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Artificial intelligence in adaptive strategy creation and implementation: Toward enhanced attentional control in strategy processes

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ABSTRACT

This article focuses on the deployment of proprietary artificial intelligence (AI) systems in strategy creation and implementation processes, with a specific focus on their role in enhancing organizational attentional control. By employing the attention-based view (ABV) as an overarching theoretical framework, we examine how company-specific AI systems trained on proprietary data can support strategy processes. We identify three key contributions of AI in strategy creation and implementation processes: (1) broadening organizational attention to external and internal developments, (2) democratizing strategic processes through improved transparency and inclusivity, and (3) accelerating feedback loops with real-time monitoring of strategy implementation progress. Potential challenges associated with the deployment of AI systems for attentional control are also addressed. The paper concludes by putting forward potential directions for future research.

1. Introduction

The deployment and use of company-specific artificial intelligence (AI) systems to support strategy creation and implementation processes represents a novel and largely unexplored area in the field of strategic management. Many organizations have proprietary knowledge of their own capabilities and business environment that is not effectively understood and widely shared within the organization (e.g., Lifshitz-Assaf, 2018). Training proprietary data to a custom, company-specific AI system can enhance the intelligence and adaptability of an organization's strategy creation, sharing, and implementation processes. Such custom-trained AI models can be deployed to support strategic analysis, strategy development, and strategy implementation processes, offering insights and recommendations that are highly contextualized and aligned with the company's specific needs and goals (von Krogh et al., 2021).

We define an internal company-specific AI system as *a tailored artificial intelligence infrastructure, trained on both proprietary and publicly available data, that leverages Machine Learning (ML) or Generative AI technologies to meet the unique needs and goals of a particular organization*. The use of such systems to support strategy creation and implementation presents a multitude of unanswered questions that would warrant further theory-building and research. These questions include, for example, the choice of optimal data for training

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the system, how to mitigate potential biases and noise associated with available internal data, how to integrate AI systems into existing organizational structures, processes, and decision-making, and what kinds of organizational changes would be required to take full advantage of such systems. Given the novelty of this topic area, we will outline in this paper some of the main areas in which we see some of the most important research opportunities.

We draw on the attention-based view (ABV) as an overarching theoretical framework to investigate how the integration of proprietary AI models influences the attentional processes and the structural distribution of attention in organizations (Ocasio, 1997, 2011; Ocasio et al., 2018). The attention-based view posits that organizational behavior and decision-making are shaped by the allocation of attention, which is a scarce resource subject to structural and cognitive limitations (Ocasio, 1997, 2011; Ocasio and Joseph, 2018; Ocasio et al., 2018). By leveraging company-specific AI systems that incorporate their own proprietary data, organizations can (1) improve their attentional capacity by allowing them to process and synthesize real-time vast amounts of data from diverse sources, both internal and external to the firm, (2) leverage the collective intelligence of the organization more effectively by enabling organizational members more open access to strategy development through an internal AI system that allows them to probe the organization's strategy from their own perspective, and (3) enhance the speed at which they are able to attend to emerging internal and external developments and to make sense to them. Building on the ABV, we will next discuss these three different areas in more depth and put forward an agenda for future research on the use of AI in strategy creation and implementation processes.

Theoretical foundation

The attention-based view (ABV) of the firm has become an increasingly important lens in the study of the adaptation of organizations to changes occurring in their environments (e.g., Eklund, Raj, & Eggers, Forthcoming; Love, 2023; Ocasio et al., 2023) and the dynamics of feedback in adaptive strategy implementation (Weiser et al., 2020). This has necessitated the development of a more dynamic view of organizational attention that would extend beyond the more static formal communication channels of traditional Chandlerian M-form organizations (Joseph et al., 2024; Ocasio et al., 2023). Calls have been made to better account for the organic nature of attention, going beyond the more rigid top management-centric "pipes and prisms" conception of attention channels of the original ABV (Laamanen, 2019; Love, 2023; Ocasio et al., 2023; Plotnikova et al., 2023).

One of the novel areas of research in the ABV is the theory of attentional control (e.g., Love, 2023) that William Ocasio coined as an extension and elaboration of the ABV (Ocasio, 2025) as he received the AOM OMT Division's Distinguished Scholar Award in 2023. According to Ocasio, all human behavior is influenced by a combination of embodied and automated attention and attentional control. While attentional control at the individual level refers to the cognitive ability of individuals to focus and direct attention to specific information while filtering other stimuli, at the organizational level, it shapes which set of stimuli the organization is more likely to attend to and which action alternatives are more likely to be considered and adopted (Ocasio, 2025).

Attentional control is shaped by the structural distribution of attention at the organizational level, attentional perspective(s) of embedded agents at the individual level, and communication practices and artificial intelligence (AI) at the algorithmic level. It occurs through situated, both formal and informal, and verbal and non-verbal communication channels (Ocasio and Wohlgezogen, 2010). While there is prior research on how formal communication channels and structural distribution of attention can be used for attentional control (Gaba and Joseph, 2013; Joseph and Ocasio, 2012; Joseph and Wilson, 2018), the rapid changes in today's business environment have made formal communication channels insufficient for managing the need for continuously shifting attention patterns (Ocasio et al., 2018, 2023). To address this challenge, Love (2023) put forward the concept of "emergent attentional control systems" through which organizations are able to shape the direction of organizational attention more dynamically. According to Love, the emergent attentional control systems have three key defining characteristics: (1) emergent issue-specific communication channels, (2) dynamic reconfiguration of roles that loosen the coupling between roles and formal positions, and (3) interactive control practices that enable sustained joint attentional engagement and faster attention cycles. We elaborate in this paper on how proprietary company-specific AI systems could be used as algorithmic means to augment attentional control systems' interactive control practices for joint attentional engagement and faster attention cycles.

Attentional control in today's dynamic organizations is neither deterministic nor one-directional, top-down control of organizational attention, such as in traditional Chandlerian M-form hierarchies (e.g., Joseph and Ocasio, 2012; Ocasio and Joseph, 2008; Ocasio et al., 2023; Ocasio and Joseph, 2006). Faster feedback and continuous shifts in attention are needed in dynamic environments in which the prediction of even a moderately distant future is subject to continuous reassessment (Brown and Eisenhardt, 1997; Eisenhardt et al., 2010). Attentional control in fast-moving environments requires balancing between the stability and coherence of attention (Rerup, 2009) to maintain sufficient stability for moving into a desired direction while also preserving the ability to continuously reassess the direction and take corrective measures as needed to ensure the adaptability of strategy implementation (Love, 2023; Weiser et al., 2020; Weiser and Laamanen, 2022).

Such interactive control can be best accomplished through a continuous, open internal organizational dialogue (e.g., Simons, 1994), outcome controls that fit faster attention cycles ("rapid-tempo attention cycles"; Love, 2023), and deliberate management of the evolution of attention control practices. Open internal dialogue and communication that cross internal organizational boundaries are central here, as they bring different perspectives into the discussion, making communication channels important arenas for interactive attentional control (Love, 2023; Ocasio et al., 2018). This resonates well with recent strategy process and practice research on open strategy and how opening up the strategy process to broader participation and internal dialogue can benefit strategy creation and implementation (Burgelman et al., 2018; Hautz et al., 2017; Ocasio et al., 2023; Whittington et al., 2011).

We advance the existing research on the dynamic ABV by arguing that the use of AI *can* support *management in improving their attentional capacity and the breadth of attention,* and thereby also their attentional control, by allowing them to process and synthesize

real-time larger amounts of data from diverse sources, both internal and external to the firm and by enabling them to identify and better focus on decision-relevant information. Algorithmic support for attention control (Ocasio, 2025) enables management to interactively attend to a broader range of issues than they would have been with their own information-processing limitations and cognitive biases (Forbes and Milliken, 1999; Gregoire et al., 2010; Hambrick and Mason, 1984; Narayan et al., 2021; Ridge et al., 2017). Despite the larger volume of information processed in real-time, AI can reduce cognitive overload (Eklund and Mannor, 2021) by assisting in synthesizing the information and identifying the more relevant signals for management.

Second, we argue that a company-internal proprietary *AI system has the potential to enable organizations to democratize the strategy process* by opening it up to a larger group of organizational members (e.g., Splitter et al., 2023). While AI can be used interactively to more effectively synthesize and respond to the input provided by the organization for the strategy process to focus the attention of the organization, it can also be used to enhance attentional control by shaping the collective understanding of employees of the strategy of an organization by providing them an access to AI systems outputs, such as a proprietary company-internal Chatbot trained with internal proprietary strategy information that can answer any question relating to strategy.

Third, by implementing pattern recognition with the help of machine learning algorithms, *AI can also be used to speed up the feedback loop from strategy implementation* by tracking the progress of strategy implementation in real-time based on the data exhaust from activities, projects, and programs around the organization. This tracking can be used to develop outcome controls that fit faster attention cycles ("rapid-tempo attention cycles"; Love, 2023), central in interactive attention control systems. Overall, while the first lever above helps enhance the comprehensiveness and accuracy of attention focus, the second lever helps in refining and distributing it to the organization as a novel way of achieving structural distribution of attention, and the third lever helps in creating a real-time feedback loop to monitor and adapt the attention focus of the organization.

2. Comprehensive processing and synthesis of strategy-relevant information

Due to its origin in the behavioral theory of the firm (BTOF) (Cohen et al., 1972; Cyert & March 1963; March and Simon, 1958), the attention-based view (ABV) builds on the assumption that organizational decision-makers are boundedly rational (Simon, 1957). Accordingly, the strategic issues that managers and other organizational members notice and attend to are limited by different cognitive, behavioral, and situational biases. While the issues that individuals choose to focus their attention on may be the most optimal ones, the focus of attention may also be biased, for example, due to the backgrounds of different individuals ("embedded agents") and the organizations they are part of (Vuori et al., 2024).

Prior research on strategic issue management has found that strategic issue framing (e.g., threat, opportunity, feasibility, urgency) (e.g., Dutton and Duncan, 1987; Jackson and Dutton, 1988; Julian and Ofori-Dankwa, 2008) and cognitive load (Laamanen et al., 2018) of decision-makers can lead an organization to overemphasize some issues over others. Such unbalanced emphasis may influence the organization's direction and impact how and when it adapts in response to emerging strategic challenges. Recent research adopting the attention lens has become increasingly interested in how organizations can update their strategies when the environment changes, and what the potential behavioral biases involved in assessing the environment are (e.g., Eklund et al., Forthcoming; Joseph and Wilson, 2018; Schulze and Brusoni, 2022).

Given the increasing information processing capacity enabled by AI, it is necessary to reassess the concept of bounded rationality in the context of strategic issue management and how the limits of bounded rationality are changing (Weiser and von Krogh, 2023). AI can enhance the breadth of attention by producing a more comprehensive analysis of the business environment. AI can also enhance management's ability to determine probabilities of different future outcomes based on its own prediction models. When such probabilities cannot be assigned, AI systems can help develop scenarios and simulate outcomes to provide a better understanding of what the different outcomes could look like (Feuerriegel et al., 2025). Hence, while AI cannot fully eliminate bounded rationality in decision-making under uncertainty (von Krogh, 2018), it can partially relax some of the cognitive and behavioral limitations associated with bounded rationality.

Being able to anticipate, recognize, and react to weak signals and the changes in an organization's peripheral (non-core) environment is an important part of every organization's ongoing strategy work (Aguilar, 1967; Day and Schoemaker, 2006; Eklund et al., Forthcoming; Foster and Kaplan, 2001; Porter, 1980). Organizations need an understanding of how their customers' preferences are evolving, what actions competitors are engaging in, and what opportunities new technologies offer (e.g., Bower and Christensen, 1995; Christensen and Overdorf, 2000). AI can contribute to trend analysis and pattern recognition (Bansal et al., 2018; D'Amico, Delteil, Hazan, Tricoli, & Montard, 2025) by providing the attentional infrastructure that helps broaden the management's attention (Nicolini and Korica, 2021). A recent McKinsey article on the use of AI to support strategy development highlighted the use of AI systems to develop "growth scans" that synthesize data from diverse sources—such as annual reports, patents, customer reviews, and purchasing behavior—to identify frequently pursued strategic adjacencies and assess their alignment with a company's own growth priorities (D'Amico et al., 2025).

While AI-enabled processing and synthesis of strategy-relevant information can enhance attentional breadth through the comprehensiveness of strategy-relevant information processing, it is not void of potential biases. As Kellogg et al. (2020) note in their review article on algorithmic control, AI systems often inherit and can even amplify biases in training data. This can be a particular challenge for an AI system trained by the company's internal proprietary data, which can entail biases that are difficult for even managers themselves to recognize. This was the case with Amazon's hiring algorithm, which reinforced past practices rather than surfacing novel talent. Given the opacity of AI systems, detecting biases may be difficult internally (Lebovitz et al., 2022; Prikshat et al., 2023). There is also a risk that when modelers work with different parameters and set the analytical boundaries, they implicitly direct attention toward historical patterns rather than emergent possibilities. Systems developed in this way may engender strategies that

focus on "what is" rather than "what could be." Finally, without explicit integration of "soft factors" such as company culture and values into the analytic framework, AI simply captures statistical correlations, failing to align strategy with organizational purpose (Kolbjørnsrud, 2024). Hence, humans also continue to play an essential role in curating, interrogating, and contextualizing the AI system outputs.

Given that organizations cannot afford to ignore the potential of AI systems to enhance their attentional capacity and attentional breadth, it is essential to embed into the process continuous, interactive learning loops where humans assess the AI outputs, challenge unexpected findings, and feed corrections back into the system to surface and correct algorithmic biases (Raisch and Fomina, 2025). Alongside the need for human-AI augmentation (Gronsund and Aanestad, 2020; Raisch and Krakowski, 2021), the AI systems used for processing and synthesizing strategy-relevant information should be designed with transparency in mind, with AI algorithms not only providing answers, but also explicating and justifying their reasoning (Kolbjørnsrud, 2024). Moreover, the proprietary information should be used to deepen the publicly available information, not to limit the external search scope.

3. Democratizing of strategy creation and implementation processes

Building on the idea of "open innovation" (e.g., Chesbrough, 2003), there has been a growing interest in the concept of "open strategy" (Burgelman et al., 2018, 2021; Splitter et al., 2023; Splitter et al., 2019). The pioneering work of Whittington and colleagues (Whittington et al., 2011), Special Issues in Long Range Planning (Hautz et al., 2017) and Organization Studies (Splitter et al., 2023), and recent books (e.g., Stadler, Hautz, Matzler, & von den Eichen, 2021; Whittington, 2019) have stimulated a rich stream of research on open strategy practices (Belmondo and Sargis-Roussel, 2023; Cai and Canales, 2022; Dobusch & Kapeller, 2017, 2018; Gegenhuber and Dobusch, 2017; Holstein and Rantakari, 2023; Langenmayr et al., 2024; Lundgren-Henriksson and Sorsa, 2023; Stjerne et al., 2022).

Hautz et al. (2017) define open strategy as "*a dynamic bundle of practices that affords internal and external actors greater strategic transparency and/or inclusion, the balance and extent of which respond to evolving contingencies derived from both within and without organizational boundaries*" (Hautz et al., 2017: 298). While openness in the strategy process can generally be associated with favorable outcomes both in terms of strategy quality and employee motivation and commitment, in line with prior research on the benefits of strategy process participation (e.g., Collier et al., 2004; Floyd and Wooldridge, 1992; Wooldridge and Floyd, 1990), Hautz and colleagues also highlight potential tensions and dilemmas associated with openness. These relate, for example, to the potential need to compromise on speed, flexibility, and control over the strategy process, and the risk of undermining commitment due to unmet expectations about the impact of contributions provided by organizational members. For example, when a new CEO asks employees to submit their ideas on how to improve the organization, they may receive thousands of emails with diverse suggestions, making it impossible to implement all the ideas and challenging to respond to each one individually. Processing these inputs with an AI system helps top management to focus on the most important themes emerging from the organization. While such sensitive information cannot be uploaded to publicly available AI systems due to the sensitive nature of the information, secure company-specific AI systems, secure APIs, and retrieval augmented generation (RAG) make it possible to input this data into a secure AI Chatbot to organize the data and to make sense of the patterns emerging from the extensive input provided by the employees. To recognize the contributions of the employees and to further enhance attentional engagement, AI systems can also be used to provide personalized responses to the employees detailing how their input was accounted for in the strategy development process and the resulting strategy.

In addition, a company's internal AI Chatbot trained on proprietary strategy materials covering corporate strategy and strategies of the different divisions, business units, and country organizations, as well as the external market intelligence, can be used for enhancing strategy communication. Interacting with the company's strategy materials through the Chatbot interface can be used as a personalized means for structural distribution of attention. It can contribute to the coherence of organizational attention by aiding managers at all levels to better understand the strategy of the organization and how their own strategies and strategic goals are related to it and to the strategies of other organizational entities. Being equipped with a deeper collective understanding of the company's strategy, market situation, and strategies of the different divisions and business units also contributes to attentional vigilance as it enables the different organizational members to develop more advanced strategies for their own units and to better fit their own units' strategies to the strategy of the company as a whole.

By enabling organizational members more broadly to "interact with the strategy of the organization," a company's internal AI strategy chatbot helps foster an interactive dialogue on strategy inside the organization. It enhances attentional engagement in the organization, providing a foundation for an interactive attention control system in which organizational attention can be shaped dynamically in real time. By helping management to overcome some of the dilemmas associated with the open strategy practices (Hautz et al., 2017; Lingo, 2023), an AI strategy chatbot can enhance both the quality of resulting strategies and the commitment of the organizational members to adaptively implement them.

Relatedly, major consulting firms have conducted experiments with AI-driven knowledge-retrieval systems that index and analyze their entire repositories of strategic engagements. For example, BCG's GENE employs advanced natural-language processing and case-based reasoning algorithms to parse proprietary research reports and confidential interview data to identify analogous business scenarios and emergent frameworks. McKinsey's Lilli leverages a century's worth of client deliverables and external literature to generate context-rich strategic recommendations, optimizing relevance through iterative feedback loops. Preliminary experiences suggest that these systems reduce time-to-insight and increase the diversity of strategic solution alternatives, thereby reinforcing organizational memory and cultivating an adaptive learning culture that dynamically refines the firm's collective strategic competence.

While prior research has shown that AI systems can discriminate among users based on their capacity and willingness to engage

with opaque outputs, privileging those with advanced interrogation skills or a predisposition to trust algorithmic authority (Lebovitz et al., 2022; Vanneste & Puranam, Forthcoming), an AI Chatbot can democratize access to complex strategic content and enhance attentional engagement by translating corporate vision, market analyses, and divisional goals into natural language dialogue without requiring deep technical expertise or sophisticated AI-interrogation routines. One potential downside of opening up strategy this way is that top management cedes granular control over how strategic messages are personalized in each dialogue. An AI strategy chatbot can introduce subtle misalignments or distortions, potentially also weakening attentional coherence and collective sensemaking of the strategy within the organization, and thereby creating the need for management to keep a close eye on the evolving dialogues to prevent potential strategic drift.

4. Faster reaction time to external and internal strategic issues

In addition to enhancing the breadth of organizational attention to external developments and the quality of the interactive internal dialogue on strategy inside the company, a company's internal AI system may also help reduce management's reaction time to different external and internal issues. Strategy researchers have, in recent years become increasingly interested in the adaptive dynamics of strategy implementation (e.g., Ahearne et al., 2014; Klingebiel and De Meyer, 2013; Weiser et al., 2020). While traditional research on strategy implementation built on the structural contingency view in examining how to create strategy implementation plans and put in place appropriate leadership, structures, and controls (e.g., Galbraith and Nathanson, 1978; Hrebiniak and Joyce, 1984; Nutt, 1986, 1989, 1998), the more recent research has focused on how organizations respond to different strategy implementation actions by the senior management and why strategy implementation often fails (e.g., Alcadipani et al., 2018; Beer and Eisenstat, 2000; Jarzabkowski et al., 2019; Lee and Puranam, 2016; Martin, 2010; Spee and Jarzabkowski, 2017).

However, these two streams of research still exist independently (Weiser et al., 2020). The feedback loop from strategy implementation challenges back to strategy creation has received only limited attention in the strategy implementation literature (e.g., Joseph et al., 2016; Klingebiel and De Meyer, 2013; Weiser et al., 2020) A recent review of the four decades of strategy implementation research by Weiser et al. (2020) called for more research on the dynamics of feedback from challenges in strategy implementation to the adaptation of strategies and strategy implementation plans. Although performance measurement and management systems, such as the Balanced Scorecard (Kaplan and Norton, 1992, 2004, 2008) and Objectives-and-Key-Results (OKR) (Doerr, 2018) can provide feedback on strategy implementation, this feedback is not real-time and is limited by the pre-specified outcome measures identified by management ex-ante, instead of capturing the unexpected challenges.

The use of AI systems may help overcome some of these challenges, enabling management to get faster feedback on how strategy implementation is progressing in the organization. Specifically, machine learning (ML) can be used to track the patterns of actions by employees in real-time through multimodal data (Luo et al., 2024; Shrestha et al., 2021). It can be used to compile and analyze data on calendar invites, discussions in the intranet discussion groups, the content of the documents created by employees in the corporate cloud, offers sent out to potential clients, meeting minutes, and even transcripts of Teams and Zoom meetings (e.g., using Microsoft's Copilot). Processing the large volume of data that employees in an organization produce (e.g., Leonardi, 2021) makes it possible to get first-hand feedback on strategy implementation progress in real-time, enabling senior management to see whether the organization is moving in the direction outlined in its strategy or whether it is drifting in another direction or not moving at all. For example, Futurice, a digital software and engineering company, used machine learning algorithms to automate the extraction of topics from unstructured textual data based on Flowdock and Slack discussions and found that what the organization was talking about was quite different than what the top management had intended it to focus on (Harju et al., 2020). Receiving such feedback allows senior management to understand the present focus of organizational attention and where it is heading. It ensures senior management's sustained attention to strategy implementation progress, potential deviations from intended strategies, and timely judgments on potential needs for strategy adaptation.

Despite these benefits, real-time AI-based feedback systems can also inadvertently lead to increasing centralization and fuel micromanagement, as every calendar invite, document edit, and chat message can be tracked. When faced with such algorithmic control, employees can experience stress (Cram et al., 2022) and engage in "algoactivism" to resist algorithmic control (Kellogg et al., 2020). For example, Vuori et al. (Forthcoming) found that employees engaged in gaming the AI system by "detailing", "withdrawing", or even "manipulating" their digital footprints to influence how the system sees them. Moreover, given that not all employees generate equal "digital exhaust", the AI system's real-time picture can be both patchy and entail systematic biases. These dynamics can erode the quality of the information received and undermine the engagement that adaptive strategies depend on. To counteract these risks, management should communicate clearly the principles that define what data points are acceptable and ethical for training the algorithms, and for what purpose the system can and cannot be used (Vuori et al., Forthcoming). They should build trust in top management's use of the data, clarify privacy policies, and provide an opt-out mechanism to ensure that real-time AI monitoring remains a tool for collective learning and creative adaptation rather than a source of surveillance and strategic rigidity. The more agentic and autonomous an AI system appears, the more they are also likely to trigger scepticism and be seen as threatening among employees when they are perceived to act according to a specific agenda (Vanneste & Puranam, Forthcoming).

In the existing research on the attention-based view, attention is generally regarded as something that is good for those who are attended to. Extensive research on the attention-based view has examined the subsidiaries of multinational companies and found that attention from the corporate headquarters is generally positively related to resources received by the subsidiary and the support that the different subsidiary initiatives get (e.g., Ambos and Birkinshaw, 2010; Belenzon et al., 2019; Laamanen, 2019). Yet, too much attention, specifically when associated with deliberate attention control, could also have negative consequences. While attention can cause the kinds of counterreactions – resistance, manipulation, and loss of motivation – as described above, it can also cause deeper

changes in the adaptive capacity and innovativeness of the organization. It can lead to the loss of "foolishness" that has been argued to be beneficial for organizational adaptive intelligence (March, 2006), suffocating autonomous strategic behavior that enables individual organization members to recognize and explore new opportunities outside the direct oversight of senior management. Burgelman's (1983, 1991, 1994, 2002) research on organizational evolution builds on the assumption that organizations have two types of strategy-making processes: induced and autonomous. Induced strategic behavior is closely aligned with the implementation of the existing strategy. In contrast, autonomous strategic behavior is related to the recognition of new opportunities by individual organization members who are kept "under the radar" of the senior management by middle managers who "hide and protect" the early ideas before they are strong enough to survive the internal ecological selection by the senior management to become part of the company's strategy (Burgelman, 1996).

5. Discussion and directions for future research

Due to the novelty of the research area, there is only limited empirical evidence on the effects of AI on competitive advantage for organizations (Barney and Reeves, 2024; Cook et al., 2024; Gaessler and Piezunka, 2023; Krakowski et al., 2023). We argue that company-internal proprietary AI systems implementation can contribute to competitive advantage when embedded into organizations' strategic creation and implementation processes so that they provide better attention control for managers, through enhanced comprehensiveness of attention, democratization of the strategy creation, and implementation processes, as well as the ability to attend faster to different emerging internal and external developments.

This reasoning aligns with Kemp's (2024) conceptual work, which posits that an organization's competitive advantage from AI systems depends on how effectively the AI is embedded into its experiential, relational, and strategic frameworks through the processes of grounding, bounding, and recasting. Grounding involves selecting and curating the data used to train the AI, which is central when augmenting a company's strategy processes with an internal AI system. Bounding refers to a firm's ability to prevent competitors from accessing its data sources, thereby maintaining a unique competitive edge. Recasting refers to "the adaptation of internal technologies and routines to contextualize AI in a firm's system of task, relational, and strategic interdependencies." (Kemp, 2024: 18). When an AI system trained with company-internal proprietary data is used to support strategy creation and implementation processes, these three theoretical mechanisms may help explain how such AI systems can contribute to enhancing and sustaining a firm's competitive advantage.

Based on the benefits that companies are already now reaping with the most widely used publicly available conversational AI systems, it is not difficult to see how these benefits can be further enhanced in an organization's strategy process when the systems are trained with company-internal proprietary data. We identified three areas in which companies can benefit from AI systems deployment to support strategy creation and implementation (Table 1). While the benefits of comprehensiveness and speed could have been achieved with the more traditional machine learning algorithms programmed for big data analysis, pattern recognition and prediction, the introduction of Chatbots using generative AI provides a user-friendly interface for a broader group of organizational members to participate in strategy creation and implementation processes.

Accordingly, the implementation of AI systems can contribute to the comprehensiveness of external environment monitoring and thereby enhance external attention breadth (Eklund and Mannor, 2021; Zhong et al., 2021), combined with an enhanced ability to synthesize and identify the most important information. Democratization of strategy creation and implementation processes contributes to improved attentional coherence and engagement (e.g., Joseph et al., 2024; Laureiro-Martinez et al., 2023; Ocasio, 2011) and attentional vigilance on the part of the organization. Real-time follow-up and feedback from strategy implementation contributes to the sustaining of attention (Nicolini and Mengis, 2024; Ocasio et al., 2023).

Fig. 1 illustrates how AI systems reshape both the creation and implementation of strategy by enhancing different dimensions of organizational attention and by linking these dimensions in a dynamic feedback loop.

When firms deploy AI models that build on both publicly available and internal proprietary data they gain a more comprehensive, high-resolution view of the external environment. Traditional environmental scans rely on periodic reports, manual curation of third-

Table 1
Expected benefits of company-specific AI algorithms trained with proprietary company-internal data.

Potential benefits	*Strategy creation*	*Strategy implementation*
More comprehensive and efficient processing of strategy-relevant data	Ability to process larger amounts of data on customers, competitors, and partners to create more detailed strategies for each customer and to counter the potential actions of competitors	Ability to process and identify patterns in the large amounts of everyday strategy-relevant data produced by the organization
Democratization of strategy processes, "open strategy"	Easier accessibility of strategy-relevant external and internal information across the organization helps to assess strategic positioning alternatives and the corresponding internal capabilities	Enhanced understanding of the top-level strategy and its underlying key assumptions as well as the strategies of the other organizational units in the organization
Faster reaction time to external or internal strategic issues	Continuous, real-time follow-up of competitors, customers, collaboration partners, and other developments in the external business environment, enabling faster reaction time	Continuous, real-time follow-up of the progress of strategy implementation enables a faster feedback loop inside the organization to react to different emerging developments and deviations in strategy implementation

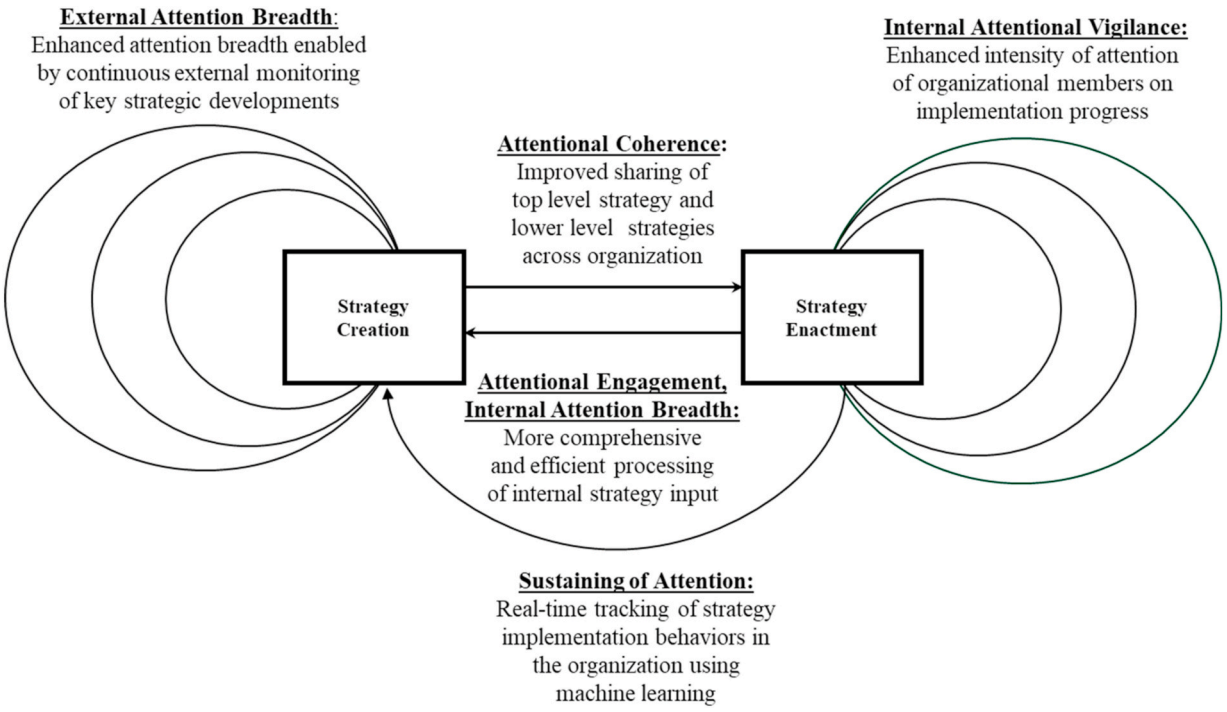


Fig. 1. The role of AI in Enhancing Organizational Attention in Adaptive Strategy.

party data, or expert judgment, which can miss subtle but strategically critical signals. In contrast, a well-trained AI can continuously monitor a richer set of data streams, synthesize them in real time, and surface the most salient trends or anomalies. This "enhanced external attention breadth" means that decision-makers do not have to rely solely on snapshots of market intelligence or their own intuitive judgment. Instead, the breadth of their attention is expanded with the help of a rolling, algorithmically curated feed of signals, which enables them to better understand strategic developments that would previously have been more difficult for them to recognize.

By making analytical tools and insights accessible to a wider range of organizational actors, AI systems can enhance attentional engagement and coherence across the organization. AI systems trained with internal strategy materials can be incorporated workflows of middle managers, project teams, and even frontline employees. When more people have access to the same AI-generated hypotheses, projections, or clustering of market segments, the organization's collective attention becomes more coherent: individuals across levels can quickly align on which external signals matter most and why. Democratized access can reduce "attention fragmentation" that often occurs when insights are siloed within specialized teams. Finally, during implementation, AI systems can provide real-time monitoring of both operational metrics and emergent behaviors. They can detect deviations from expected performance, unexpected external shocks, or shifts in customer sentiment, and then communicate those insights back to senior management and local teams. This "sustaining of attention" ensures that management has the ability to continuously adapt strategy implementation when needed.

Through these three enhancements—broadened external attention, democratized internal attention coherence, and continuous attention-sustaining feedback—AI systems can fundamentally change how strategy is both created and enacted. In traditional strategy implementation models (Weiser et al., 2020), the arrow from "Strategy Creation" to "Strategy Enactment" is often viewed as a one-way

Table 2
Potential pitfalls of company-specific AI algorithms trained with proprietary company-internal data.

Potential Pitfalls	*Strategy creation*	*Strategy implementation*
Algorithmic Bias	Proprietary data biases can reinforce historical path dependencies, obscuring novel opportunities. Opaqueness makes it hard to detect blind spots.	Uneven "digital exhaust" across different employees can yield patchy, skewed real-time monitoring results.
Strategic Coherence	Internal strategy chatbot can introduce subtle misalignments or distortions, potentially weakening attentional coherence and collective sensemaking of strategy within the organization	Real-time monitoring can reduce the occurrence of autonomous strategic behavior when being watched over by the senior management enhancing internal coherence at the expense of external attentional engagement.
Adverse Reactions	Extreme reactions to the AI system's outputs can range from blind trust to complete rejection, leading to sub-optimal outcomes for attentional engagement and coherence.	"Algoactivism" and "manipulation" of the digital exhaust undermine data quality. Surveillance concerns may erode trust and collective organizational learning.

flow, feeding back only at discrete intervals. In Fig. 1, we redraw this relationship as a bidirectional loop. Enhanced external attention breadth informs more nuanced, data-driven strategy creation; greater attentional coherence among diverse actors ensures smoother handoffs from planning to execution; and real-time feedback sustains the organization's focus, allowing insights from implementation to engage in continuous strategic creation. Thereby, Fig. 1 captures the cascading influence of AI on organizational attention and illustrates how these dynamics drive a more adaptive strategy process in which creation and implementation continuously reinforce one another.

Despite the benefits, there are also potential challenges that need careful attention, as shown in Table 2. First, algorithmic bias can influence both strategy creation and enactment—models trained on proprietary internal data can incorporate historical path dependencies, causing decision makers to overweight past patterns rather than exploring more disruptive strategic options. During implementation, uneven "digital exhaust" produced by different employees can bias monitoring, causing management to misinterpret performance signals or miss localized issues entirely. Without sufficient transparency into how inputs are weighted or which features drive predictions, managers may be unable to identify or correct skewed recommendations, leading to a false sense of confidence in flawed insights. Second, threats to strategic coherence may arise when AI-driven tools inadvertently introduce subtle misalignments. Third, adverse human reactions can undermine attentional engagement. For example, individuals could manipulate the digital exhaust that they create. Such behaviors degrade the integrity of the data, feeding both strategy creation and real-time monitoring, ultimately weakening the system to provide high-quality data for strategy creation and follow-up.

These potential pitfalls highlight the need for transparent model governance, human-in-the-loop oversight, and clear communication about data use (e.g., Burrell, 2016; Kellogg et al., 2020; Shrestha et al., 2019; Vuori et al., Forthcoming) to ensure that AI system's bidirectional feedback loop enhances, rather than undermines, organizational attention and adaptability. Organizations must invest in explainable AI techniques, regularly audit model outputs for bias, and establish feedback channels so that frontline employees can flag questionable insights. By coupling algorithmic recommendations with managers' domain expertise (e.g., Lebovitz et al., 2022; Raisch and Fomina, 2025), firms can mitigate blind spots and foster trust. Additionally, implementing opt-out mechanisms can reassure employees that continuous monitoring will not be used punitively, preserving their autonomy and willingness to experiment. By proactively addressing these challenges, firms can increase the likelihood that the attentional benefits enabled by AI translate into adaptive strategic outcomes.

Directions for future research

Given the limited research on the use of AI systems trained with internal proprietary strategy materials to support strategy creation and implementation, significant further research will be needed on the topic area. The widely cited study published by Harvard Business School that tested the effect of generative AI on the productivity and quality of BCG strategy consultants is one of the few early empirical studies on the potential usefulness of AI to support strategy development (Dell'Acqua et al., 2023). While the study demonstrated well the potential of AI systems to enhance the productivity of the BCG strategy consultants with hypothetical strategy tasks, it did not allow the authors to examine the benefits that an AI system trained with proprietary strategy documents could bring.

Although there are other studies that have examined the embedding of AI into the existing organizational routines and processes in other professional contexts, for example, the study by Lebovitz et al. (2022), which explored how medical professionals at a U.S. hospital grappled with the opacity of AI tools when making critical diagnostic judgments, and the research by Waardenburg et al. (2022), which examined how knowledge brokers within the Dutch police navigate and translate opaque algorithmic predictions to support operational decision-making, research on the use of AI in strategy creation and implementation processes continues to be still quite limited.

There are several potential avenues for empirical research that could enrich our understanding of the contribution of company-specific AI system deployments to strategy processes. Ethnographic studies could provide important insights into the organizational processes associated with the use of AI to support strategy creation and implementation (Anthony et al., 2023). Such research could examine, for example, the role of different contextual factors that influence the adoption of AI in strategic decision-making processes. Comparative case studies could further illuminate the boundary conditions and contingencies that influence the successful integration of AI into existing strategy creation and implementation processes.

Building on the different potential uses of AI in attention control, empirical research could examine which of the outlined benefits are the most challenging to achieve and which contribute the most to competitive advantage. In Fig. 1, the different impacts of AI on attention control are presented as part of a cohesive system of strategy creation and implementation. However, AI can also be applied in a more piecemeal fashion, for example, for democratizing the strategy process or for tracking the progress of strategy implementation. Recognizing that it may not be feasible to realize all these benefits simultaneously, the integration of AI into strategy creation and implementation processes should be approached incrementally. This approach allows management to gradually adapt existing organizational routines to align with new ways of working. Identifying the pitfalls and success factors in such technology adoption processes would be a vital area for future research.

Investigating the behavioral and cognitive aspects of human-AI interactions in strategy creation and implementation processes represents another interesting research opportunity. Building on prior work on technology adoption (e.g., Edmondson et al., 2001; Prikshat et al., 2023; Woiceshyn and Daellenbach, 2005), scholars could examine how decision-makers process, interpret, and respond to AI-generated strategic insights and feedback (Lebovitz et al., 2022; Tong et al., 2021). Such studies could explore the cognitive biases, heuristics, and decision-making patterns that emerge when AI systems are incorporated into strategy creation and implementation processes. By combining controlled experiments with in-depth qualitative observations of cross-functional strategy teams, scholars could examine to what extent group dynamics and potential trust deficits mediate whether AI tools enhance or distort

organizational attention and engagement.

Another potential avenue for future research is to examine how proprietary AI systems influence organizational structures. On one hand, AI systems can contribute to centralization of decision authority by enabling management to aggregate external and internal data streams, oversee real-time performance metrics, and issue top-down guidance based on algorithmic insights. This centralization can strengthen strategic coherence by ensuring that all units act on a unified attentional control, but it also risks curtailing frontline autonomy and hampering local experimentation. On the other hand, introducing strategy Chatbots directly into business units democratizes strategic decision-making by equipping local teams with detailed, context-specific strategic understanding, enhancing decentralized autonomy. Future research could examine how organizations adapt to this structural squeeze. Do middle managers transition into roles focused on strategic integration, culture building, or cross-unit collaboration, or are their responsibilities largely absorbed by AI systems and redistributed among other hierarchical levels? A longitudinal, multi-method approach could track shifts in organizational charts—measuring changes in reporting spans, layer counts, and role titles—while also conducting in-depth interviews with affected managers to capture how their job identities and skill requirements evolve.

A potential source of data in future research would be to examine the interaction logs generated by AI-enabled chatbots and other decision-support interfaces. By systematically analyzing these conversation traces, researchers could observe how managers pose queries, interpret AI-provided summaries or recommendations, and adjust their strategic judgments in response to evolving AI prompts. Combining quantitative log-file analysis (e.g., frequency and sequencing of questions, time spent on AI-suggested options, patterns of follow-up inquiries) with qualitative methods could enhance our understanding of when and why human actors defer to, contest, or elaborate on AI outputs at each stage of the strategy process. For example, when using Chatbots for strategy communication, log data could show which organizational levels engage most with AI-facilitated ideation sessions, and interviews could help explain how frontline actors translate algorithmic insights into practical action plans. By triangulating interaction logs, behavioral observations, and outcome measures, researchers could generate rich, multi-level insights into the conditions under which human–AI enhance adaptive strategy creation and implementation.

Finally, future research could also investigate the boundary conditions and trade-offs associated with AI-enabled attentional control systems in organizations. For example, examining how algorithmic opacity influences employees' use of AI systems in strategy creation and implementation could enhance the understanding of the role of opacity in undermining attentional engagement and coherence. Scholars could also examine the learning dynamics that unfold as organizations gain experience with these systems. Finally, a longitudinal analysis examining contextual factors could uncover the conditions under which real-time monitoring and control may inadvertently hamper employee motivation and reduce their autonomous strategic behavior, thereby reducing the potential benefits of AI systems for enhanced attentional control.

6. Conclusion

The use of proprietary AI systems to support organizational strategy processes represents a novel topic area in strategic management research. By training AI systems on proprietary internal data sources, firms can potentially enhance their strategic analysis capabilities, democratize strategy development by more effectively implementing open strategy practices, and enable adaptive implementation via continuous real-time monitoring and feedback loops. However, the dark side of AI-enabled attentional control also warrants investigation into whether continuous observation may inadvertently undermine employee motivation, autonomous strategic behaviors, and organizational innovativeness. Through empirical research, future studies can examine the micro-foundations, socio-technical dynamics, and organizational prerequisites relating to the use of AI to support strategy creation and implementation processes. Investigating the contingencies that shape the trade-offs between strategic alignment and adaptability is important for understanding AI system's implications for strategic processes, strategy practices, and firm outcomes. This emerging area represents fertile ground for research at the intersection of strategy and information systems. We put forward attention-based view (ABV) as a potential theoretical lens by examining how proprietary AI systems can augment organizations' attention capacity and the speed at which it can shift its attention to other important strategic issues. Examining the potential dark side of AI-based real-time monitoring of organizational activities can also help in broadening the theoretical scope of the ABV by highlighting the possible negative consequences of continuous organizational attention. With our focus on adaptive strategy creation and implementation processes, we echo the recent call for research on algorithmic attentional control through AI that "it is essential to develop a deeper understanding of the attentional mechanisms that underpin these technologies and how they, directly and indirectly, exercise attentional control, often without human's full awareness" (Ocasio, 2025: 10).

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Data availability

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References

Aguilar, F.J., 1967. Scanning the Business Environment. McMillan, New York, NY.
Ahearne, M., Lam, S.K., Kraus, F., 2014. Performance impact of middle managers' adaptive strategy implementation: the role of social capital. Strateg. Manag. J. 35 (1), 68–87.
Alcadipani, R., Hassard, J., Islam, G., 2018. "I Shot the Sheriff": Irony, sarcasm and the changing Nature of workplace resistance. J. Manag. Stud. 55 (8), 1452–1487.
Ambos, T.C., Birkinshaw, J., 2010. Headquarters' attention and its effect on subsidiary performance. Manag. Int. Rev. 50 (4), 449–469.
Anthony, C., Bechky, B.A., Fayard, A.L., 2023. "Collaborating" with ai: taking a system view to explore the future of work. Organ. Sci.
Bansal, P., Kim, A., Wood, M.O., 2018. Hidden in plain sight: the importance of scale in organizations' attention to issues. Acad. Manag. Rev. 43 (2), 217–241.
Barney, J.B., Reeves, M., 2024. AI won't give you a new sustainable advantage. Harv. Bus. Rev. 72–79.
Beer, M., Eisenstat, R.A., 2000. The silent killers of strategy implementation and learning. Sloan Manag. Rev. 41 (4), 29–40.
Belenzon, S., Hashai, N., Patacconi, A., 2019. The Architecture of attention: Group structure and subsidiary autonomy. Strateg. Manag. J. 40 (10), 1610–1643.
Belmondo, C., Sargis-Roussel, C., 2023. The political dynamics of opening participation in strategy: the role of strategy specialists' legitimacy and disposition to openness. Organ. Stud. 44 (4), 613–635.
Bower, J.L., Christensen, C.M., 1995. Disruptive technologies - catching the wave. Harv. Bus. Rev. 73 (1), 43–53.
Brown, S.L., Eisenhardt, K.M., 1997. The art of continuous change: linking complexity theory and time-paced evolution in relentlessly shifting organizations. Adm. Sci. Q. 42 (1), 1–34.
Burgelman, R.A., 1983. A model of the interaction of strategic behavior, corporate context, and the concept of strategy. Acad. Manag. Rev. 8 (1), 61–70.
Burgelman, R.A., 1991. Intraorganizational ecology of strategy making and organizational adaptation: theory and field research. Organ. Sci. 2, 239–262.
Burgelman, R.A., 1994. Fading memories - a process theory of strategic business exit in dynamic environments. Adm. Sci. Q. 39 (1), 24–56.
Burgelman, R.A., 1996. A process model of strategic business exit: implications for an evolutionary perspective on strategy. Strateg. Manag. J. 17 (S1), 193–214.
Burgelman, R.A., 2002. Strategy as vector and the inertia of coevolutionary Lock-In. Adm. Sci. Q. 47 (2), 325–357.
Burgelman, R.A., Floyd, S.W., Laamanen, T., Mantere, S., Vaara, E., Whittington, R., 2018. Strategy processes and practices: dialogues and intersections. Strateg. Manag. J. 39 (3), 531–558.
Burgelman, R.A., Floyd, S.W., Laamanen, T., Mantere, S., Vaara, E., Whittington, R., 2021. Strategy processes and practices. In: Duhaime, I.M., Hitt, M.A., Lyles, M.A. (Eds.), Strategic Management: State of the Field and Its Future, 0. Oxford University Press.
Burrell, J., 2016. How the machine 'Thinks': understanding opacity in machine learning algorithms. Big Data & Society 3 (1), 2053951715622512.
Cai, J., Canales, J.I., 2022. Dual strategy process in open strategizing. Long. Range Plan. 55 (6).
Chesbrough, H.W., 2003. Open Innovation: the New Imperative for Creating and Profiting from Technology. Harvard Business School Press, Boston.
Christensen, C.M., Overdorf, M., 2000. Meeting the challenge of disruptive change. Harv. Bus. Rev. 78 (2), 66-+.
Cohen, M.D., March, J.G., Olsen, J.P., 1972. A garbage can model of organizational choice. Adm. Sci. Q. 17, 1–25.
Collier, N., Fishwick, F., Floyd, S.W., 2004. Managerial involvement and perceptions of strategy process. Long. Range Plan. 37 (1), 67–83.
Cook, S., Hagiu, A., Wright, J., 2024. Turn generative AI from an existential threat into a competitive advantage. Harv. Bus. Rev. 102 (1), 118–125.
Cram, W.A., Martin, W., Monideepa, T., Benlian, A., 2022. Examining the impact of algorithmic control on uber drivers' technostress. J. Manag. Inf. Syst. 39 (2), 426–453.
Cyert, R.M., March, J.G., 1963. A Behavioral Theory of the Firm. Prentice Hall, Englewood Cliffs, CA.
D'Amico, A., Delteil, B., Hazan, E., Tricoli, A., Montard, A., 2025. In: Co, M. (Ed.), How AI Is Transforming Strategy Development.
Day, G.S., Schoemaker, P.J.H., 2006. PBripheral Vision: Detecting the Weak Signals that Will Make or Break Your Company. Harvard Business School.
Dell'Acqua, F., McFowland, E., Mollick, E.R., Lifshitz-Assaf, H., Kellogg, K., Rajendran, S., Krayer, L., Candelon, F., Lakhani, K., 2023. Navigating the Jagged Technological Frontier: Field Experimental Evidence of the Effects of AI on Knowledge Worker Productivity and Quality. Harvard Business School Technology & Operations Management Unit, Cambridge, MA.
Dobusch, L., Kapeller, J., 2017. Open strategy-making with crowds and communities: comparing wikimedia and creative commons. Long. Range Plan.
Dobusch, L., Kapeller, J., 2018. Open strategy-making with crowds and communities: comparing wikimedia and creative commons. Long. Range Plan. 51 (4), 561–579.
Doerr, J., 2018. Measure what Matters. Portfolio Penguin, London, England.
Dutton, J.E., Duncan, R.B., 1987. The creation of momentum for change through the process of strategic issue diagnosis. Strateg. Manag. J. 8 (3), 279–295.
Edmondson, A.C., Bohmer, R.M., Pisano, G.P., 2001. Disrupted routines: team learning and new technology implementation in hospitals. Adm. Sci. Q. 46 (4), 685–716.
Eisenhardt, K.M., Furr, N.R., Bingham, C.B., 2010. Microfoundations of performance: balancing efficiency and flexibility in dynamic environments. Organ. Sci. 21 (6), 1263–1273.
Eklund, J., Raj, M., Eggers, J.P., 2025. Attention focus and new opportunities: the moderating role of managerial attention to alternative issues. Organ. Sci. 36 (1), 21–39.
Eklund, J.C., Mannor, M.J., 2021. Keep your eye on the ball or on the field? Exploring the performance implications of executive strategic attention. Acad. Manag. J. 64 (6), 1685–1713.
Feuerriegel, S., Shrestha, Y.R., von Krogh, G., 2025. A New Machine Learning Approach Answers What-If Questions. MIT Sloan Management Review.
Floyd, S.W., Wooldridge, B., 1992. Middle management involvement in strategy and its Association with strategic type - a research note. Strateg. Manag. J. 13, 153–167.
Forbes, D.P., Milliken, F.J., 1999. Cognition and corporate governance: understanding boards of directors as strategic decision-making groups. Acad. Manag. Rev. 24 (3), 489–505.
Foster, R.N., Kaplan, S., 2001. Creative Destruction: Why Companies that are Built to Last Underperform the Market – and How to Successfully Transform them New York: Currency (Doubleday).
Gaba, V., Joseph, J., 2013. Corporate structure and performance feedback: aspirations and adaptation in M-Form firms. Organ. Sci. 24 (4), 1102–1119.
Gaessler, F., Piezunka, H., 2023. Training with AI: evidence from chess computers. Strateg. Manag. J. 44 (11), 2724–2750.
Galbraith, J.R., Nathanson, D.A., 1978. Strategy Implementation: the Role of Structure and Process. West Pub. Co, St.Paul.
Gegenhuber, T., Dobusch, L., 2017. Making an impression through openness: how open strategy-making practices change in the evolution of new ventures. Long. Range Plan. 50 (3), 337–354.
Gregoire, D.A., Barr, P.S., Shepherd, D.A., 2010. Cognitive processes of opportunity recognition: the role of structural alignment. Organ. Sci. 21 (2), 413–431.
Gronsund, T., Aanestad, M., 2020. Augmenting the algorithm: emerging human-in-the-loop work configurations. J. Strat. Inf. Syst. 29 (2).
Hambrick, D.C., Mason, P.A., 1984. Upper echelons: the organization a reflection of its top managers. Acad. Manag. Rev. 9, 193–206.
Harju, A., Buffart, M., Leppälä, M., 2020. What is our strategy, really? Futurice, 2025: Futurice.
Hautz, J., Seidl, D., Whittington, R., 2017. Open strategy: dimensions, Dilemmas, dynamics. Long. Range Plan. 50 (3), 298–309.
Holstein, J., Rantakari, A., 2023. Space and the dynamic between openness and closure: open strategizing in the TV series borgen. Organ. Stud. 44 (1), 53–75.
Hrebiniak, L.G., Joyce, W.F., 1984. Implementing Strategy. MacMillan, New York.
Jackson, S.E., Dutton, J.E., 1988. Discerning threats and opportunities. Adm. Sci. Q. 33 (3), 370–387.
Jarzabkowski, P., Le, J., Balogun, J., 2019. The social practice of coevolving strategy and structure to realize mandated radical change. Acad. Manag. J. 62 (3), 850–882.
Joseph, J., Klingebiel, R., Wilson, A.J., 2016. Organizational structure and performance feedback: centralization, aspirations, and termination decisions. Organ. Sci. 27 (5), 1065–1083.
Joseph, J., Laureiro-Martinez, D., Nigam, A., Ocasio, W., Rerup, C., 2024. Research frontiers on the attention-based view of the firm. Strateg. Organ.

Joseph, J., Ocasio, W., 2012. Architecture, Attention, and adaptation in the Multibusiness firm: General electric from 1951 to 2001. Strateg. Manag. J. 33 (6), 633–660.
Joseph, J., Wilson, A.J., 2018. The growth of the firm: an attention-based view. Strateg. Manag. J. 39 (6), 1779–1800.
Julian, S.D., Ofori-Dankwa, J.C., 2008. Toward an integrative cartography of two strategic issue diagnosis frameworks. Strateg. Manag. J. 29 (1), 93–114.
Kaplan, R.S., Norton, D.P., 1992. The balanced scorecard - measures that drive performance. Harv. Bus. Rev. 71–79.
Kaplan, R.S., Norton, D.P., 2004. Strategy maps. Converting Intangible Assets into Tangible Outcomes. Harvard Business School Press, Boston.
Kaplan, R.S., Norton, D.P., 2008. Mastering the management system. Harv. Bus. Rev. 86 (1), 62-+.
Kellogg, K.C., Valentine, M., Christin, A., 2020. Algorithms at work: the new contested terrain of control. Acad. Manag. Ann. 14 (1), 366–410.
Kemp, A., 2024. Competitive advantage through artificial intelligence: toward a theory of situated Ai. Acad. Manag. Rev. 49 (3), 618–635.
Klingebiel, R., De Meyer, A.D., 2013. Becoming aware of the unknown: decision making during the implementation of a strategic initiative. Organ. Sci. 24 (1), 133–153.
Kolbjørnsrud, V., 2024. Designing the intelligent organization: six principles for Human-AI collaboration. Calif. Manag. Rev. 66 (2), 44–64.
Krakowski, S., Luger, J., Raisch, S., 2023. Artificial intelligence and the changing sources of competitive advantage. Strateg. Manag. J. 44 (6), 1425–1452.
Laamanen, T., 2019. Dynamic attention-based view of corporate headquarters in mncs. Journal of Organization Design 8 (1).
Laamanen, T., Maula, M., Kajanto, M., Kunnas, P., 2018. The role of cognitive load in effective strategic issue management. Long. Range Plan. 51 (4), 625–639.
Langenmayr, T., Seidl, D., Splitter, V., 2024. Interdiscursive struggles: managing the Co-Existence of the conventional and open strategy discourse. Strateg. Manag. J.
Laureiro-Martinez, D., Arrieta, J.P., Brusoni, S., 2023. Microfoundations of problem solving: attentional engagement predicts problem-solving strategies. Organ. Sci.
Lebovitz, S., Lifshitz-Assaf, H., Levina, N., 2022. To engage or not to engage with Al for critical judgments: how professionals deal with opacity when using AI for medical diagnosis. Organ. Sci. 33 (1), 126–148.
Lee, E., Puranam, P., 2016. The implementation imperative: why one should implement Even imperfect strategies perfectly. Strateg. Manag. J. 37 (8), 1529–1546.
Leonardi, P.M., 2021. Covid-19 and the new technologies of organizing: Digital exhaust, digital footprints, and artificial intelligence in the wake of remote work. J. Manag. Stud. 58 (1), 247–251.
Lifshitz-Assaf, H., 2018. Dismantling knowledge boundaries at NASA: the critical role of professional identity in open innovation. Adm. Sci. Q. 63 (4), 746–782.
Lingo, E.L., 2023. Digital curation and creative brokering: managing information overload in open organizing. Organ. Stud. 44 (1), 105–133.
Love, E.G., 2023. Attentional control systems for emergent strategic issues in the post-chandlerian world. Strateg. Organ.
Lundgren-Henriksson, E.L., Sorsa, V., 2023. Open strategizing on social media: a process model of emotional mechanisms and outcomes from Un-Orchestrated participation. Long. Range Plan. 56 (3).
Luo, X.M., Jia, N., Ouyang, E.Y., Fang, Z., 2024. Introducing machine-learning-based data fusion methods for analyzing multimodal data: an application of measuring trustworthiness of microenterprises. Strateg. Manag. J.
March, J.G., 2006. Rationality, foolishness, and adaptive intelligence. Strateg. Manag. J. 27 (3), 201–214.
March, J.G., Simon, H.A., 1958. Organizations. John Wiley & Sons, Inc, New York.
Martin, R.L., 2010. How hierarchy can hurt strategy execution. Harv. Bus. Rev. 88 (7–8), 74–75.
Narayan, S., Sidhu, J.S., Volberda, H.W., 2021. From attention to action: the influence of cognitive and ideological diversity in top management teams on business model innovation. J. Manag. Stud. 58 (8), 2082–2110.
Nicolini, D., Korica, M., 2021. Attentional engagement as practice: a study of the attentional infrastructure of healthcare chief executive officers. Organ. Sci. 32 (5), 1273–1299.
Nicolini, D., Mengis, J., 2024. Toward a practice-theoretical view of the situated Nature of attention. Strateg. Organ. 22 (1), 211–234.
Nutt, P.C., 1986. Tactics of implementation. Acad. Manag. J. 29 (2), 230–261.
Nutt, P.C., 1989. Selecting tactics to implement strategic plans. Strateg. Manag. J. 10 (2), 145–161.
Nutt, P.C., 1998. Leverage, resistance and the success of implementation approaches. J. Manag. Stud. 35 (2), 213–240.
Ocasio, W., 1997. Towards an attention-based view of the firm. Strateg. Manag. J. 18 (S1), 187–206.
Ocasio, W., 2011. Attention to attention. Organ. Sci. 22 (5), 1286–1296.
Ocasio, W., 2025. Attentional control: institutions, management, organizations, and algorithms. J. Manag. Inq. 34 (1), 3–18.
Ocasio, W., Joseph, J., 2008. Rise and fall - or transformation? The evolution of strategic planning at the general electric company, 1940-2006. Long. Range Plan. 41 (3), 248–272.
Ocasio, W., Joseph, J., 2018. The attention-based view of great strategies. Strateg. Sci. 3 (1), 289–294.
Ocasio, W., Laamanen, T., Vaara, E., 2018. Communication and attention dynamics: an attention-based view of strategic change. Strateg. Manag. J. 39 (1), 155–167.
Ocasio, W., Wohlgezogen, F., 2010. Attention and control. Organizational Control. Cambridge University Press, pp. 191–221.
Ocasio, W., Yakis-Douglas, B., Boynton, D., Laamanen, T., Rerup, C., Vaara, E., Whittington, R., 2023. It's a different world: a dialog on the attention-based view in a post-chandlerian world. J. Manag. Inq. 32 (2), 107–119.
Ocasio, W.P., Joseph, J., 2006. Governance channels and organizational design at general electric: 1950-2001. In: Eriksen, B., Burton, R., Håkonsson, D.D. (Eds.), Organization Design: the Dynamics of Adaptation and Change and the Evolving state-of-the-art.
Plotnikova, A., Pandza, K., Whittington, R., 2023. Bending the pipes: regaining attention through reinvention and renewal. Strateg. Organ.
Porter, M.E., 1980. Competitive Strategy: Techniques for Analyzing Industries and Competitors. The Free Press, New York.
Prikshat, V., Malik, A., Budhwar, P., 2023. AI-Augmented hrm: antecedents, assimilation and multilevel consequences. Hum. Resour. Manag. Rev. 33 (1).
Raisch, S., Fomina, K., 2025. Combining human and artificial intelligence: hybrid problem-solving in organizations. Acad. Manag. Rev. 50 (2), 441–464.
Raisch, S., Krakowski, S., 2021. Artificial intelligence and management: the automation-augmentation paradox. Acad. Manag. Rev. 46 (1), 192–210.
Rerup, C., 2009. Attentional triangulation: learning from unexpected rare crises. Organ. Sci. 20 (5), 876–893.
Ridge, J.W., Johnson, S., Hill, A.D., Bolton, J., 2017. The role of top management team attention in new product introductions. J. Bus. Res. 70, 17–24.
Schulze, A., Brusoni, S., 2022. How dynamic capabilities change ordinary capabilities: reconnecting attention control and problem-solving. Strateg. Manag. J. 43 (12), 2447–2477.
Shrestha, Y.R., Ben-Menahem, S.M., von Krogh, G., 2019. Organizational decision-making structures in the age of artificial intelligence. Calif. Manag. Rev. 61 (4), 66–83.
Shrestha, Y.R., He, V.F., Puranam, P., von Krogh, G., 2021. Algorithm supported induction for building theory: how can we use prediction models to theorize? Organ. Sci. 32 (3), 856–880.
Simon, H., 1957. Models of Man: Social and Rational. John Wiley & Sons, Inc, New York, NY.
Simons, R., 1994. How new top managers use control systems as levers of strategic renewal. Strateg. Manag. J. 15 (3), 169–189.
Spee, P., Jarzabkowski, P., 2017. Agreeing on what? Creating joint accounts of strategic change. Organ. Sci. 28 (1), 152–176.
Splitter, V., Dobusch, L., von Krogh, G., Whittington, R., Walgenbach, P., 2023. Openness as organizing principle: introduction to the special issue. Organ. Stud. 44 (1), 7–27.
Splitter, V., Seidl, D., Whittington, R., 2019. Practice-Theoretical Perspectives on Open Strategy: Implications of a Strong Programme.
Stadler, C., Hautz, J., Matzler, K., von den Eichen, S.F., 2021. Open Strategy: Mastering Disruption from Outside the C-Suite. The MIT Press.
Stjerne, I., Geraldi, J., Wenzel, M., 2022. Strategic practice drift: how open strategy infiltrates the strategy process. J. Manag. Stud.
Tong, S.L., Jia, N., Luo, X.M., Fang, Z., 2021. The Janus face of artificial intelligence feedback: deployment versus disclosure effects on employee performance. Strateg. Manag. J. 42 (9), 1600–1631.
Vanneste, B.S., Puranam, P., Forthcoming. Artificial intelligence, trust, and perceptions of agency. Acad. Manag. Rev. 0(ja): amr.2022.0041. https://doi.org/10.5465/amr.2022.0041.
von Krogh, G., 2018. Artificial intelligence in organizations: new opportunities for phenomenon-based theorizing. Acad. Manag. Discov. 4 (4), 404–409.

von Krogh, G., Ben-Menahem, S.M., Shrestha, Y.R., 2021. Artificial intelligence in strategizing: prospects and challenges. In: Duhaime, I.M., Hitt, M.A., Lyles, M.A. (Eds.), SBrategic Management: State of the Field and Its Future: 0. Oxford University Press.
Vuori, N., Burkhard, B., Laamanen, T., Bingham, C., 2024. Heuristics in organizations: toward an integrative process model. Acad. Manag. Ann. 18 (2), 670–711.
Vuori, N., Burkhard, B., & Pitkäranta, L. Forthcoming. It's amazing – but terrifying!: unveiling the combined effect of emotional and cognitive trust on organizational member' behaviours, Ai performance, and adoption. J. Manag. Stud., n/a(n/a). https://doi.org/10.1111/joms.13177.
Waardenburg, L., Huysman, M., Sergeeva, A.V., 2022. In the land of the blind, the one-eyed man is king: knowledge brokerage in the age of learning algorithms. Organ. Sci. 33 (1), 59–82.
Weiser, A.-K., Jarzabkowski, P., Laamanen, T., 2020. Completing the adaptive turn: an integrative view of strategy implementation. Acad. Manag. Ann. 14 (2), 969–1031.
Weiser, A.-K., Laamanen, T., 2022. Extending the dynamic equilibrium model of paradox: unveiling the dissipative dynamics in organizations. Organization Theory 3 (3), 26317877221090317.
Weiser, A.-K., von Krogh, G., 2023. Artificial intelligence and radical uncertainty. Eur. Manag. Rev. 20 (4), 711–717.
Whittington, R., 2019. Opening Strategy Professional Strategists and Practice Change, 1960 to Today. Oxford University Press, Oxford, United Kingdom.
Whittington, R., Cailluet, L., Yakis-Douglas, B., 2011. Opening strategy: evolution of a precarious profession. Br. J. Manag. 22 (3), 531–544.
Woiceshyn, J., Daellenbach, U., 2005. Integrative capability and technology adoption: evidence from oil firms. Ind. Corp. Change 14 (2), 307–342.
Wooldridge, B., Floyd, S.W., 1990. The strategy process, middle management involvement, and organizational performance. Strateg. Manag. J. 11 (3), 231–241.
Zhong, W.G., Ma, Z.M., Tong, T.W., Zhang, Y.C., Xie, L.Q., 2021. Customer concentration, executive attention, and firm search behavior. Acad. Manag. J. 64 (5), 1625–1647.

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