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The Convergence of Corporate Strategy When Competing Firms Delegate Strategic Analysis to Shared Foundation Models Trained on Overlapping Knowledge

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Abstract

Foundation models are increasingly capable of generating strategic alternatives, evaluating business choices, synthesizing environmental information, and supporting managerial judgment. Their organizational diffusion creates a competitive problem that differs from conventional questions about whether artificial intelligence improves individual decision quality. When competing firms delegate portions of strategic analysis to models trained on substantially overlapping knowledge, individually rational adoption may alter the distribution of strategic variety across the market. This article develops a Systems / Feedback Theory account of that possibility. It conceptualizes strategic convergence as an emergent system outcome produced when shared analytical infrastructure, overlapping representations, recurrent delegation, organizational learning, and market feedback reinforce one another strongly enough to outweigh firm-specific sources of heterogeneity. The account distinguishes convergence in problem framing and candidate alternatives from convergence in final strategic action and competitive performance. It also identifies countervailing mechanisms—including situated use, proprietary information, retained human judgment, alternative analytical configurations, and endogenous capability adaptation—that can preserve or restore strategic differentiation. The central argument is therefore conditional: foundation-model commonality creates convergence pressure, but realized strategic convergence depends on the relative strength, timing, and interaction of reinforcing and balancing feedbacks across firms.

Keywords Corporate strategy, Generative artificial intelligence, Systems thinking, Foundation models, Strategic convergence, Competitive heterogeneity

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Introduction

Strategic analysis is becoming an increasingly plausible domain for delegation to large language models and related foundation-model systems. Recent evidence indicates that such models can generate strategically relevant recommendations and may display systematic conformity when responding to institutional pressures [1]. In controlled entrepreneurial and investment settings, large language models have also demonstrated an ability to generate and evaluate strategic alternatives at levels sufficiently strong to make their use in strategic search organizationally

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consequential [2]. The emerging issue is therefore no longer confined to whether artificial intelligence can contribute to strategy work. It concerns what happens to the distribution of strategic judgments when many competing firms obtain part of that contribution from closely related analytical infrastructures.

The possibility of convergence cannot be inferred simply from strong model performance. Evaluation by individual models can remain inconsistent or biased, while aggregation across evaluations can yield substantially different rankings [3]. Foundation models are themselves designed as reusable pretrained infrastructures whose capabilities are adapted through prompting, fine-tuning, retrieval, and other downstream mechanisms [4]. A shared technological substrate consequently creates commonality without eliminating variation. The relevant theoretical problem is to explain when that commonality remains an input condition and when it becomes amplified through organizational use into correlated strategic framing, alternatives, and action.

The scale of adoption makes this distinction strategically significant. Generative AI has diffused rapidly into work, although organizational climates, occupational conditions, and modes of use remain heterogeneous [5]. At the same time, research linking artificial intelligence and strategic management already spans multiple decision domains without providing a settled explanation of how widespread reliance on related models may alter competitive heterogeneity at the population level [6]. Much existing work asks how AI improves, automates, or augments a focal firm's decisions. The system-level question examined here is different: under what conditions can individually rational delegation by multiple firms endogenously reduce the strategic variety on which competitive differentiation partly depends?

A Systems / Feedback Theory perspective is appropriate because the proposed effect need not originate in any firm's intention to imitate rivals. Strategic similarity may instead emerge from repeated interaction among common analytical inputs, organizational delegation, managerial responses, observed market outcomes, and subsequent adjustments in reliance on AI. The same system can also contain balancing processes that interrupt convergence. Accordingly, the article treats strategic convergence as a possible dynamic property of a competitive population rather than a direct technological effect of foundation-model adoption.

Strategic Heterogeneity and Competitive Advantage

Competitive strategy presupposes consequential differences among firms. Dynamic-capabilities theory links strategic outcomes to firm-specific capacities for sensing, seizing, and reconfiguring opportunities through particular business-model choices [7]. Research on business-model innovation likewise shows that organizational responses are heterogeneous and contingent rather than reducible to a single replicable pathway [8]. These traditions make strategic heterogeneity analytically prior to the convergence problem: if firms differed only because they possessed different analytical technologies, a common foundation model could readily eliminate difference. In practice, heterogeneity also resides in assets, organizational histories, routines, managerial attention, stakeholder relationships, accumulated knowledge, and implementation capacity.

Artificial intelligence may nevertheless change which sources of heterogeneity matter. Theory on AI and competitive advantage suggests that algorithmic capability can alter the composition of strategically valuable resources and complementary organizational capabilities [9]. Yet access to similar technical models need not imply equivalent organizational capability. The concept of situated AI emphasizes activities through which firms ground AI in local information, bound its decision domain, and recast organizational processes around its use [10]. These activities can make a broadly accessible technology strategically firm-specific.

This distinction is essential for the argument developed here. AI-enabled value creation depends on how analytical capability is combined with business models, data, organizational design, and mechanisms for appropriating value [11]. Strategic convergence therefore should not be defined as equality of performance, resource positions, or realized competitive outcomes. In this article, it denotes a reduction in cross-firm variation in the way strategically relevant problems are represented, which alternatives enter serious consideration, and how those alternatives are initially

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evaluated. Firms may converge analytically while continuing to diverge in implementation, timing, complementary assets, or outcomes. Conversely, firms using the same model may remain analytically heterogeneous when local organizational inputs exert sufficient countervailing influence.

Foundation Models as Shared Analytical Infrastructure

Generative AI differs from many earlier analytical systems because a single pretrained model can support numerous downstream knowledge tasks through natural-language interaction and adaptation [12]. In strategic settings, this creates the possibility that firms do not merely purchase comparable software functionality; they repeatedly consult systems whose internal representations have been learned from substantially overlapping bodies of public knowledge. Once these systems become embedded in recurring strategic analysis, their significance depends on how decision work is allocated between humans and algorithms.

Organizational research identifies multiple possible human–AI decision structures, including delegation, sequential configurations, and aggregation of human and algorithmic judgments [13]. Deep-learning systems can augment organizational targeting, monitoring, and scheduling while leaving important elements of contextual interpretation with organizational actors [14]. The automation–augmentation paradox further indicates that increasing algorithmic capability does not produce a single stable division of labor: automation and augmentation may develop simultaneously within the same organization [15]. Consequently, foundation models should be treated as a potentially shared analytical infrastructure whose coupling to actual strategic choice varies by decision architecture.

That coupling is also bounded by task and user heterogeneity. Field evidence on knowledge work demonstrates a jagged capability frontier: AI assistance can substantially improve performance on tasks that fall within model capabilities while producing weaker or adverse results beyond those boundaries [16]. Deployed generative-AI systems likewise produce heterogeneous effects across workers, experience levels, and problem types [17]. Such findings constrain any claim that shared access mechanically standardizes strategic cognition. A common model can generate different organizational consequences because firms ask different questions, possess different information, allocate different decision rights, and differ in their ability to recognize when model output should be accepted, revised, or rejected.

The system-level implication is therefore conditional. Shared foundation models create a common analytical coupling point, but competitive convergence requires that this coupling persist across repeated rounds of problem representation, alternative generation, evaluation, and organizational response. At the same time, situated knowledge, alternative decision architectures, and retained human judgment can act as balancing forces. **Figure 1** represents this tension as a feedback architecture in which convergence pressure arises from common analytical infrastructure while firm-specific interpretation and capability differences continually push the system back toward heterogeneous strategic trajectories.

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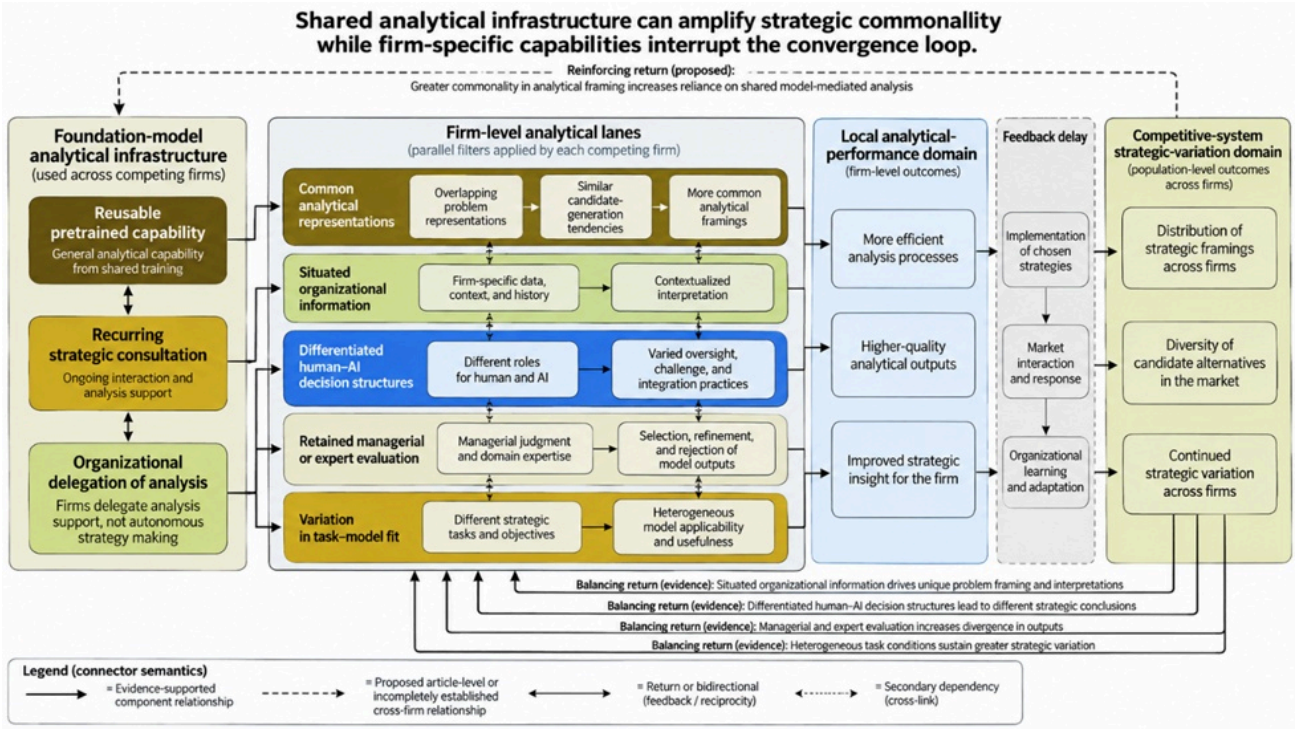

Figure 1. Shared analytical infrastructure can amplify strategic commonality while firm-specific capabilities interrupt the convergence loop

Overlapping Training Knowledge

The first convergence mechanism arises from correlation rather than identity. Formal analysis of algorithmic monoculture shows that when many decision makers rely on the same algorithmic system, individually attractive choices can become correlated in ways that generate system-level consequences not visible from the perspective of a single user [18]. Experimental evidence in generative creativity provides a related local-versus-collective distinction: AI assistance can improve individual creative output while simultaneously reducing diversity across the population of outputs [19]. Neither result demonstrates strategic convergence among firms, but together they establish an important systems premise—local gains from common analytical assistance can coexist with a reduction in population-level variation.

Model plurality does not necessarily eliminate this possibility. Comparative evidence indicates that outputs from different large language models may be more similar to one another than independent human outputs in some creative tasks [20]. Yet human–AI search configurations can materially change the alternatives generated during innovation problem solving [21]. The relevant variable is therefore not merely whether competing firms subscribe to different providers. What matters is how independent their effective analytical search spaces remain after accounting for overlapping training knowledge, model design, elicitation practices, organizational information, and human intervention.

Organizational placement further conditions whether overlapping learned knowledge matters strategically. AI use varies across stages of innovation activity and does not contribute uniformly across the innovation process [22]. Research on generative AI and innovation management likewise identifies unresolved variation in agency, ecosystem design, organizational arrangements, and emerging dominant configurations [23]. Overlapping training knowledge should consequently be understood as a potential source of correlated analytical priors, not a completed theory of strategic convergence.

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The analytically important distinction is between several forms of commonality that may look equivalent at the technology level but have different system consequences. A common pretrained substrate, similar learned representations, repeated use of comparable prompts, and organizational filtering through proprietary knowledge do not impose the same degree of correlation on strategic analysis. **Table 1** separates these conditions before the argument moves to the stronger question of when analytical commonality becomes convergence in problem framing and alternatives.

Table 1. Distinct sources of analytical overlap create different pressures toward cross-firm strategic commonality

Source of analytical overlap	Where commonality enters strategic analysis	Expected pattern of cross-firm correlation	Firm-specific filter capable of weakening correlation	Systems implication
Shared foundation-model substrate	Broad representations and general-purpose generative capability	Common conceptual vocabulary and recurring patterns of association may become available across firms	Proprietary retrieval, fine-tuning, local data, alternative models	Creates a common coupling point but does not determine strategic output
Overlapping learned knowledge	Problem representations and associations derived from similar training information	Firms may begin analysis from partially correlated priors about causes, categories, competitors, or feasible actions	Distinct experiential knowledge and organization-specific interpretation	Raises the probability that independent-looking analysis begins from similar representational spaces
Similar elicitation and analytical routines	Prompt structures, decomposition procedures, scenario templates, evaluation criteria	Candidate sets and evaluative comparisons may become more alike even when firms do not observe one another	Different search protocols, adversarial prompting, independent human reframing	Converts technological commonality into process-level commonality
Repeated model-mediated strategic consultation	Successive rounds of framing, option generation, evaluation, and revision	Early similarity can persist or accumulate across later decision cycles	Deliberate model rotation, independent analysis, local experimentation	Enables reinforcing feedback because previous model-shaped analysis influences subsequent questions
Organizational filtering of shared outputs	Human judgment, decision rights, proprietary information, implementation knowledge	Correlation can either survive organizational review or be substantially attenuated	Situated expertise, dissent, differentiated incentives and decision architecture	Determines whether shared analytical inputs remain common or are transformed into heterogeneous strategies
Market and organizational feedback following AI-supported choices	Subsequent interpretation of results and revision of future analytical reliance	Similar feedback interpretation can reinforce commonality; heterogeneous local feedback can restore divergence	Different assets, timing, customer responses, learning routines	Makes convergence potentially dynamic and reversible rather than a one-time model effect

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Convergence of Problem Framing and Strategic Alternatives

Correlated analytical priors become competitively consequential only when they influence the strategic search process repeatedly enough to narrow variation in what firms treat as important problems and credible responses. Systems research on strategic learning shows that feedback delays can produce convergence toward strategies with rapidly observable returns even when those strategies are inefficient over longer horizons [24]. The implication for shared-model environments is not that foundation models reproduce this experimental result directly. It is that delayed feedback creates conditions in which organizations may continue relying on analytical representations that appear locally successful before their broader strategic consequences become visible.

The direction of feedback is not necessarily homogenizing. System-dynamics interventions can help decision makers externalize assumptions, trace causal relations, and identify alternative strategic pathways that ordinary planning processes may neglect [25]. Explicitly representing feedback may therefore operate as a balancing mechanism when it exposes assumptions embedded in recurring AI-supported analysis. The theoretical issue is how the architecture of learning interacts with the architecture of analytical delegation.

The proposed reinforcing mechanism in this article has several linked stages. When competing firms repeatedly consult models whose learned representations substantially overlap, the firms may become more likely to define ambiguous strategic conditions through similar categories. Similar framing can increase overlap in generated candidate actions. Similar evaluative criteria can then raise the probability that comparable alternatives survive early screening. If firms act on those alternatives, some portion of the resulting market environment becomes endogenous to the common analytical logic that helped produce the actions. Later strategic consultations then take place in an environment partially shaped by earlier model-mediated decisions. No individual firm needs to intend imitation for strategic commonality to become self-reinforcing.

Several distinctions prevent this mechanism from becoming a technological-determinist claim. First, convergence in framing can occur without convergence in final choice because organizations may apply different constraints, risk tolerances, resources, or implementation capabilities. Second, similarity in final strategies may arise from common industry shocks or objectively dominant responses rather than common model use. Third, common model access may increase rather than reduce strategic variety when firms use the systems to search more broadly, contest default assumptions, or combine generated alternatives with differentiated local knowledge. Finally, feedback can reverse direction as firms observe strategic crowding and deliberately seek less common analytical positions.

Strategic convergence is therefore best treated as a dynamic population outcome whose probability depends on the balance between reinforcing commonality and balancing heterogeneity. Shared models supply one possible source of correlated priors; organizational delegation determines how strongly those priors enter strategy; delays affect when firms can recognize consequences; and firm-specific knowledge determines whether repeated model use continues to compress or instead re-expand strategic variation. The next part develops the heterogeneity-preserving mechanisms, integrates these feedbacks into the strategic convergence framework, and converts the resulting system logic into discriminating propositions and competitive implications.

Mechanisms Preserving or Restoring Strategic Heterogeneity

Shared analytical infrastructure does not remove the organizational processes through which firms interpret, contest, and implement strategic advice. In a preregistered field experiment involving product-innovation work, generative AI helped individuals span functional knowledge boundaries, yet human judgment remained consequential in evaluating and selecting outputs [26]. This combination matters for competitive heterogeneity. The same technology may reduce differences in early-stage search while leaving later-stage selection exposed to different expertise, incentives, and

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organizational priorities. Convergence pressure can therefore weaken whenever the decision architecture preserves meaningful human discrimination after model-supported generation.

Organizational interpretation can create an additional balancing force. Comparative evidence from organizations using the same AI simulation technology shows that representational practices shape how much certainty and authority users attribute to model outputs [27]. Experimental evidence likewise indicates that generative-AI assistance does not affect all users identically [28]. Common tools can therefore enter different interpretive environments and produce different consequences. What matters for the present theory is not merely whether human involvement remains, but whether that involvement introduces genuinely independent information, alternative causal accounts, or competing evaluative criteria.

Heterogeneity can also be restored dynamically. Evidence from AI-scaling processes indicates that data pipelines, algorithm development, business-model design, and organizational capabilities can co-evolve through repeated feedback [29]. Firms that initially rely on similar foundation-model capabilities may therefore diverge as local experimentation changes what they know, what data they collect, which tasks they delegate, and which expertise they retain. In systems terms, these are balancing and adaptive loops: they do not eliminate the common substrate, but they can reduce the correlation transmitted from that substrate into later strategic choices.

Strategic Convergence Framework

The resulting framework treats strategic convergence as a population-level trajectory generated by interaction between reinforcing and balancing feedback. Reinforcing pressure is strongest when competing firms depend heavily on similar model-mediated representations, use comparable analytical routines, and interpret early favorable outcomes as evidence that continued reliance is warranted. Balancing pressure grows when firms inject proprietary information, preserve independent expertise, redesign human–AI decision structures, or learn differently from local outcomes. Evidence from three field experiments with software developers reinforces the broader point that common generative-AI technologies can produce heterogeneous productivity effects across firms and user groups [30]. Shared technology therefore does not determine a single organizational response function.

A second feedback operates through capability adaptation. Organizational responses to generative AI can alter later skill demand rather than leaving the human capability stock fixed. Evidence from publicly listed firms indicates selective reductions in demand for several organizing skills following the diffusion of generative AI, while other skill categories remained more stable [31]. For this article, the important implication is endogenous: if reliance on common analytical systems gradually reduces independent interpretive or integrative capabilities, balancing feedback may weaken over time. If firms instead preserve or deepen differentiated expertise, the same diffusion process may strengthen re-differentiation.

The framework therefore predicts trajectories rather than a universal equilibrium. Similar levels of AI use may correspond to different system states depending on the strength of common analytical coupling, the independence of firm-specific filters, feedback delays, and capability adaptation. **Table 2** distinguishes the principal configurations that follow from this logic.

Table 2. Feedback configurations that produce distinct strategic-convergence trajectories

System configuration	Shared-model analytical coupling	Firm-specific balancing capacity	Feedback timing	Expected strategic trajectory	Observation that would challenge the configuration
Coupled convergence	Strong and recurrent across	Weak or declining	Similar and relatively delayed	Strategic framings and candidate sets become	Persistent divergence despite

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	framing, generation, and evaluation			progressively more alike	comparable delegation and weak local differentiation
Bounded analytical alignment	Strong in early analysis but weaker in final evaluation or implementation	Moderate and concentrated in later decision stages	Mixed	Firms share problem representations but retain different final strategies	Final choices converge as strongly as early analytical outputs
Delayed lock-in	Initially moderate but reinforced by apparently successful repeated use	Weakens as independent expertise or routines atrophy	Long enough to obscure broader competitive consequences	Early gains are followed by persistent strategic crowding	Rapid corrective learning restores heterogeneity before reliance deepens
Adaptive re-differentiation	Initially strong	Strengthens through local learning, proprietary data, alternative models, or retained expertise	Differentiated local feedback becomes salient	Temporary convergence is followed by renewed strategic separation	Local learning increases while analytical outputs remain persistently homogeneous
Bifurcated competition	Similar initial infrastructure but unequal organizational capacity to reinterpret or challenge it	Strong in some firms and weak in others	Uneven	One subset clusters around common strategies while another develops differentiated trajectories	Firms with materially different balancing capacities remain equally convergent

Propositions

The framework generates discriminating propositions only if convergence is treated as conditional on system structure. First, shared-model overlap should matter most when delegation is sufficiently deep to carry model-mediated representations across several stages of strategic analysis and when independent organizational filters are weak. Evidence that large language models can display substantial individual and collective creativity under some elicitation conditions cautions against treating model commonality as equivalent to low diversity [32]. Accordingly:

Proposition 1. Greater overlap in foundation-model analytical inputs will be associated with stronger cross-firm convergence in strategic framing and candidate alternatives when recurrent analytical delegation is high and firm-specific interpretive, informational, and model-diversification mechanisms are weak.

Second, convergence should vary by decision stage. Evidence reviewed earlier indicates that human judgment, aggregation, and organizational configuration can modify model-supported evaluation even when AI contributes strongly to generation. Therefore:

Proposition 2. Cross-firm convergence will be stronger in problem framing and candidate generation than in final strategic selection when organizations retain independent evaluative authority, differentiated local information, and meaningful capacity to reject or recompose model-generated alternatives.

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Third, feedback timing should determine whether early similarity stabilizes or reverses. Delayed market consequences can prolong reliance on strategies that appear locally successful, whereas differentiated local learning can strengthen balancing loops.

Proposition 3. Feedback delay will strengthen persistence of model-associated strategic convergence when firms receive similar short-horizon signals, but the effect will weaken or reverse as heterogeneous local feedback, proprietary learning, and capability adaptation become sufficiently influential.

These propositions separate the article's explanation from simpler claims that similar technologies automatically create similar strategies. **Figure 2** maps the boundary conditions that distinguish convergence from persistent heterogeneity, temporary alignment, and later re-differentiation.

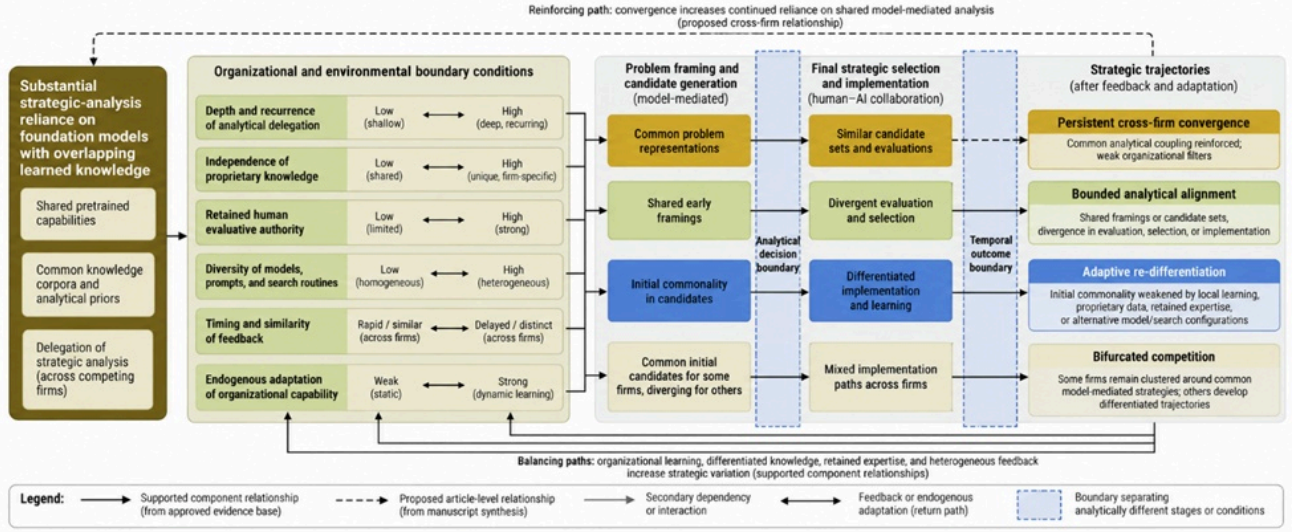

Figure 2. Similar shared-model dependence produces different strategic trajectories when organizational differentiation and feedback conditions cross distinct boundaries

Competitive Implications

If shared foundation models compress variation in generic strategic analysis, competitive advantage is likely to migrate toward complements that remain difficult to standardize. Firm-specific data, experiential knowledge, situated interpretation, experimentation, implementation speed, and organizational capacity to challenge model outputs become more valuable when competitors can access similar generic analytical capabilities [9]. Strategic heterogeneity may therefore persist even as one layer of analysis becomes commoditized, because differentiation shifts toward the processes through which common analytical capability is contextualized and acted upon [10].

The systems perspective also cautions against evaluating AI-supported strategy solely through focal-firm productivity. Individually beneficial adoption can coexist with greater strategic crowding when many firms respond to related representations and signals. In such conditions, the competitive value of an apparently strong recommendation can decline as similar firms pursue it. The practical implication is not that organizations should avoid foundation models, but that they should preserve independent sources of strategic variation and monitor whether repeated AI-supported analysis is narrowing the range of problems and options considered.

Long-run effects will depend on endogenous adaptation. Organizations may preserve differentiated expertise and diversify their analytical routines, or they may gradually reorganize around the shared infrastructure and become more dependent on it. Because those responses feed back into later strategic analysis, competitive convergence should be

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studied as a trajectory rather than a fixed state. The relevant managerial question is consequently not whether a foundation model is shared, but whether the surrounding organizational system continues to generate independent information, interpretation, experimentation, and challenge.

Conclusion

Competing firms can delegate strategic analysis to foundation models trained on overlapping knowledge without becoming strategically identical. Shared models create a potential convergence pressure because they can introduce correlated representations, problem frames, candidate alternatives, and evaluative tendencies into multiple organizations. Whether that pressure becomes persistent strategic convergence depends on the system around the models.

The strongest conclusion is conditional. Convergence becomes more plausible when recurrent delegation is deep, organizational filters are weak, feedback is delayed or similar across firms, and continued reliance erodes independent analytical capability. It weakens when firms retain differentiated knowledge, human evaluative authority, alternative search routines, proprietary learning, and the capacity to adapt their use of AI in response to local outcomes. Strategic convergence is therefore not a direct consequence of foundation-model adoption. It is an emergent competitive trajectory produced when reinforcing commonality outweighs balancing heterogeneity across repeated cycles of analysis, action, feedback, and organizational adaptation.

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