The Role of AI in Revolutionizing Strategy Formulation and Execution

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WORK IN PROGRESS

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INTRODUCTION

Generative artificial intelligence (AI) is a transformative technology with the potential to revolutionize industries by rapidly analyzing vast datasets and providing insights through generating text, images, videos, and other content based on the data it has been trained on (Jia, Luo, Fang, and Liao, 2024; Shrestha, Ben-Menahem and Von Krogh, 2020). Management scholars suggest that in contrast to other technologies, generative AI can fundamentally reshape how organizations approach strategy formulation and implementation, potentially leading to significant improvements in company performance (Wilson and Daugherty, 2024; Krakowski, Luger and Raisch, 2023). Despite this promise, the mechanisms by which companies can effectively leverage generative AI in their strategy work remain unclear for two primary reasons (Kemp, 2024; Moser, Glaser and Lindebaum, 2024)

First, most empirical studies on generative AI primarily focus on individual use of AI outside the strategic management context. For instance, research has examined doctors diagnosing cancer (Lebovitz, Lifshitz-Assaf, and Levina, 2022), healthcare patients utilizing virtual health advisors (Kyung and Kwon, 2022), and participants testing self-driving vehicles (Zhang, Tao, Qu, Zhang, Lin, and Zhang., 2019). In contact, strategy formulation and implementation are complex socio-dynamic processes that involve "actions, interactions, and negotiations of multiple actors and the situated practices that they draw upon in accomplishing that activity" (Jarzabkowski, 2007: 8). The understanding of how micro-level phenomena—such as individual-level psychological reaction to AI—aggregate into meso-level processes, such as socio-dynamic processes during strategizing, and macro-level organizational outcomes, such as firm performance, is essential. (Bechky, 2020; Kouamé and Langley, 2018; Felin, Foss and Ployhart, 2015; Foss and Pedersen, 2016).

Second, as generative AI technologies—such as ChatGPT, Claude, and Microsoft CoPilot—have become widely accessible and offer similar functionalities across organizations, it remains unclear how companies can leverage these tools to gain a competitive edge and outperform their rivals (Kemp, 2024). This presents a critical challenge, as sustainable competitive advantage traditionally stems from resources that are rare and difficult to imitate (Barney, 1991). Given generative AI's widespread availability, the key question is not whether organizations can access AI, but how they can uniquely integrate and optimize its use to drive strategic differentiation and long-term success.

This study aims to explore *how and why management board members respond to generative AI and what the implications of these responses are on strategy work and firm performance*. We conducted an inductive field study across seven management boards within three industrial companies specializing in technologies and services. Our data included 78 interviews with management board members—including middle managers, senior managers, and vice presidents—and AI specialists from IT functions. Furthermore, we observed 18 meetings focused on strategizing. We also analyzed surveys conducted by the case companies regarding the use of generative AI and employee satisfaction with AI tools such as Copilot and ChatGPT.

RESEARCH SETTING AND METHODOLOGY

We employed a real-life inductive approach that integrates multi-case study methodology with grounded theory principles (Eisenhardt, Graebner, and Sonenshein, 2016

Context

The study design encompasses seven management boards distributed across seven business units within three companies. While two of the three companies are subsidiaries of a larger conglomerate, each operates as a distinct entity with unique products, services, organizational structure, and management team. All three companies are industrial firms that offer technologies and services across various industries to customers in Europe, the Middle East (India), Africa (EMEA and EMEIA), Asia-Pacific, and North America. Table 1 provides details on our cases[1].

Insert Table 1 about here

The sizes of the management boards for our seven cases ranged from 5 to 8 members. These boards convened weekly to address a range of strategic issues, including revenue growth, resource allocation for strategy execution, and analysis of competitors' strategies. Additionally, these meetings served as a forum for members to share updates on the daily operations of their respective teams.

Data collection

Given the sensitivity surrounding topics such as strategy work and the use of AI within corporate environments, we assured all participating organizations of complete anonymity to facilitate access to their management boards. We mutually agreed to store all data on the companies' secure repositories and to maintain strict confidentiality regarding the identities of the companies, as well as the names and job titles of our informants. These measures not only foster trust among participants but also strengthen the integrity of the research process, enabling candid discussions on potentially sensitive or contentious topics.

To ensure data triangulation and trustworthiness (Eisenhardt, 1989), we gathered data from four distinct sources: (1) strategy meetings/workshops observations, (2) formal post-meetings and post-workshop interviews, and (3) surveys about the use of generative AI and the purpose of its use conducted by the case company. We conducted a total of 78 formal interviews and observed 18 meetings and workshops. In addition, we collected approximately 16 hours of informal conversation with our informant during the meeting breaks, lunch, on bus rides from the airports to the offices, and waiting in the airports. Table 2 illustrates information about formal interviews, observations, and informants in each team.

Insert Table 2 about here

Data analysis

Although our analysis involved an iterative process of engaging with our accumulating data, emerging insights, and theoretical frameworks, we structured our presentation of data analysis for clarity. We uploaded transcripts of meeting observations and interviews to Atlas.ti immediately following the interviews and meeting observations. Subsequently, we conducted a line-by-line coding of the transcripts in accordance with Corbin and Strauss's (2008) methodology. Figure 1 illustrates our data structure.

Insert Figure 1 about here

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[1] We masked the names of the company and all informants to ensure anonymity, This did not affect our results.

FINDINGS

Traditional strategizing before generative AI

Before generative AI, the process of strategy formulation and execution was largely shaped by management boards, which traditionally relied on established methodologies (SWOT analysis, scenario strategic planning, blue ocean strategy (market analysis, and creating a new space unique from competitors, setting strategic objectives and KPIs, and so on) and artifacts (e.g., PowerPoint, Excel, Whiteboard, metrics) to set goals, allocate resources, establish actionable steps for achieving their strategic objectives, and monitor and adjust the strategy's unfolding.

> We often perform an in-depth market analysis that looks at industry trends and the competition, along with SWOT assessments to pinpoint our strengths, weaknesses, opportunities, and threats. (Alpha A, Member 7)

This reliance on traditional techniques and artifacts guided strategy formulation and execution processes and influenced organizations' overall direction in a rapidly changing business environment. When facing more complex challenges or seeking fresh perspectives, management boards have "turned to external consultants, such as Deloitte, PwC, and Accenture, for specialized expertise and strategic guidance" (Beta A, Member 5).

In our case companies, all management boards took pride in "being the primary architects and executors of our strategy" (Beta, B, Member 4), viewing this responsibility "as our core responsibility" (Gamma, B, Member 2). The responsibility in strategy formulation and execution reinforced their identity as strategists:

> For a lot of us, developing strategy isn't just something to check off our to-do list—it's something we take pride in and a way we can really make a difference for the company down the road. (Beta, A, Member 1)

The shift in strategy work

Our findings reveal that during strategy meetings, Beta's Boards A and B and Gamma's Boards A and C collectively engaged in the situated construction of AI enthusiasm, leading them to adapt their strategy work to emerging generative AI opportunities. Specifically, these boards developed and implemented two novel types of strategizing: AI-augmented iterative strategizing and AI-augmented intelligence strategizing. Additionally, IT specialists played an increasingly prominent role in strategy work, gradually emerging as key actors in strategy formulation and execution. These adaptations enhanced the speed and quality of strategy formulation and implementation, ultimately improving performance.

In contrast, the three management boards—specifically, Alpha Boards A and B and Gamma Board B—collectively constructed shared AI aversion by publicly shaming colleagues who used AI to augment their skills and stigmatizing AI use in organizations. As a result, they maintained traditional strategic practices and excluded IT specialists, viewing them solely as support functions. These boards did not report increased productivity. Instead, they experienced a weak performance. Table 4 illustrates socio-psychological dynamics and shifts in strategy work.

Insert Table 2 about here

DISCUSSION

We developed a socio-psychological dynamics model that underlies a process through which management boards engage in the co-construction and reinforcement of negative (positive) affective responses to AI in different situations, thereby forming AI aversion (AI enthusiasm), thus adjusting or not strategy work. Figure 2 illustrates our model.

Insert Figure 2 about here

Our model proposes that individual fears—such as concerns about being perceived as incompetent or inauthentic, as well as apprehension over losing a leading role in strategizing—play a critical role in shaping whether strategists experiment with AI and develop AI literacy [1]. The level of individual AI literacy can set off either a positive or negative cycle within management boards. When a majority of board members have prior experience with AI and develop AI literacy, they are more likely to initiate the situated collective construction of AI enthusiasm [2a]. This process unfolds through (a) sharing positive affect from individual use of AI, (b) constructing positive affect by collectively experimenting with AI, and (c) proactively organizing AI training, leading to a sense of empowerment and enthusiasm as members expand their AI expertise. A collectively constructed AI enthusiasm increases the likelihood of a shift toward AI-augmented strategy work, which involves adopting new forms of strategizing and incorporating new strategic actors, such as IT and AI specialists [3a]. The adoption of AI-augmented strategizing accelerates decision-making, enhances coordination among strategists, reduces intra-team conflict, and ultimately strengthens company performance [4a]. This improved performance, in turn, reinforces AI enthusiasm, fueling a self-reinforcing cycle of AI adoption [5a] and literacy development [2a].

In contrast, when the majority of management board members lack experience with AI, a fundamentally different dynamic can emerge—one characterized by the situated collective construction of AI aversion [2b]. This aversion manifests through several mechanisms: (a) socially shaming individuals who adopt AI, (b) openly stigmatizing AI use, and (c) covertly leveraging AI to enhance personal skills, while not sharing positive affect from its use.

As AI aversion takes hold, organizations become anchored in traditional strategy work—resisting the adoption of AI-augmented practices and preventing IT specialists from participating in strategy work [3b]. This reluctance to integrate AI ultimately weakens the company’s strategic agility and decision-making, leading to diminished overall performance [4b]. As performance declines, skepticism and resistance toward AI deepen, reinforcing a self-perpetuating cycle of AI aversion [5b] that further impedes innovation and adaptability.

We make a significant contribution to the strategy literature by developing the model that illustrates the socio-psychological mechanisms underpinning why and how some management boards and organizations can harness generative AI effectively while others struggle to do so. The existing research on AI’s impact on organizational performance offers conflicting evidence. Our model provides a nuanced explanation for these inconsistencies. For instance, some studies (e.g., Acemoglu et al., 2022) have reported the absence of a clear correlation between investments in AI tools and company performance, suggesting that big data and AI technologies may disrupt board cohesion, leading to difficulties in achieving consensus and making effective collective decisions. On the other hand, other research (e.g., Babina, Fedyk, He, and Hodson, 2022) has presented compelling evidence of a positive association between AI investments and improved company growth and valuations, arguing that AI augments decision-making processes by overcoming the cognitive limitations of human agents (Murray, Rhymer, and Sirmon, 2021), and that AI-driven predictions often surpass human judgment (Agrawal, Gans, and Goldfarb, 2019).

AI implication for performance

We contribute to the management literature by reconciling conflicting evidence on the role of AI in strategy work and performance. We demonstrate that it may be difficult to explain the performance impact of AI at the macro-level due to the influence of underlying micro- and meso-level factors. As our study reveals, team members' affective reactions, as well as the social dynamics within teams and their approach to strategizing, play a pivotal role in determining whether organizations can successfully leverage AI. These micro-level factors, such as situated collective contraction of affective reactions toward AI, and meso-level factors, such as a shift in strategizing within teams, can significantly shape a company's overall performance. Thus, we argue that these human-centered dynamics shed light on the relationship between AI investment and organizational outcomes, which explains the variation in performance results reported across studies.

We contribute to the strategy literature by addressing a critical gap identified by recent scholars: the need to understand how micro-level phenomena—such as individual behaviors and team dynamics—aggregate into macro-level organizational outcomes (Kouamé and Langley, 2018; Felin, Foss, and Ployhart, 2015; Foss and Pedersen, 2016). Our research highlights the role of collectively constructed aversion or enthusiasm toward AI adoption, demonstrating how these shared attitudes shape strategizing processes and, ultimately, influence organizational performance. By emphasizing the significance of these underlying micro- and meso-level mechanisms, we offer a more nuanced and comprehensive explanation of the variations in AI adoption across organizations.

AI-driven shift in strategy work

We contribute to management literature by identifying two novel forms of AI-augmented strategizing—AI-augmented iterative strategizing and AI-augmented intelligence strategizing—and demonstrating how they enhance strategy work quality and firm performance. Our study extends the Strategy-as-Practice perspective by incorporating AI as a socio-material artifact that reshapes strategizing processes. Prior research has emphasized the role of tools such as PowerPoint presentations, visual decision aids, and strategic planning cycles (Vaara & Whittington, 2012; Knight, Paroutis, & Heracleous, 2018). We build on this stream of research by demonstrating that AI is not merely a passive tool but an active agent that influences strategists' cognitive processes, decision-making behaviors, and social interactions.

Furthermore, while prior studies have explored procedural and interactive strategizing (Hendry, Kiel, & Nicholson, 2010) and the affective dimensions of strategizing (Liu & Maitlis, 2014), our research reveals how collectively constructed AI enthusiasm or aversion shapes AI adoption in strategizing. This insight helps explain why some organizations integrate AI seamlessly into strategy work, while others resist its adoption, ultimately impacting organizational performance.

Our research contributes significantly to the strategy literature by illuminating the emergent role of the IT function in the broader context of organizational strategizing. Traditionally, the IT function has been viewed primarily as a technical enabler responsible for maintaining infrastructure and facilitating the use of technology. However, our study reveals that the IT function plays a much more strategic role, serving not only as a technology facilitator but also as a critical influencer of readiness for AI adoption. By bridging insights from Strategy-as-Practice and AI adoption research, our study offers a more comprehensive perspective on the evolving landscape of strategizing in the digital era.

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Table 1: Cases description

	IT function	Business Unit	Management board size	Industry	Revenue	Market regions
Alpha	Centralized IT function	Business Unit 1	7	Technologies and Services	US$ 3.5 bl	Europe, the Middle East, and Africa
		Business Unit 2	8	Technologies and Services	US$ 2.7 bl	Asia Pacific
Beta	Centralized IT function	Business Unit 1	7	Technologies and Services	US$ 2.5 bl	North America Europe, the Middle East, and Africa Asia Pacific
		Business Unit 2	7	Technologies and Services	US$ 1.7 bl	North America Europe, the Middle East, and Africa Asia-Pacific
Gamma	Own IT function	Business Unit 1	6	Technologies and Services	US$ 900 ml	Europe, the Middle East, India, and Africa
	Own IT function	Business unit 2	7	Technologies and Services	US$ 600 ml	North America
	Own IT function	Business Unit 3	5	Technologies and Services	US$ 300 ml	Asia Pacific

able 2: Socio-psychological dynamics and types of strategizing

Types of AI use	AI literacy at the beginning	Social-psychological dynamics	Type of Strategizing	New strategy actors	Definition	Self-reported performance
		Negative cycle	**Traditional strategy work**			**Weakened firm performance**
Hidden individual use	Only one or two team members use AI to augment their own skills	• Anger and frustration at team members who use AI • Social shaming for using AI • Stigmatization of AI		No	Strategy work based on traditional methods (SWOT analysis, scenario strategic planning, blue ocean strategy market analysis, and creating a new space unique from competitors, setting strategic objectives and KPIs, and so on), and artifacts (e.g., PowerPoint, Excel, Whiteboard, metrics) to set goals, allocate resources, establish actionable steps for achieving their strategic objectives, and monitor and adjust the strategy's unfolding	• Losing customers • Delaying projects • Generating extra costs
		Positive cycle	**AI-augmented strategy work**			**Increased firm performance**
Combination of collective and open individual use	The majority of or all team members use AI to augment team-level practices and processes and to augment their own skills	Increasing shared excitement about AIs	AI-augmented iterative strategizing.	IT specialists	The dynamic and continuous cycle of collective engagement with artificial intelligence to generate prompts for AI, analysis of AI-generated outputs, refining prompts based on insights gained, and perpetuating this iterative exchange.	• Increasing satisfaction of current customers • Acquiring new customers • Increasing speed of projects delivering
Combination of collective and open individual use	The majority of or all team members use AI to augment team-level practices and processes and to augment their own skills	Increasing shared excitement about AI	AI-augmented intelligence strategizing	IT specialists	Utilizing AI technologies—such as large language models (LLMs) and tools like Microsoft CoPilot—to instantly collect, analyze, and interpret extensive internal and external data	• Increasing satisfaction of current customers • Acquiring new customers • Increasing speed of projects delivering

Figure 1: Data structure

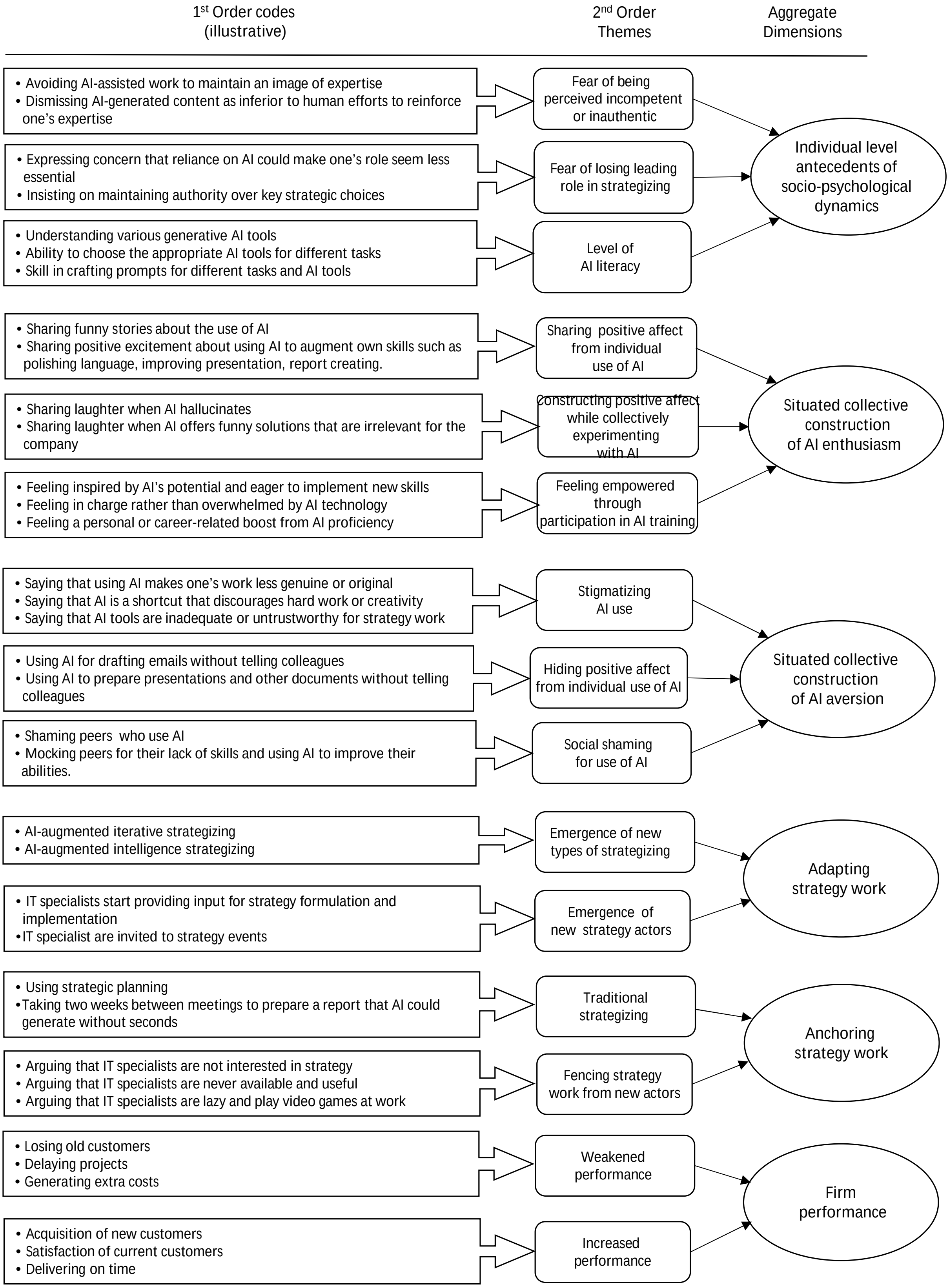

Figure 2: Socio-physiological dynamics, strategizing type, and firm performance