from DSS → SAI → Autonomous Enterprise creates three structural dynamics:

1. **Deployment Velocity Increases:** Organizations are driven to accelerate model experimentation, shorten time-to-deployment, and automate pipelines. However, according to [17], this acceleration often results in: “ML systems are rarely just code; they are complex data dependencies.” This means that the primary complexity is not in the model, but in its ecosystem.
2. **Pipeline Complexity Explosion:** Every production model typically relies on: feature pipelines, data ingestion, preprocessing logic, serving infrastructure, and a monitoring stack. As scale increases, organizations experience pipeline entanglement. [24] show that reliable production ML systems require: data validation, model validation, and continuous monitoring. Without these, debt accumulates silently.
3. **Increasingly Fragile Data Dependencies:** Unlike deterministic software, AI relies heavily on data that is: dynamic, non-stationary, and often not fully controlled. According to [28], that data quality issues are a major source of failure in production ML. This makes technical debt in AI data-coupled debt, not just code debt.

There are four forms of technical debt that are most dangerous:

1. **Hidden Feedback Loops** - Occur when model output influences future data that is then used to train the model. According to [29], feedback loops can narrow exploration, amplify bias, and decrease long-term quality. In an autonomous enterprise, the risk increases due to faster decisions, shorter loops, and reduced human intervention—this is silent strategic drift.
2. **Data Dependency Fragility** - Because small changes in upstream data can impair model performance, alter input distributions, and trigger undetected failures. These changes occur because concept drift often goes undetected until performance has already dropped significantly [25]. In an autonomous enterprise, this fragility is exacerbated by real-time pipelines, streaming data, and cross-domain data meshes, making the system brittle at scale.
3. **Configuration Debt** - Occurs when an AI system has many hyperparameters, rule exceptions, manual thresholds, and feature flags. Without strong governance, configurations develop into configuration sprawl. Configuration complexity correlates with increased failure rates, debugging difficulties, and slow recovery.
4. **Undeclared Consumers** - Occurs when model output is used by other systems without formal contracts, version control, or dependency tracking. This aligns with [17], who emphasize that this creates invisible coupling. Consequently, when the model changes, downstream systems are damaged, business decisions are disrupted, and debugging becomes extremely difficult. In autonomous organizations, this can trigger a cascade of failures.

Technical Debt as a Function of Architectural Autonomy. The higher the autonomy, the higher the accumulation of hidden debt. Autonomy increases, so do decision velocity, system interdependence, feedback density, and model retraining frequency. All of these factors accelerate debt compounding. Therefore, the Proposed Conceptual Model:

1. DSS Era - human-driven, low feedback coupling, and mostly visible debt.
2. SAI Era - AI-assisted, medium coupling, and partially hidden debt.
3. Autonomous Enterprise - self-acting, high coupling, and exponential hidden debt. Architectural Autonomy → Technical Debt Accumulation Risk.

Technical Debt is an "Architectural Time Bomb" with three dangerous properties:

1. **Non-linear Growth** - Debt does not grow linearly. As complexity increases, interactions between components explode, debugging costs increase exponentially, and recovery times lengthen.
2. **Low Observability** - Much debt is invisible in standard metrics: model accuracy remains high, latency is normal, and the system appears healthy. However, structurally, the system becomes fragile.

3.8 Data-Centric AI as a New Paradigm Shift

AI advancements have been dominated by a model-centric approach, namely improving performance through more complex model architectures, hyperparameter tuning, and model competition. However, [30] posits a crucial shift: "Improving data quality often yields greater gains than improving model architecture." This statement marks the transition to data-centric AI, where the primary source of advantage shifts from algorithms to data quality and engineering. Based on the old paradigm's growing saturation, the following occurs:

1. Diminishing Returns on Model Complexity: Modern models approaching their performance limits on certain datasets indicate that architectural improvements yield marginal gain, computational costs increase sharply, and operational complexity soars. This aligns with [31] observation that early emphasis on more data often outperforms more sophisticated algorithms in many cases, which serves as the initial foundation for data-centric thinking.
2. Real-World ML Failures Are More Often Caused by Data. Failures of production Machine Learning (ML) systems often stem from label noise, data drift, schema change, and sampling bias. [24] showed that the readiness of production Machine Learning (ML) is highly dependent on data validation, not just model validation.
3. Model Commoditization. With the advent of open-source models, foundation models, and autoML (Machine Learning), model-based advantages are increasingly easy to imitate, while high-quality data is idiosyncratic and difficult to predict. According to [32], from a dynamic capabilities perspective, the source of sustainable advantage is a capability that is difficult to imitate—and proprietary data meets this criterion.

Substantively, data-centric AI is not simply "cleaning data," but rather a systemic change in how organizations operate, including designing pipelines, managing quality, operating feedback loops, and establishing governance. The key pillars of data-centric AI include:

1. Data Quality Engineering, which focuses on label accuracy, coverage, representativeness, consistency, and timeliness. Hidden label errors can significantly degrade model performance, even when metrics appear favorable [33], a phenomenon known as the hidden performance ceiling.
2. Continuous Data Improvement Loop: Unlike traditional, static approaches, data-centric AI is iterative: deploy models, identify errors, correct data, retrain, monitor, and repeat, creating a data flywheel. [30] emphasizes that superior organizations build systematic processes to continuously improve data.
3. Data Governance: The strategic implications of data-centric AI pipelines are significant, as they require governance encompassing data lineage, data contracts, access control, quality SLAs, and compliance checks. Highlighting that production ML requires a much more rigorous data management approach than traditional analytics [28].
4. Dataset Engineering as a Core Capability, with new roles emerging, such as data curator, label engineer, data quality analyst, and ML data engineer, indicates that value creation is shifting upstream in the pipeline.

This implies that AI (AI) strategies in the old model formed a superior algorithm → superior performance, while in the new model, a superior data pipeline → superior adaptive intelligence.

In the context of AI, this means that the superior organization is not the one with the most complex models, but rather the one with the most reliable supply chain data.

Traditionally, data governance has been viewed as a compliance function, back-office IT, and support activity. However, in the data-centric paradigm, governance becomes an enabler of AI performance, a risk control mechanism, and a foundation for autonomy. This aligns with [16], who emphasized that next-generation digital platforms depend on the ability to manage data in an integrated manner across ecosystems.

Implementing an AI (AI) strategy in the old model results in a superior algorithm → superior performance, while in the new model, a superior data pipeline → superior adaptive intelligence.

In the context of AI, this means that the superior organization is not the one with the most complex model, but rather the one with the most reliable supply chain data.

Traditionally, data governance has been viewed as a function of compliance, back-office IT, and support activities. However, in the data-centric paradigm, governance becomes an enabler of AI performance, a risk control mechanism, and a foundation for autonomy. This is in line with [16], who emphasized that next-generation digital platforms depend on the ability to manage data in an integrated manner across ecosystems.

Autonomous Enterprises require continuous learning, reliable feedback, and adaptive decision loops. All of these are highly dependent on data quality. Without data-centric discipline, autonomy will experience rapid drift, bias amplification, reward misalignment, and increase technical debt. In other words, autonomy scales only as fast as data quality allows.

Data-centric AI is also a mechanism to prevent technical debt. Recall the opinion of [17]:

Much debt stems from undeclared data dependencies, fragile pipelines, and feedback loops. A data-centric approach mitigates this risk through data contracts, schema validation, continuous monitoring, and dataset versioning.

Therefore: Data-centric maturity → lower hidden technical debt. Risks and Trade-Offs: Given this paradigm, caution is needed.

1. Data Ops Complexity: creating more complex data pipelines, requiring new tooling, and increasing governance costs.
2. Organizational Friction: AI requires cultural shifts, such as from a hero model to a data discipline, from ad-hoc experiments to industrial pipelines, or from silos to cross-functional data ownership. [34] stated that the Data Mesh concept emphasizes that distributed data ownership requires mature federated governance.
3. Over-Governance Risk: If too rigid, data governance can slow experimentation, hinder innovation, and increase bureaucratic costs, creating governance-agility tensions

3.9 Human–AI Cognitive Reconfiguration

The transformation from Decision Support Systems (DSS) to Strategic Artificial Intelligence (SAI) is not only technological and architectural, but also cognitive-organizational. The literature shows that the integration of AI into the decision-making process triggers a phenomenon deeper than simply augmenting human capabilities: the reconfiguration of human cognition. In the context of classic DSS, the system functions as an analytical tool that extends human computational capacity without significantly changing the decision-maker's thinking patterns. However, in the modern AI era particularly with the advent of machine learning and large language models AI has begun to act as a cognitive partner, generating hypotheses, recommending strategies, and even triggering problem framing. According to [35], human AI interaction creates a new form of human AI symbiosis where the boundaries between human and machine cognitive processing are increasingly blurred. This shift marks the transition from decision augmentation to cognitive co-evolution, where human and AI capabilities develop interdependently.

The core mechanism of Cognitive Reconfiguration consists of three mechanisms:

1. Cognitive Offloading - One of the most fundamental mechanisms is cognitive offloading, the human tendency to delegate cognitive burdens to automated systems. In the context of Strategic AI:
 - a. Complex analysis → outsourced to AI
 - b. Scenario exploration → performed by AI agents
 - c. Information processing → increasingly automated

In the short term, this increases efficiency. However, in the long term, it also raises the risk of cognitive atrophy, namely the decline in human analytical abilities due to excessive reliance on AI. [20] have long warned that high levels of automation can lead to skill degradation, loss of situational awareness, and automation complacency. In a highly autonomous Strategic AI environment, this risk becomes even more relevant.

2. Automation Bias and Algorithmic Authority - Humans tend to overweight the recommendations of automated systems a phenomenon known as automation bias. The impact in the context of AI is that AI recommendations are more likely to be questioned, AI errors can slip undetected, and over-trust in the system occurs. [36] point to the phenomenon of algorithmic appreciation, where individuals trust algorithmic recommendations more than humans in certain contexts. However, a paradox arises because other studies have found algorithm aversion, the tendency to reject algorithms after seeing minor errors. This duality creates a new challenge in Strategic AI design: organizations must achieve calibrated trust, not just high trust.
3. Cognitive Load Redistribution: AI doesn't always reduce cognitive load; it often redistributes it. In traditional DSS, the primary burden is data analysis, while in Strategic AI, the burden shifts to interpreting AI output, validating recommendations, ethical oversight, and exception handling. As a result, the human role shifts from: analyst → supervisor → governor of AI. According to Jarrahi (2018), human value in the AI era actually increases in the domains of contextual judgment, ethical reasoning, and sensemaking in ambiguous situations. This strengthens the argument that Strategic AI does not eliminate the role of humans, but rather repositions them cognitively.

Human–AI Teaming and the Evolving Centaur Model

According to recent research in human–autonomy teaming, optimal performance occurs when AI excels at pattern detection and humans excel at contextual reasoning, both integrated through an orchestration layer. However, the literature shows that many organizations fail because they focus solely on model performance without designing interaction protocols between humans and AI. Determinants of successful teaming include: transparency level, explainability depth, timing of AI intervention, and human override capability. Without this design, Strategic AI risks creating:

1. over-automation
2. under-utilization
3. trust misalignment

New Risks: Cognitive Deskilling and Strategic Myopia

1. Cognitive Deskilling - When AI takes over routine analytical processes, humans risk losing diagnostic capabilities, autonomous forecasting capabilities, and deep sensemaking capabilities. This phenomenon has been observed in various highly automated domains. In the context of enterprise AI, this risk can develop into organizational cognitive fragility, a condition where an organization is no longer able to operate optimally without AI.
2. A more subtle risk is AI-based strategic myopia. Because AI relies heavily on historical data and statistical patterns, organizations can become overly focused on exploiting outdated patterns, becoming less sensitive to black swan events, and experiencing local over-optimization. This aligns with [37] warning that AI can accelerate learning, but it can also accelerate path dependence if not properly calibrated.

4.0 Toward AI-Native Organizational Design

The evolution toward Strategic AI ultimately implies not only technological change but also organizational redesign. Traditional DSS operated within functional silos, whereas AI-native firms increasingly adopt cross-functional, data-centric operating models.

Recent research suggests that competitive advantage in the AI era depends on embedding AI into the firm's micro-decision fabric rather than treating it as an analytical layer [38]. This shift produces what can be conceptualized as an AI-native organization, characterized by:

1. continuous decision automation
2. embedded experimentation loops
3. platform-based data governance
4. human-AI symbiotic workflows

Importantly, AI-native design does not eliminate human roles but redistributes them toward supervision, exception handling, and strategic framing. This aligns with the emerging centaur model of decision making, where human judgment and machine intelligence co-evolve rather than substitute one another.

4. Conclusion

This study confirms that the evolution from Decision Support Systems (DSS) to Strategic Artificial Intelligence (SAI) represents a fundamental architectural and strategic transformation rather than a simple technological upgrade. The systematic review demonstrates a clear shift from model-driven, centralized, and on-premise DSS architectures toward decentralized, agent-based, and LLM-integrated systems capable of autonomous strategic reasoning. This transition redefines business value from operational efficiency and forecasting accuracy to organizational agility, innovation capacity, and sustained competitive advantage. The proposed DSS-SAI Convergence Framework identifies architectural autonomy as the primary driver enabling faster sensing-acting cycles and the emergence of "agentic knowledge" as a new source of competitive differentiation. Practically, organizations must move from static infrastructure toward orchestration-based, explainable AI ecosystems while strengthening governance mechanisms to mitigate strategic opacity risks. Future research should empirically test the framework across sectors and develop quantitative indicators to measure how architectural autonomy contributes to firm performance and long-term strategic resilience.

Reference

- [1] D. J. Power and R. Sharda, "Model-driven decision support systems: Concepts and research directions," *Decis. Support Syst.*, vol. 43, no. 3, pp. 1044–1061, 2007, doi: <https://doi.org/10.1016/j.dss.2005.05.030>.
- [2] G. Vial, "Understanding digital transformation: A review and a research agenda," *Manag. Digit. Transform.*, pp. 13–66, 2021, doi: <https://doi.org/10.1016/j.jsis.2019.01.003>.
- [3] T. Davenport and P. Tiwari, "Is your company's data ready for generative AI," *Harv. Bus. Rev.*, vol. 2024, 2024.
- [4] V. Arvidsson, J. Holmström, and K. Lyytinen, "Digital transformation by outflanking: How peripheral agents transform resisting organizations," *J. Strateg. Inf. Syst.*, vol. 35, no. 1, p.

- 101924, 2026, doi: <https://doi.org/10.1016/j.jsis.2023.101762>.
- [5] Y. R. Shrestha, S. M. Ben-Menahem, and G. Von Krogh, “Organizational decision-making structures in the age of artificial intelligence,” *Calif. Manage. Rev.*, vol. 61, no. 4, pp. 66–83, 2019, doi: <https://doi.org/10.1177/0008125619862257>.
- [6] M. J. Page *et al.*, “The PRISMA 2020 statement: an updated guideline for reporting systematic reviews,” *bmj*, vol. 372, 2021, doi: <https://doi.org/10.1136/bmj.n71>.
- [7] H. Snyder, “Literature review as a research methodology: An overview and guidelines,” *J. Bus. Res.*, vol. 104, pp. 333–339, 2019, doi: <https://doi.org/10.1016/j.jbusres.2019.07.039>.
- [8] Y. Wang, L. Kung, and T. A. Byrd, “Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations,” *Technol. Forecast. Soc. Change*, vol. 126, pp. 3–13, 2018, doi: <https://doi.org/10.1016/j.techfore.2015.12.019>.
- [9] A. Rai, “Explainable AI: From black box to glass box,” *J. Acad. Mark. Sci.*, vol. 48, no. 1, pp. 137–141, 2020.
- [10] J. R. Evans, S. T. Foster Jr, and Z. Guo, “A retrospective view of research in the quality management journal: a thematic and keyword analysis,” *Qual. Manag. J.*, vol. 20, no. 1, pp. 37–47, 2013.
- [11] C. Heavin and D. J. Power, “Challenges for digital transformation—towards a conceptual decision support guide for managers,” *J. Decis. Syst.*, vol. 27, no. sup1, pp. 38–45, 2018.
- [12] T. Schwarzmüller, P. Brosi, D. Duman, and I. M. Welpel, “How does the digital transformation affect organizations? Key themes of change in work design and leadership,” *Manag. Rev.*, vol. 29, no. 2, pp. 114–138, 2018.
- [13] K. McGrath and A. Maiye, “The role of institutions in ICT innovation: learning from interventions in a Nigerian e-government initiative,” *Inf. Technol. Dev.*, vol. 16, no. 4, pp. 260–278, 2010.
- [14] G. C. Kane, D. Palmer, A. N. Phillips, D. Kiron, and N. Buckley, “Strategy, not technology, drives digital transformation,” *MIT Sloan Manag. Rev.*, 2015.
- [15] S. Kraus, F. Schiavone, A. Pluzhnikova, and A. C. Invernizzi, “Digital transformation in healthcare: Analyzing the current state-of-research,” *J. Bus. Res.*, vol. 123, pp. 557–567, 2021.
- [16] A. Rai, P. Constantinides, and S. Sarker, “Editor’s comments: Next-generation digital platforms: Toward human–AI hybrids,” *MIS quarterly*, vol. 43, no. 1. Management Information Systems Research Center, University of Minnesota, pp. iii–ix, 2019.
- [17] D. Sculley *et al.*, “Hidden technical debt in machine learning systems,” *Adv. Neural Inf. Process. Syst.*, vol. 28, 2015.
- [18] D. Amodei, C. Olah, J. Steinhardt, P. Christiano, J. Schulman, and D. Mané, “Concrete problems in AI safety,” *arXiv Prepr. arXiv1606.06565*, 2016.
- [19] J. Pearl, *Causality*. Cambridge university press, 2009.
- [20] R. Parasuraman, T. B. Sheridan, and C. D. Wickens, “A model for types and levels of human interaction with automation,” *IEEE Trans. Syst. man, Cybern. A Syst. Humans*, vol. 30, no. 3, pp. 286–297, 2000.
- [21] T. W. Malone and K. Crowston, “The interdisciplinary study of coordination,” *ACM Comput. Surv.*, vol. 26, no. 1, pp. 87–119, 1994.
- [22] J. Reason, *Human error*. Cambridge university press, 1990.
- [23] W. van der Aalst, “Process mining: data science in action,” (*No Title*), 2016.
- [24] E. Breck, S. Cai, E. Nielsen, M. Salib, and D. Sculley, “The ML test score: A rubric for ML production readiness and technical debt reduction,” in *2017 IEEE international conference on big data (big data)*, 2017, pp. 1123–1132.
- [25] J. Lu, A. Liu, F. Dong, F. Gu, J. Gama, and G. Zhang, “Learning under concept drift: A review,” *IEEE Trans. Knowl. Data Eng.*, vol. 31, no. 12, pp. 2346–2363, 2018.
- [26] C. Argyris and D. A. Schön, “Organizational learning: A theory of action perspective,” *Rev. Esp. Invest. Sociol.*, no. 77/78, pp. 345–348, 1997.
- [27] S. Amershi *et al.*, “Software engineering for machine learning: A case study,” in *2019 IEEE/ACM 41st International Conference on Software Engineering: Software Engineering in*

- Practice (ICSE-SEIP)*, 2019, pp. 291–300.
- [28] N. Polyzotis, S. Roy, S. E. Whang, and M. Zinkevich, “Data management challenges in production machine learning,” in *Proceedings of the 2017 ACM international conference on management of data*, 2017, pp. 1723–1726.
- [29] A. J. B. Chaney, B. M. Stewart, and B. E. Engelhardt, “How algorithmic confounding in recommendation systems increases homogeneity and decreases utility,” in *Proceedings of the 12th ACM conference on recommender systems*, 2018, pp. 224–232.
- [30] A. Ng, “MLOps: From model-centric to data-centric AI. DeepLearning. AI,” *IEEE Spectr.*, 2021.
- [31] A. Halevy, P. Norvig, and F. Pereira, “The unreasonable effectiveness of data,” *IEEE Intell. Syst.*, vol. 24, no. 2, pp. 8–12, 2009.
- [32] D. J. Teece, “Business models and dynamic capabilities,” *Long Range Plann.*, vol. 51, no. 1, pp. 40–49, 2018.
- [33] C. Northcutt, L. Jiang, and I. Chuang, “Confident learning: Estimating uncertainty in dataset labels,” *J. Artif. Intell. Res.*, vol. 70, pp. 1373–1411, 2021.
- [34] Z. Dehghani, *Data mesh*. Marcombo, 2022.
- [35] M. H. Jarrahi, “Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making,” *Bus. Horiz.*, vol. 61, no. 4, pp. 577–586, 2018.
- [36] J. M. Logg, J. A. Minson, and D. A. Moore, “Algorithm appreciation: People prefer algorithmic to human judgment,” *Organ. Behav. Hum. Decis. Process.*, vol. 151, pp. 90–103, 2019.
- [37] E. Brynjolfsson, D. Rock, and C. Syverson, “The productivity J-curve: How intangibles complement general purpose technologies,” *Am. Econ. J. Macroecon.*, vol. 13, no. 1, pp. 333–372, 2021.
- [38] E. Brynjolfsson and A. McAfee, “The business of artificial intelligence,” *Harv. Bus. Rev.*, vol. 7, no. 1, pp. 1–2, 2017.