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WHEN AI BECOMES THE STRATEGIST: HUMAN AI COLLABORATION, STRATEGIC CONFORMITY, AND COMPETITIVE DECISION-MAKING

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ABSTRACT
Generative artificial intelligence and large language models are increasingly used not only to support operational tasks but to generate and evaluate business strategy itself. This conceptual article examines what happens to competitive decision-making when AI moves from an analytical tool to something closer to a strategic collaborator. Drawing on human–AI complementarity theory, institutional theory, and the dynamic capabilities perspective, the article argues that AI-generated strategic advice carries a structural risk: because large language models are trained on shared bodies of business text and respond to similar prompts with similar reasoning patterns, firms that lean heavily on AI for strategic recommendations may converge toward common playbooks rather than differentiate from rivals. This risk echoes long-standing accounts of institutional isomorphism, but with a new mechanism a shared algorithmic advisor rather than shared professional norms or regulatory pressure. At the same time, evidence on human-in-the-loop decision-making suggests that keeping a human's judgment in the final step of a recommendation process need not weaken decision quality and may improve how recommendations are received and acted on. The article synthesizes this literature into a conceptual framework distinguishing condition under which human–AI collaboration is likely to preserve strategic diversity from conditions under which it is likely to produce conformity, and it closes with managerial implications for firms that want to use AI's analytical power without surrendering the strategic distinctiveness that competitive advantage depends on.

Keywords
Artificial intelligence; human AI collaboration; strategic conformity; strategic decision-making; competitive advantage; strategic diversity; human oversight

1. INTRODUCTION

1.1 Background and Context

Generative AI and large language models (LLMs) have transitioned from being a novelty to an infrastructure within businesses in recent years. What used to be a system for a narrow set of operational functions like demand forecasting, customer segmentation, fraud detection is now being called on to perform what is qualitatively different: to generate and evaluate strategic options. Recent experiments have shown that current LLM's are capable of creating and assessing business strategies, and can do so at a similar level to that of human entrepreneurs and investors, and at a much faster rate and scale than any one of them can (Csaszar et al., 2024). This change is important because the strategic decision-making process has been seen as one of the most human aspects of organizational life, characterized by uncertainty, high stakes, and feedback that is slow to arrive and difficult to interpret, and not easily optimised by machines (Csaszar et al., 2024). With this gap being bridged by AI systems, the next question on managers' minds is not just how AI can help create strategy, but what becomes of strategy itself when AI is actively involved in creating it.

1.2 Research Problem

The issue this article tackles has nothing to do with the competence of AI, but instead its impact on differentiation. If a lot of companies in the same industry use the same kind of tools—those trained on the same kinds of text, such as business papers, case studies, and market data the strategies that they recommend are likely to be similar, especially if the manager prompts the tool in the same way. This is a truncation of a well-known organizational phenomenon: over time, organizations that are subjected to the same pressures from the environment tend to develop similar structures and practices, a phenomenon called institutional isomorphism (DiMaggio & Powell, 1983). What classical accounts of isomorphism suggest with regard to regulators, shared professional training, or the emulation of visibly successful competitors, AI as a strategic advisor offers a new and more direct explanation: many competitors using the same kind of tools, trained on similar underlying materials, and receiving strategic advice that are based on common statistical patterns rather than specific insight into the firm.

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1.3 Research Gap

A growing body of scholarship has now started to record the effects of strategic decision-making through the use of AI (Csaszar et al., 2024) and downstream user reactions when a human is present in an AI-assisted decision process, on the quality of the resulting recommendation and user reaction (Yang et al., 2025). The variety of interaction patterns that enable humans and AI systems to share analytical responsibilities in the context of decision support, more broadly, has been documented in a separate and well-established literature (Gomez et al., 2024), while the barriers to integrating human and machine judgments within real organizations have been a subject of interest for organizational scholars for decades (Trunk et al., 2020). Largely underdeveloped is how the way humans work with AI in strategy creation either reinforces or diminishes the tendency toward AI-driven strategic conformity and the implications for a company's capacity to maintain competitive advantage.

1.4 Goals and Questions for Research

To provide a conceptual framework relating human–AI collaboration design to the risk of strategic conformity and to competitive positioning is the goal of this article. But how can AI and human managers play complementary roles in strategic decision-making, rather than AI replacing humans? Second, how can strategic conformity take place in the presence of firms that use AI for strategic recommendations? Thirdly, in which conditions does human oversight maintain strategic diversity and bring support rather than destroy it and competitive positioning?

1.5 Article Contribution

This article contributes to the strategy and information systems literatures in three ways. It links a growing empirical literature on the strategic capacity of AI (e.g., Csaszar et al., 2024) with an older and better-developed theoretical literature on organizational conformity (DiMaggio & Powell, 1983), and suggests that algorithmic advisors are a new and overlooked isomorphic mechanism. It builds on research on human-in-the-loop decision architectures (Yang et al., 2025) and taxonomies of human–AI interaction design (Gomez et al., 2024) to highlight certain conditions wherein collaboration design expands or limits the strategic options a firm considers. Last, it provides managers with a useful language to determine their organization's use of AI's capability to create a differentiated competitive position or a homogenized one.

2. LITERATURE REVIEW

Table 1. Summary of Verified Core Sources

Source	Outlet	Core finding	Relevance to this article
Csaszar, Ketkar, & Kim (2024)	Strategy Science	Current LLMs can generate and evaluate strategic plans at a level comparable to entrepreneurs and investors.	Establishes that AI is now a credible participant in strategy generation, not only analysis.
Yang, Bauer, Li, & Hinz (2025)	Management Science	Keeping a human banker with final say over AI-assisted investment advice did not reduce advice quality and increased customer uptake, especially for risky decisions.	Evidence that human-in-the-loop design need not trade off quality, and shapes how recommendations are used.
Trunk, Birkel, & Hartmann (2020)	Business Research	Combining human and AI judgment in strategic organizational decisions faces real, unresolved governance, ethics, and capability gaps.	Grounds the governance and role-clarity conditions needed for effective human–AI collaboration.
Gomez, Cho, Ke, Huang, & Unberath (2024)	Frontiers in Computer Science	A systematic review finds AI-assisted decision systems disproportionately rely on shallow, one-way interaction patterns rather than genuine collaboration.	Motivates the distinction between shallow and deep interaction central to this article's conceptual model.

2.1 The application of Artificial Intelligence in strategic management.

The complexity, the stakes, and the lengthy and noisy process of learning from a strategic choice in the aftermath of its implementation have made strategic decision making a peculiar human endeavor.Strategic decision making is traditionally considered a peculiarly human activity due to its complexity, its importance, and the long and noisy process that connects a strategic choice with the evidence of success or failure. The use of large language models

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in this field is still relatively new, and although there is limited empirical evidence, it is noteworthy: AI generated strategic plans have been found to be of similar quality to those created by seasoned entrepreneurs and investors in controlled comparisons (Csaszar et al., 2024). This means that AI can directly engage in the cognitive processes of planning (strategizing) such as searching for options, representing a problem, and aggregating disparate information, rather than just helping with data (Csaszar et al., 2024). Concurrently, this capability is developing in a world where the net outcomes on a particular company's performance will largely rely on how others use the same technology (Csaszar et al., 2024), in which very same competitive dynamic this article is interested.
Human-AI collaboration and decision quality.
The question of whether AI can create good analysis has been explored in a separate body of literature, rather than how human involvement affects the value of the analysis once it has been created. A large field experiment with a European savings bank demonstrates that a human banker does not harm the quality of the advice given (by a human or with AI support) compared to advice generated by AI alone (Yang et al., 2025). Perhaps more significantly, when customers were given advice from both human and AI, they were more likely to act on that combined advice than when they were only given advice from the AI (Yang et al., 2025). This is significant because it indicates that the usefulness of human input is not limited to rectifying errors made by AI but also to the confidence and appropriate use of the recommendation by the humans who will have to implement it.
This is further emphasized by work that catalogues the structural variation of human–AI collaboration, which shows that "collaboration" is not a single design point but rather a kind of interaction pattern, some of which are much more truly collaborative than others. A systematic review of the interaction patterns in AI-assisted decision-making revealed that the field has so far largely focused on technical performance, while comparatively very little attention has been given to the real collaboration and interaction between the AI and the user, with many systems following relatively shallow interaction patterns, rather than true two-way interaction (Gomez et al., 2024). This difference has implications for strategy work: If a company sees an AI system as a one-shot generator of a strategic conclusion, it is practicing a different and, this article will argue, riskier form of AI than a company that uses AI in an iterative fashion, challenging and revising its recommendation in parallel with human judgment.

2.3 Strategic Conformity and Institutional Pressure

The most obvious existing explanation for the tendency of organizations operating under comparable conditions to develop similar practices is the institutional theory. According to DiMaggio and Powell (1983) there are three mechanisms of institutional isomorphism: coercive pressures from regulation or dependence on other institutional actors, normative pressures from shared professional standards and training, and mimetic pressures from imitation under conditions of uncertainty for successful institutions. Mimetic isomorphism is particularly applicable here: DiMaggio and Powell (1983) suggest that organizations tend to imitate others just in the instances when goals are vague and when uncertainty is present in the environment, such as in many strategic decisions. If, as DiMaggio and Powell suggest, LLM training sets are co-extensive and drawn from business writing, case studies and market commentary, and if a number of competing firms submit similar queries to similar systems, the systems themselves may serve as another, more rapid and less visible channel of mimicry.

2.4 Strategic Diversity and Competitive Differentiation is a topic.

While institutional theory accounts for convergence, differentiation has been a core tenet of the strategy literature since the beginning and the basis for any firm to have a position of competitive advantage is to do something that other firms do not do, or to do a common thing in an uncommon way. Hence strategic diversity is not a by-product of competitive strategy, but rather it is quite close to the definition.So strategic diversity is not an incidental of a competitive strategy but rather close to the definition: intentional avoidance of convergence to a single, easy-to-find solution. But no matter where an AI system comes up with a suggestion for the firm's strategy, if it is also the most likely and common response to a competitive question, then it is not certain that it is the right choice for the business to follow in that way.
Technical quality and human oversight in AI recommendations is discussed.Discussion of technical quality and human oversight of AI recommendations.
The findings on human-in-the-loop decision making suggest that oversight is not a failsafe against making a mistake, but it is a component of the process and impact of making a recommendation and receiving it. The research finding that customers were more likely to follow the advice but did not have to be better quality if the manager participated in a human–AI strategic process suggests that the manager is doing something, something that a fixed sequence of algorithms would not be able to replicate. However, realizing value requires the interaction to be structured in a way that the human is not a rubberstamp at the end of an otherwise automated process, but rather is part of the interaction that can challenge AI's reasoning, as found by Gomez et al. (2024) to be a potential risk of shallow interactions.

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3. THEORETICAL FRAMEWORK

Figure 2. AI as a Channel for Institutional Isomorphism

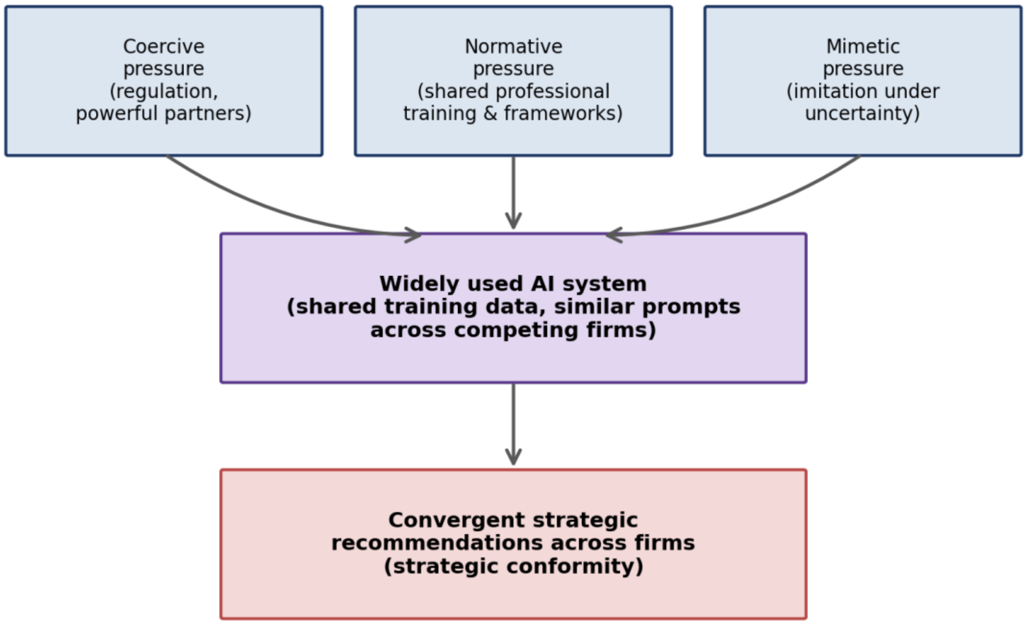

Figure 2. AI as a channel for institutional isomorphism: coercive, normative, and mimetic pressures converge on a shared AI advisor.

3.1 Human AI Complementarity

The framework presented here rests on the assumption that there are different and, indeed complementary strengths in strategic work between AI and human managers. AI systems can ingest vast amounts of market, financial, and textual data, produce a comprehensive range of potential strategies, and assess options against explicit criteria that are very fast and impossible for any human team to do (Csaszar et al., 2024). Human managers take with them their tacit and contextual knowledge of their organisation, personal accountability for results, and the ability to make the kind of judgement that transcends statistics and is creative and inventive in breaking boundaries. Unlike the common definition of complementary that is an act of division of labour where AI suggests and humans accept, here the two are complementary in the sense that what each produces is an input for the other to question.

This course provides students with a solid foundation in the institutional theory and strategic conformity.

There are three isomorphic mechanisms identified by DiMaggio and Powell (1983) with which to map onto AI-assisted strategy. Coercive pressure occurs when AI risk or compliance tools are required by regulators or strong business partners to be used, and different companies are required to submit the same inputs into decisions. An increasing number of management education courses, consultancy models, and professional qualifications integrate approaches that trigger and interpret AI-generated strategic analysis, giving them a common professional "language" that can be used throughout firms and industries. Mimetic pressure seems the most direct fit for the case described by DiMaggio and Powell (1983): a manager who is uncertain about the strategic option he needs to make but asks his query from a widely used AI system is essentially asking for the "best" answer based on the pattern of many other managers' previous strategic decisions, even if he wasn't consciously aware of asking for that.

3.3 Dynamic Capabilities Perspective

From the dynamic capabilities perspective, it is how the organization can respond to opportunities and threats rather than a specific resource that constitutes a source of competitive advantage; by responding to opportunities and threats, the organization is able to make decisions in a timely manner and reconfigure its resources to remain

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fit with its changing environment (Teece, Pisano, & Shuen, 1997). When viewed through this lens, AI should not be considered a strategy to implement, but rather as a capability that can augment the sensing and seizing phases of this cycle as long as the transforming phase will still require human judgment to synthesize the AI-generated options into a response that aligns with the firm's unique resource position and history and not just another, generic response. There is no advantage to outsourcing the transforming step to AI if the firm ends up turning that capability into a static one rapidly transformative, but no longer differentiating when everyone else has the same tool.

Figure 4. AI's Role Across the Dynamic Capabilities Cycle

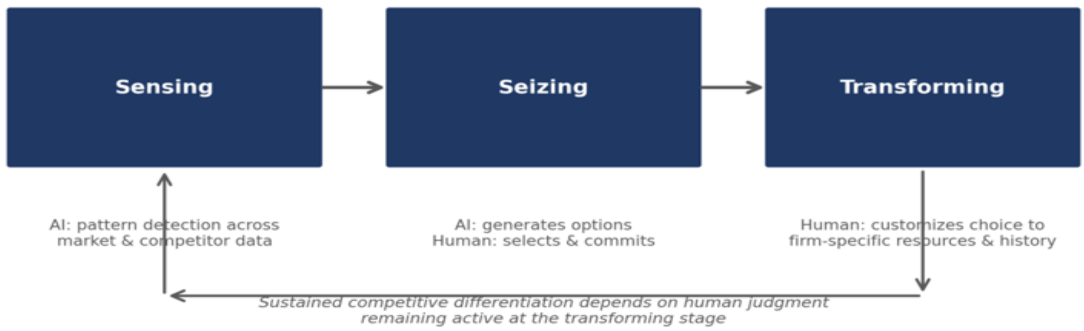

Figure 4. AI's role across the sensing seizing transforming cycle (Teece et al., 1997); differentiation depends on human judgment remaining active at the transforming stage.

3.4 A Conceptual Model

Bringing these strands together, this article proposes as a conceptual model rather than a tested empirical one that the outcome of AI-assisted strategy work can be located along two dimensions: the depth of human AI interaction (from shallow, single-pass generation to genuinely iterative contestation) and the degree of firm-specific customization applied to AI output (from accepting generic recommendations to substantially reworking them around proprietary knowledge). Shallow interaction combined with low customization is the configuration most likely to produce strategic conformity, since it most closely resembles many firms independently querying the same model in the same way. Deep interaction combined with high customization is the configuration most likely to preserve, and potentially enhance, strategic diversity, since the AI's output functions as raw material for a human strategic process rather than as the process's final output.

Figure 1. Conceptual Model: Interaction Depth, Customization, and the Risk of Strategic Conformity

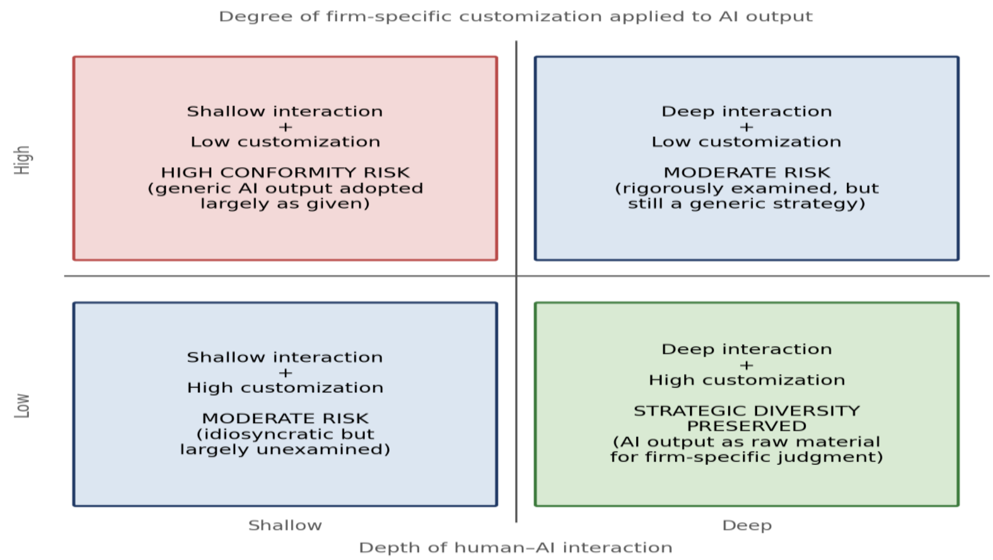

Figure 1. Conceptual model relating interaction depth and firm-specific customization to the risk of strategic conformity.

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4. HUMAN AI COLLABORATION IN STRATEGIC DECISION MAKING

Figure 3. The Iterative Human–AI Strategic Decision Cycle

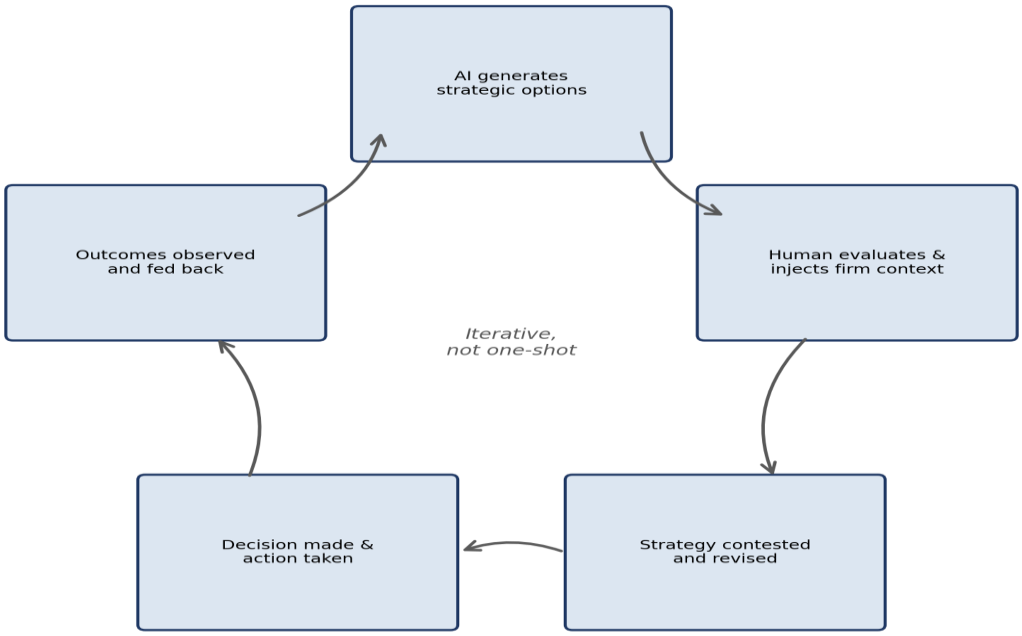

Figure 3. The iterative human AI strategic decision cycle: sustained collaboration, not a single hand-off.

4.1 Complementary Capabilities

In practice, complementary use of AI in strategy work divides responsibilities along the lines suggested by the framework above. AI is well suited to synthesizing competitor disclosures, market data, and academic and trade literature into structured summaries; generating a wide initial set of strategic options rather than the two or three a time-constrained team might otherwise consider; and stress-testing a proposed strategy against alternative scenarios or counterarguments. Human managers remain responsible for supplying the organizational context an AI system cannot independently know unwritten political constraints, relationships with key customers or partners, and the tacit understanding of what has and has not worked for this particular firm before and for making the final, accountable choice among options.

4.2 AI as Strategist versus AI as Advisor

A meaningful distinction separates AI functioning as an advisor, whose output is one input a human strategist weighs alongside others, from AI functioning as a de facto strategist, whose recommendation is adopted with little independent evaluation. The evidence that decision quality did not suffer when a human retained final authority over AI-assisted advice (Yang et al., 2025) supports treating AI as an advisor by design rather than assuming that doing so necessarily costs the firm analytical quality. The risk in treating AI output as authoritative is not confined to the possibility that a specific recommendation is wrong; it is that, right or wrong, an unexamined recommendation is more likely to resemble what other firms consulting similar systems are also being told, quietly eroding differentiation even when each individual recommendation is sound.

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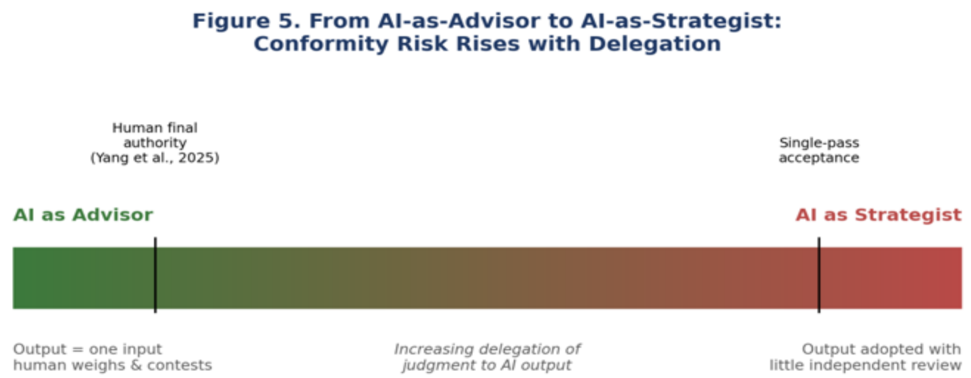

Figure 5. Conformity risk rises as firms move from treating AI as an advisor to treating it as a de facto strategist.

4.3 Conditions for Effective Collaboration

Several conditions appear to make human AI collaboration more likely to produce sound, differentiated strategic decisions. Clear articulation of strategic objectives before consulting an AI system helps ensure its output is evaluated against the firm's actual priorities rather than generic best practice. High-quality, firm-specific data and carefully constructed prompts shape the model's output toward the organization's real situation rather than an industry average. Managers benefit from asking AI systems to make their reasoning visible rather than accepting conclusions alone, which supports genuine evaluation rather than passive acceptance the deeper interaction pattern associated with more collaborative use of AI in decision support (Gomez et al., 2024). Finally, treating an initial AI-generated strategy as a draft to be iterated on, rather than a finished product, echoes the field-experiment finding that a human's substantive final involvement need not come at the cost of quality (Yang et al., 2025).

4.4 Barriers to Effective Collaboration

Several well-documented obstacles work against this ideal. Automation bias the tendency to defer to an automated recommendation even when independent evidence would suggest otherwise is a standing risk whenever a system produces confident-sounding, fluent output. Limited explainability compounds this risk, since a fluent strategic narrative can be persuasive independent of whether its underlying reasoning is sound. Practical organizational obstacles, including unclear ownership of AI-assisted decisions and the education and role-redefinition costs of integrating AI meaningfully rather than superficially into decision processes, have been documented as ongoing challenges rather than problems that have already been resolved by current tools (Trunk et al., 2020). Left unaddressed, these barriers push firms toward the shallow, low-customization pattern in the conceptual model above, and toward the strategic conformity that pattern predicts.

5. STRATEGIC CONFORMITY AND STRATEGIC DIVERSITY

5.1 Understanding Strategic Conformity

In the context of this article, strategic conformity means that the answers reached by organizations with similar strategic issues are similar, not necessarily the right answer, but one that comes from a similar process: common assumptions, common training, common adviser. There is a lot of institutional theory that has documented this tendency for decades as a result of having common professional norms, and the resemblance to what can be seen by visible industry leaders (DiMaggio & Powell, 1983); the additional of AI as a broadly shared strategic advisor offers a new, and more direct, channel.

5.2 Strategic Compliance via AIAI can inspire strategic compliance.

There are multiple ways to make this risk real as opposed to hypothetical. LLMs provide the most likely continuation of a prompt: If a strategic question has been asked in a general way, it is likely to come up with the most typical answer, not the unusual or company-specific one. Furthermore, firms in the same industry are likely to state strategic problems in similar terms, and rely on similar publicly accessible data on the market, thereby constraining the variety of inputs different firms can offer to the same system. When the uncertainty is genuine, as DiMaggio and Powell (1983) suggest would be most conducive to mimetic isomorphism, the manager could be particularly tempted to accept an AI's output as a "safe" bet that it is well-reasoned and convincing, and therefore worth considering.

5.3 Preserving Strategic Diversity

The conceptual model in Section 3 leads to potential countermeasures. Having several strategic scenarios that are intentionally divergent within an AI system, instead of relying on a single most likely scenario, brings a broader choice set for human evaluation. Inviting different perspectives and unusual interpretations of AI-generated content, instead of assuming the agreement to its recommendations is proof of a good idea, can prevent the tendency toward premature convergence. Most fundamentally, adding proprietary knowledge, unusual data sources, or a different perspective to the human part of the collaboration is what makes a generic AI output a firm-specific one, and is the biggest influence managers can have to harness the benefits of AI-assisted analysis without the homogenizing power.

Table 2. Institutional Isomorphism Mechanisms: Traditional Channel vs. AI-Mediated Channel

Mechanism (DiMaggio & Powell, 1983)	Traditional channel	AI-mediated channel	Countermeasure
Coercive	Regulation; dependency on powerful partners or funders.	Mandated or default use of a shared vendor's AI risk, compliance, or planning tool.	Retain firm discretion over how mandated tool output is interpreted, not just whether it is used.
Normative	Shared professional training, credentials, and consulting frameworks.	Management education and standard playbooks for prompting and interpreting AI output.	Vary prompts and frameworks deliberately rather than adopting one standard approach industry-wide.
Mimetic	Imitation of visibly successful rivals, especially under uncertainty.	Many firms independently querying similar models trained on overlapping data.	Generate multiple divergent AI scenarios; inject proprietary data and contrarian framing before deciding.

6. COMPETITIVE POSITIONING AND HUMAN OVERSIGHT

6.1 AI and Human Resources Policies and Programs

Analytical tasks that complement rather than drive a strategic decision are the easiest for AI to help with when it comes to competitive positioning: Summarizing vast amounts of data and information on competitors, finding new customer segments in transactional or survey data, or finding trends in markets that would otherwise be a time-consuming manual process for a human analyst. In this use, AI serves as an amplifier of the evidence base for a strategic decision, rather than determining it, allowing the decisions to remain in the hands of people within the firm, not AI.

6.2 AI recommendations can be enhanced by human oversight.

When available information is incomplete or ambiguous and the AI needs to interpret, not just aggregate, the information; when the decision requires tacit knowledge that is not represented in any data set, such as knowledge about the organization's own history, culture, or relationships; when the ethical, reputational, or stakeholder implications of the AI's recommendation extend beyond what a system optimized for a more limited objective would capture; or when the AI's recommendation appears conventional in such a way that it causes a manager to question whether there is a situation where it should be conventional. The results from the field-experiments indicate that human final authority does not decrease the quality of advice and actually increases the probability that it will be followed, which suggests the idea of oversight is not merely a defensive one, but it can have a positive impact on the outcomes (Yang et al., 2025).

There, strategic governance and accountability are what it is all about.

To maintain the above benefits, governance should not consider the process of using AI-assisted strategy as a one-off solution but rather a process that should be managed. This encompasses transparency in who is responsible for the decision and whether an AI recommendation was analysed, adjusted and implemented or rejected, as well as regular checks on whether the firm's strategic AI recommendations are in practice moving towards what competitors seem to be doing. Previous studies on organizational adoption of AI for decision making have highlighted the need for human capabilities and role clarity that such governance must provide, which usually requires intentional investments in training and in designing processes (Trunk et al., 2020).

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7. DISCUSSIONS AND IMPLICATIONS FOR MANAGEMENT

7.1 Theoretical Implications

This article builds upon the literature on human–AI collaboration by explicitly linking it to the literature on mimetic isomorphism (DiMaggio & Powell, 1983), proposing that widely used AI systems are a new and largely under-researched route to mimetic isomorphism. It takes the DCP (dynamic capabilities perspective) (Teece et al., 1997) one step further by proposing that the role of AI in creating sustainable competitive advantage is more about how the transformative process in the SST cycle is managed rather than whether a firm has implemented AI or not. It also brings evidence on human-in-the-loop decision quality (Yang et al., 2025) and interaction-pattern taxonomies (Gomez et al., 2024) that are not part of the strategy literature, thereby contributing a perspective to a strategic management question.

7.2 Managerial Implications

There are a number of implications which are practical. The use of AI should be seen as a tool that provides recommendations, but not as a final answer. This means that managers are not limited to accepting an AI-generated solution for granted, but can use it as a foundation to evaluate and then take the next steps to find a more optimal solution, especially when the AI-generated solution is a conventional one or something that could be proposed by another competitor. Institutions should create clear guidelines for developing multiple strategic options with AI and comparing them against one another, and should not be satisfied with the result of a single AI recommendation, but should support strategic experimentation based on insights that are unique to their own context. The deeper interaction pattern the article connects with preserved strategic diversity (Gomez et al., 2024) requires an investment in AI literacy sufficient to enable having a deep, constructive dialogue with the reasoning of an AI and not simply accept its conclusions. Finally, human oversight should be placed and resourced in its own right as a source of value, not as a compliance checkbox to put on top of an otherwise automated process, and be built on evidence that it does not need to be costly to decision quality (Yang et al., 2025).

Table 3. Managerial Implications: From Conformity Risk to Strategic Diversity

Risk factor	Practice to avoid	Recommended practice	Supporting logic
Shallow interaction	Accepting a single AI-generated strategic recommendation as final.	Treat AI output as a draft; iterate with contestation before deciding.	Deeper interaction is associated with more genuinely collaborative decision support (Gomez et al., 2024).
Low customization	Using generic prompts with no firm-specific data or context.	Inject proprietary data, constraints, and history into every AI-assisted analysis.	Customization is what converts a generic output into a differentiated one (Section 3.4).
Passive oversight	Treating human sign-off as a formality at the end of an automated process.	Give the human reviewer real authority and accountability for the final call.	Human final authority did not reduce advice quality and increased uptake (Yang et al., 2025).
Unexamined convergence	Assuming a conventional-sounding recommendation is a safe default.	Treat conventional AI output as a prompt to check whether the situation calls for differentiation.	Mimetic isomorphism is strongest precisely under the ambiguity common to strategic choices (DiMaggio & Powell, 1983).

7.3 Research Implications and Limitations

Due to its conceptual nature, this article does not present empirical tests of its proposed framework and the central claims that, as with other institutional theory literature (DiMaggio & Powell, 1983), and as documented in the literature (Csaszar et al., 2024; Yang et al., 2025), are consistent with the logic of institutional theory, but are best treated as propositions for future research. These include field or laboratory experiments that compare the strategic diversity of decisions made by AI, humans, and human–AI teams where the AI interacts with humans in different ways, both shallow and deep; longitudinal, cross-industry studies to examine whether firms that use similar AI tools over time, but engage in different depths of interaction, experience measurable convergence in strategic positioning over time; and further research on the causal link between interaction design (broadly defined along

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research lines that have already established taxonomy of human AI interaction (Gomez et al., 2024)) and the diversity of strategic options that a firm ultimately explores.

8. CONCLUSION

However, with AI systems now able to create and test strategies at a level close to that of a human expert (Csaszar et al., 2024), the real challenge for organizations is not if, but how they can implement the use of these tools in a way that doesn't compromise on what differentiates their work from that of a human and what makes their service stand out for competitive advantage. The article has made a case that the processes that have been used to account for organisational conformity bear new force when a widely adopted AI system becomes a common strategic counselor in an industry and that this danger is not impossible to manage. Evidence suggests that the right approach is not to reject the use of AI in strategy work, but to carefully design collaboration, in which iterative and intensive engagement and firm-specific customization of the output are paramount, and generic output is rejected (Yang et al., 2025). It is important to recognize that AI is not a substitute for the human strategist, but rather a valuable and not yet fully mature tool that can be a key differentiator in the drive for competitive advantage, all ultimately depends on the human who makes decisions about how to use it.

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