

Algorithmic isomorphism and the erosion of competitive advantage in the age of artificial intelligence: A review of emerging risks in strategic management

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Key words

algorithmic isomorphism, tacit knowledge, machine learning, managerial decisions, market homogenization

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Received: 25.06.2026

Accepted: 7.09.2026

Published: 8.10.2026

Cite this article

Czerski, P. (2026). Algorithmic isomorphism and the erosion of competitive advantage in the age of artificial intelligence: A review of emerging risks in strategic management. *Państwo i Społeczeństwo / State and Society* 26, art. 408, <https://doi.org/10.31749/2451-0858-SaS-2026-408>

Section

Management and Quality Sciences

Editor

Millena Ruskowska

Abstract

Artificial intelligence is gaining prominence not only as an operational optimization tool, but primarily as a key element shaping decision-making processes and strategic management within organizations. The public and academic debate is dominated by concerns regarding job losses, privacy violations, social manipulation and biases hidden in algorithms. The purpose of this review paper is to transpose these issues into the realm of corporate management and examine a significantly less obvious threat: algorithmic isomorphism. This entails the homogenization of business strategies resulting from widespread reliance on the same global machine learning models. The article analyzes how the imperfections of artificial intelligence systems such as the lack of transparency (the black box effect), inherent database bias and their Western-centric nature can lead to the reproduction of identical market behaviour patterns. Furthermore, the impact of these technologies on the risk of unique know-how leakage and the loss of tacit knowledge held by human managers, which is crucial for competitive advantage, is discussed. The comprehensive analysis also encompasses the transfer of market mechanisms, known from algorithmic financial

crises, to the sphere of long-term business decision-making. The conclusions point to the necessity of balancing technological innovation with a human-centric approach to protect corporate identity.

Introduction

Artificial intelligence is a highly interdisciplinary field that draws upon computer science, data science, natural sciences, humanities, mathematics and social sciences. As initially conceptualized by John McCarthy during the Dartmouth College conference in 1956, it refers to the creation of computer programs capable of performing actions that would be considered intelligent if performed by humans (McCarthy et al. 2006). In contemporary terms, major technology entities define it as a set of technologies enabling computers to perform advanced functions, including understanding language, analyzing vast amounts of data, and making recommendations (Google Cloud n.d.). The operational foundation of these technologies is machine learning and deep learning. However, the current evolutionary phase, generative artificial intelligence, goes a step further. It does not merely analyze data; it synthesizes new content, from software code to complex textual strategies (International Organization for Standardization 2024).

This evolutionary leap has shifted artificial intelligence from the domain of repetitive operational tasks directly into the realm of strategic management. As algorithms become proficient in processing thousands of pages of complex information, fields traditionally reliant on human cognitive processing, such as law, accounting, and strategic analysis, are facing profound disruption. The purpose of this review is to examine the implications of this shift. The methodological approach underpinning this review is set out in detail in Section 2. While widespread warnings focus on privacy, surveillance, and automated warfare, this article highlights a highly specific and critical vulnerability for modern enterprises: the erosion of competitive advantage through algorithmic isomorphism. This paper analyzes how the integration of artificial intelligence into long-term corporate planning creates novel epistemic and strategic risks. Section 1 defines algorithmic isomorphism and positions it within the theory of institutional isomorphism, Section 2 details the review methodology, Sections 3 through to 5 examine strategic homogenization, epistemic opacity and data exposure, and systemic bias and market volatility as interrelated manifestations of algorithmic isomorphism. Finally, Section 6 discusses the limitations of this conceptual analysis and proposes directions for future empirical research.

Section 1: Algorithmic isomorphism: definition and its place in organizational theory

Before proceeding, it is necessary to define precisely the central construct of this review and to position it within existing organizational theory. The concept of isomorphism entered organizational scholarship through the work of John W. Meyer and Brian Rowan (1977), who argued that formal organizational structures often reflect institutionalized myths and ceremonial rules rather than technical efficiency, and Paul J. DiMaggio and Walter W. Powell (1983), who identified three mechanisms through which organizations operating in the same field come to resemble one another over time. These are coercive isomorphism, which arises from political influence and the problem of legitimacy, mimetic isomorphism, which arises from standard responses to uncertainty, whereby organizations model themselves on other organizations perceived as more legitimate or successful, and normative isomorphism, associated with professionalization.

This paper introduces the concept of algorithmic isomorphism, defined here as the process by which the strategies, decision-making processes and market behaviours of independent firms converge as a result of their reliance on the same, or structurally equivalent, global artificial intelligence models. Algorithmic isomorphism shares a structural affinity with mimetic isomorphism in that both produce convergent organizational behaviour under conditions of uncertainty. It differs from it in its underlying mechanism: classical mimetic isomorphism requires organizations to consciously observe and imitate the practices of peers they regard as successful, whereas algorithmic isomorphism can arise without any such deliberate benchmarking. Because firms independently query models trained on overlapping corpora and optimized under comparable objective functions, convergence emerges as an unintended by-product of shared technological infrastructure rather than as the outcome of intentional imitation. In this sense, algorithmic isomorphism proposes a fourth, technologically mediated channel of organizational homogenization, which operates alongside and potentially reinforces the coercive, mimetic and normative mechanisms identified by DiMaggio and Powell (1983).

The sections that follow examine three interrelated conditions that make this technologically mediated convergence plausible: the reliance of strategic planning on a small number of dominant models trained on non-representative data (Section 3), the epistemic opacity of these models and the exposure of proprietary knowledge to shared infrastructure (Section 4), and the demonstrated capacity of structurally similar algorithms to produce synchronized, systemic outcomes in adjacent domains such as human capital management and financial markets (Section 5).

Section 2: Methodology

This article is a critical conceptual review (Snyder 2019), a review type suited to synthesizing insights across disparate literatures in order to construct a new theoretical lens, namely, algorithmic isomorphism, rather than to exhaustively catalogue an already well-defined body of empirical studies. A systematic review methodology was judged premature for this purpose, since the object of the review is a proposed construct rather than an established research stream with a stable body of primary studies to synthesize.

The literature underlying the theoretical argument was identified through searches of Scopus, Web of Science and Google Scholar, using combinations of the terms:

- “algorithmic isomorphism”,
- “institutional isomorphism”,
- “artificial intelligence” and “strategic management”,
- “algorithmic bias”,
- “algorithmic management”,
- “tacit knowledge” and “artificial intelligence”,
- “algorithmic trading” and “systemic risk”.

Foundational theoretical works (e.g. on institutional isomorphism and the resource-based view of the firm) were included without date restriction; literature specific to contemporary artificial intelligence systems was prioritized from 2018 onwards, reflecting the emergence of large-scale generative models. Peer-reviewed journal articles were treated as the primary evidentiary basis for theoretical claims. Industry and institutional reports (e.g. McKinsey, Goldman Sachs, UNESCO) were used exclusively to source current, quantitative estimates, such as the scale of workforce automation or the linguistic composition of training data, that are not yet available in the peer-reviewed literature, and are cited as descriptive data rather than as theoretical authority.

The corporate cases discussed in this review, namely, the 2018 discontinuation of an automated recruitment tool at Amazon, the 2010 Flash Crash, and the 2012 Knight Capital trading incident, were selected as paradigmatic, widely documented illustrations of, respectively, algorithmic bias amplification and the systemic fragility that can arise when structurally similar automated systems interact at scale. They are presented as structural analogies that motivate the theoretical argument, not as a representative or exhaustive sample, and not as direct empirical evidence for algorithmic isomorphism in strategic decision-making specifically; this distinction, and its implications for the scope of the paper’s claims, is discussed further in Section 6.

Section 3: The transition to strategic automation and the threat of algorithmic isomorphism

The initial integration of artificial intelligence into business focused heavily on efficiency and automation. This trend continues to accelerate, raising significant concerns about the displacement of the workforce. By 2030, tasks accounting for up to 30 percent of the hours currently worked in the United States economy could be automated, with certain demographic groups being disproportionately affected (Ellingrud et al. 2023). Furthermore, global estimates suggest that up to 300 million full-time jobs could be lost or severely altered due to the automation capabilities of these systems (Briggs 2023).

While early automation primarily impacted manual and repetitive tasks, sometimes resulting in a 50 to 70 percent decrease in wages for affected workers (Kelly 2021), the rise of generative technologies is rapidly encroaching upon white-collar work (Cerullo 2024). In the context of corporate management, this signifies that artificial intelligence is now being tasked with activities that form the core of strategic planning: market forecasting, competitor analysis, and investment recommendations. Reading and synthesizing extensive market reports, a task previously requiring teams of highly skilled analysts, can now be executed comprehensively by an algorithm in seconds. However, transitioning these responsibilities to artificial intelligence introduces a fundamental risk to the uniqueness of a company's strategic posture.

The essence of strategic management is differentiation. A company achieves a competitive advantage by developing a unique value proposition and executing strategies that competitors cannot easily replicate. The widespread adoption of generative artificial intelligence threatens to dismantle this foundational principle through the mechanism of algorithmic isomorphism, as conceptualized in Section 2.

Large language models and deep learning algorithms are trained on massive datasets. However, these datasets are overwhelmingly homogeneous. According to UNESCO (2024), only 100 out of the 7,000 natural languages in the world have been utilized to train the leading chatbots. Furthermore, 90 percent of on-line higher education materials are produced in the European Union and North America, deeply embedding Western perspectives into the training data. This homogeneity is compounded by the demographic uniformity of the developers themselves. As Olga Russakovsky noted, artificial intelligence researchers are predominantly men from specific racial backgrounds and high socioeconomic statuses, which creates a narrow view of global problems and limits the diverse perspectives necessary for innovative strategic thinking (Smith 2019).

If multiple competing firms within an industry utilize the same underlying artificial intelligence models to formulate their strategic initiatives, the algorithms, drawing from the same global datasets and governed by the same optimization

protocols, can plausibly be expected to generate correlated, averaged recommendations rather than genuinely differentiated ones. Under these conditions, companies risk inadvertently aligning their market behaviours, marketing campaigns, and product developments, a process of technological homogenization which, this paper argues, may erode firms' capacity to sustain a differentiated strategic identity (see Proposition 1, Section 6). This risk is amplified, rather than mitigated, by the epistemic and organizational dynamics examined in the following two sections.

Section 4: Epistemic opacity and the exposure of proprietary knowledge

The danger of strategic homogenization is exacerbated by the lack of transparency inherent in deep learning models. These models are notoriously complex, often acting as a black box even to the developers who created them. This limited transparency obscures how and why an artificial intelligence system arrives at its specific conclusions or strategic recommendations (Rodriguez 2026).

In corporate management, deploying strategies without fully understanding their underlying rationale introduces profound epistemic risk. Executives may find themselves endorsing strategic pivots or resource allocations based on an algorithm's output, without knowing whether the underlying data was flawed, biased, or simply misinterpreted. While the industry is exploring explainable artificial intelligence to provide clarity (Turri 2022), the widespread application of such transparent systems remains distant. Compounding this issue is the tendency of major technology firms to conceal the operational details and potential dangers of their products, a practice that has prompted public warnings from former employees of organizations like OpenAI and Google DeepMind (Burga 2024). Without legislative intervention or internal corporate safeguards, relying on opaque systems for critical business decisions severely compromises managerial accountability.

To extract maximum value from artificial intelligence in strategic planning, companies must input their highly sensitive, proprietary data (such as financial forecasts, trade secrets and internal communications) into these models. This creates a severe vulnerability regarding data privacy, which has been identified as the foremost concern for modern enterprises (Haskins, Caci 2024).

These systems frequently collect and retain user data to continuously train and refine their models. Consequently, the information provided by one company may not be secure from exposure to others. A historical precedent for this vulnerability occurred in 2023 when an error in a popular generative system allowed users to see the chat histories of other active users (OpenAI 2023). In the realm of strategic management, such an incident could be catastrophic. If a firm's unique

intellectual property or strategic intent is absorbed into a shared model, it could implicitly inform the responses generated for a competitor. The lack of robust federal regulations protecting corporate data from artificial intelligence ingestion further magnifies the risk of losing proprietary know-how.

Beyond the risk of a single leak of this kind, this opacity compounds algorithmic isomorphism in a subtler way: because managers cannot verify whether a given recommendation reflects their firm's specific circumstances or an output effectively averaged across a vendor's entire client base, the same structural conditions that make strategic guidance difficult to audit also make convergent, homogenized guidance difficult to detect.

Section 5: Systemic bias, market volatility, and the erosion of human influence

Algorithmic isomorphism is not confined to product and market strategy; it extends to the domain of human capital management, where reliance on structurally similar models can produce convergent (and, when the underlying models are biased, convergently discriminatory) outcomes across firms that would otherwise design distinct hiring practices. A substantial body of research documents how algorithms increasingly direct, evaluate and discipline work inside organizations, making algorithmic control a new contested terrain of organizational life (Kellogg et al. 2020). The application of artificial intelligence tools to strategic human resource management, executive recruitment and internal cultural alignment introduces profound corporate risks. Algorithms are fundamentally non-neutral mathematical constructs; they actively inherit, consolidate and amplify historical prejudices embedded within the legacy data used to train them (Smith 2019). When corporate leaders rely blindly on automated talent acquisition models, they risk reproducing institutional discrimination, explicitly undermining internal diversity, equity and inclusion mandates (Maskey 2022).

A striking commercial illustration of this systemic failure occurred when the global e-commerce enterprise Amazon developed an experimental, automated recruitment algorithm designed to review job applications and identify top-tier executive talent. The engineering team trained the underlying machine learning models on a historical database consisting of resumes submitted to the company over the preceding ten-year period. Because the technology sector was historically dominated by male professionals, the algorithm independently derived an operational pattern concluding that male candidates were inherently preferable. Consequently, the software began systematically penalizing resumes that included the word women's or referenced specific all-women's academic institutions. Despite repeated attempts by engineers to purge the software of this

bias, the company was forced to dismantle the project entirely in 2018 because the artificial intelligence continued to execute obscured, unalterable discriminatory patterns against female professionals. Because the underlying pattern, which involves training on historically skewed applicant data, is not unique to Amazon but common to any organization that adopts comparable off-the-shelf or vendor-supplied recruitment algorithms (see also Obermeyer et al. 2019, for an analogous pattern in healthcare allocation algorithms), this failure illustrates how algorithmic isomorphism can manifest as convergent bias rather than convergent strategy: firms that never shared a recruiting philosophy can end up sharing the same discriminatory blind spot.

This institutional vulnerability extends across all dimensions of contemporary strategic management. Modern platforms that promise to objectively evaluate leadership potential by analyzing facial micro-expressions, vocal inflections and linguistic patterns during video interviews remain deeply compromised by data and algorithmic biases (Rodriguez 2026). These models routinely fail to account for cultural variations, regional dialects or the unique communication styles of neurodivergent individuals and individuals with disabilities. When an organization anchors its long-term succession planning in these tools, it inadvertently marginalizes non-conventional leaders who possess the precise creative capacity required to drive disruptive innovation.

Furthermore, this reliance facilitates a broader ethical decay and a severe erosion of professional integrity within corporate structures. The uncritical proliferation of generative technologies enables the automated production of strategic reports, market analyses, and executive briefings, which profoundly degrades the internal academic and professional ethos while simultaneously suppressing individual creative thought (Wang 2022). When biased algorithms are seamlessly integrated to evaluate supply chain risks, assess creditworthiness or allocate corporate resources, they actively exacerbate socioeconomic disparities. Organizations that embed these flawed systems into their core operations expose themselves to immense reputational damage, customer alienation and severe regulatory liabilities.

The financial services sector offers an ominous blueprint regarding the systemic hazards of completely removing human oversight from high-velocity decision-making environments. The evolution of high-frequency algorithmic trading demonstrates how autonomous systems, optimized exclusively for rapid execution and short-term capital accumulation, can precipitate catastrophic structural collapses on a macroeconomic scale (Empirica 2023). These algorithms operate completely divorced from broader geopolitical realities, macroeconomic contexts or basic human psychological factors, such as collective panic and trust. In moments of heightened market tension, automated trading systems trigger highly destructive, cascading feedback loops, driving extreme market volatility and systemic fragility (Dánielsson et al. 2022).

A historic and definitive example of this vulnerability occurred on May 6, 2010, an event widely studied in financial economics as the flash crash (Kirilenko et al. 2017). Within a span of just thirty-six minutes, major United States stock indices, including the Dow Jones Industrial Average, suffered an unprecedented, instantaneous plunge of nearly 1,000 points, wiping out almost one trillion dollars in market value. Subsequent investigations by federal regulatory agencies revealed that the panic was initiated by a single algorithmic sell order executed by an institutional asset manager. This program interacted aggressively with hundreds of high-frequency trading algorithms operated by competing institutions. These systems automatically, and without any human intervention or contextual verification, began rapidly selling off shares to one another, creating an uncontrollable mathematical downward spiral. Before human traders could comprehend the nature of the anomaly and manually halt the execution servers, the autonomous network had brought the global financial marketplace to the brink of complete paralysis.

An equally instructive corporate failure occurred in August 2012, involving Knight Capital Group, which was at the time one of the largest market makers on Wall Street. The firm deployed a new, inadequately verified automated trading software update across its core production servers. Due to a critical installation error, an autonomous algorithm was accidentally activated in a legacy environment and began executing millions of erratic transactions at a volume of thousands of trades per second. Within less than forty-five minutes, Knight Capital Group incurred a massive, irreversible cash loss of 440 million dollars. This structural disaster instantly pushed a highly stable, well-capitalized institution into insolvency, forcing its immediate acquisition by a competitor. This case remains a stark reminder of contemporary operational risk: the absence of immediate human kill-switches over autonomous corporate software can completely destroy an enterprise in less than an hour.

It is important to note that the Flash Crash and the Knight Capital incident concern automated trade execution rather than long-term strategic decision-making, and neither constitutes direct evidence of algorithmic isomorphism in the sense defined in Section 1. They are presented here as structural analogies: both cases demonstrate that when a sufficiently large number of market participants operate structurally similar automated systems, the interaction of those systems can produce synchronized, system-wide outcomes that no individual actor intended or could unilaterally prevent. The relevance of this dynamic to strategic management lies not in the financial mechanism itself, but in the general principle it illustrates: that a shared algorithmic infrastructure can generate emergent, correlated behaviour across formally independent decision-makers.

Transposing these hazardous dynamics into general corporate strategy reveals identical threats within non-financial sectors. Contemporary enterprises are rapidly deploying automated platforms to govern supply chain logistics, dynamic

pricing models and automated raw material procurement. If a minor global disruption or a corrupted data packet enters these interconnected systems, the algorithms may simultaneously execute synchronized decisions to cancel vendor contracts, inflate product pricing or freeze manufacturing lines, throwing entire industrial sectors into an artificial paralysis.

Ultimately, this uncritical trajectory towards full technological dependence risks the total erasure of human subjectivity and managerial intuition. Over-indexing on mathematical models stifles organizational empathy, which is indispensable during crisis management, workforce retention and multi-stakeholder negotiations. From the perspective of organizational theory, the most devastating consequence of this shift is the systematic destruction of tacit knowledge (Polanyi 1966). Tacit knowledge represents a deeply internalized corporate wisdom, forged through decades of personal managerial experience, intuitive pattern recognition, long-term relationship building and a nuanced understanding of local cultural landscapes. This invaluable intellectual asset cannot be codified, digitized or fed into any foundational training dataset (UNESCO 2024). Comparable dynamics have been documented at the level of professional expertise, where the introduction of learning algorithms displaces established occupational knowledge and reshapes whose judgement counts as authoritative (Faraj et al. 2018). When an executive board surrenders its decision-making authority to artificial intelligence models, treating them as strategic oracles, the organization's unique capacity to flexibly navigate unprecedented, non-linear global crises is permanently compromised. The erosion of this tacit, firm-specific knowledge base is, in the argument advanced here, what ultimately converts algorithmic isomorphism from a strategic inconvenience into a deeper risk to competitive differentiation: it depletes the very reservoir of idiosyncratic, non-codifiable insight from which a genuinely distinctive strategy would otherwise be drawn.

Section 6: Limitations and directions for future research

This review is conceptual in nature and, as such, does not test the algorithmic isomorphism thesis against empirical data; the corporate and financial cases discussed above serve an illustrative function, motivating and clarifying the proposed construct rather than confirming it. Readers should therefore treat the central claims of this paper as theoretical propositions offered for future empirical scrutiny rather than as established findings. Three such propositions follow directly from the argument developed in Sections 3 through 5.

Proposition 1. Firms that rely on the same, or a small number of structurally similar, global artificial intelligence models to support strategic decision-making will exhibit greater convergence in strategy, messaging and product development than comparable firms that do not rely on such models.

Proposition 2. The opacity of the models used (the black box effect) will weaken managers' ability to distinguish firm-specific recommendations from recommendations that are effectively averaged across a vendor's client base, thereby increasing the likelihood of undetected strategic convergence.

Proposition 3. The degree of strategic isomorphism observed within an industry will increase with the concentration of the market for the underlying artificial intelligence models used within that industry.

Testing these propositions calls for research designs beyond the scope of a conceptual review: comparative textual-similarity analysis (e.g. natural language processing techniques applied to strategic plans, marketing materials or AI-assisted market analyses produced by competing firms using the same model vendors), survey- or interview-based research with executives regarding their reliance on, and trust in, AI-generated strategic recommendations, and longitudinal case studies tracking strategic differentiation in industries before and after the widespread adoption of a dominant AI vendor. We encourage future empirical work along these lines, and offer the conceptual apparatus developed here (specifically, the definition of algorithmic isomorphism and its positioning relative to institutional isomorphism theory) as a starting framework for that research.

Conclusion

The rapid advancement of artificial intelligence undoubtedly introduces extraordinary analytical frameworks and optimization capabilities to the discipline of strategic management. However, an uncritical infatuation with generative models introduces specific, non-trivial risks that threaten the very core of corporate identity. This paper has argued that algorithmic isomorphism plausibly contributes to a homogenization of corporate strategies across industries, potentially undermining the capacity of an enterprise to establish a sustainable competitive advantage predicated on rare, valuable and inimitable organizational resources (Barney 1991). As set out in Section 6, this argument is advanced as a theoretical proposition intended to orient future empirical research, rather than as an empirically established causal account.

Organizations striving to retain their strategic independence in a highly digitalized economic landscape must urgently re-evaluate the architecture of their corporate knowledge management systems. It is an operational imperative for firms to cultivate proprietary, isolated data repositories and deploy closed, niche analytical models that effectively shield sensitive corporate know-how from leaking into public training ecosystems. More importantly, contemporary strategic management must remain anchored in a human-centric paradigm. Artificial intelligence systems must be strictly confined to an augmentative role, thereby expanding the cognitive capabilities of executives rather than supplanting their

critical reasoning, ethical boundaries, and irreplaceable tacit knowledge. The implementation of high-tech solutions must be balanced with strict adherence to emerging regulatory frameworks, including the AI Bill of Rights (The White House n.d.) and international guidelines on responsible technological development (International Organization for Standardization 2024). Only through this balanced approach can contemporary leaders fully exploit the benefits of technological progress while firmly safeguarding the unique identity, long-term resilience and ethical foundation of their business organizations.

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Conceptualization: P.C.

Methodology: P.C.

Formal analysis: P.C.

Resources: P.C.

Writing – original draft: P.C.

Writing – review & editing: P.C.

Supplementary Materials

No supplementary materials are associated with this manuscript.

Funding

This research received no external funding.

Ethics Approval Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

Research data and detailed source compilations are available from the corresponding author upon reasonable request.

Declaration of Generative AI Use

During the preparation of this manuscript, the author used Gemini for English spell-checking and double-checking literature references. The author subsequently reviewed and edited the content and takes full responsibility for the final version of the manuscript.

Acknowledgments

No external assistance, support, or contributions were received during the preparation of this manuscript.

Conflict of Interest

The author declares no conflict of interest.