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Strategic AI Orientation and Technological Innovation: Evidence From Managerial Insights and Panel Data

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ABSTRACT

Artificial intelligence (AI) is disrupting innovation. However, our understanding of firm-level consequences remains limited. While firms are starting to develop a strategic AI orientation (i.e., goals and strategic directions), we neither know how firms establish a strategic AI orientation nor whether it suffices to increase firms' technological innovation. We explore these questions in two studies. In Study I, we conduct 42 interviews with AI managers in large firms. Using the attention-based view to structure the qualitative insights, we build deductive hypotheses on the relationship between AI orientation and technological innovation. Study II tests our hypotheses quantitatively, using natural language processing to develop a text-based measure of firms' strategic AI orientation. Applying this measure to S&P 500 firms between 2012 and 2021, we find that strategic AI orientation relates positively to firms' technological innovation, also across technology domains. CEOs' IT-related education strengthens this link. These insights contribute to AI-innovation research. First, we validate and refine the construct *strategic AI orientation* and its mechanism that links it to technological innovation. Second, we establish a positive AI-innovation relationship from a strategic perspective, enhancing the external validity of research in this domain. Overall, this article offers a starting point for strategic AI research.

1 | Introduction

Digital transformation disrupts corporate innovation (Wetzels 2021). Recently, this is driven by artificial intelligence (AI), particularly machine learning, that is, self-improving algorithms that derive patterns from data to perform cognitive tasks priorly considered exclusively human (LeCun et al. 2015). As AI uncovers previously unconsidered solutions, it may enable innovation, such as identifying novel fragrances (Symrise 2024), drugs (Callaway 2023), and business models (Spanjol and Noble 2023). Due to this transformational impact, research at the nexus of AI and innovation burgeons (e.g., Gama and Magistretti 2025), advancing particularly rapidly at the individual and team levels (e.g., Eicke et al. 2025; Freisinger et al. 2024; Jia et al. 2023).

However, we know little about AI's innovative role at the firm level. While initial research studies firms' productive use of AI and its effects on innovation (e.g., Rammer et al. 2022), we do not know whether the precursor to productive use—firms' strategic orientation toward AI—affects firms' innovativeness. This is vital because, despite the media frenzy about AI, most firms are not yet using AI productively (Dahlke et al. 2024). Instead, firms start to develop an AI orientation: "*strategic direction and*

Summary

- Firms increasingly develop AI strategies. However, the defining features of such a strategic perspective have previously remained ambiguous and our understanding of its impact was limited. Our research tackles these issues; this article provides clear recommendations for the strategic management of AI:
  - A strategic embedding of AI extends beyond AI's technological facet.
  - Firms seeking to develop an AI strategy should consider
    - *capabilities* (e.g., upskilling employees, establishing AI business translators),
    - *technological foundations* (e.g., ensuring data quality, leveraging platforms), and
    - *governance* (e.g., creating AI departments, adhering to a code of conduct).
  - Firms that focus top management attention on AI are more technologically innovative, even across technological areas. Hence, firms should not only leverage AI for efficiency but as well for innovation.
- We outline further practical recommendations in Section 4.3 of this article.

goals associated with introducing and applying AI technology" (J. Li, Li, Wang, and Thatcher 2021, 1604). In practice, an AI orientation reveals managerial attention to AI, manifesting in AI strategies or AI departments (van Giffen and Ludwig 2023). For instance, Pfizer and Boeing have appointed Chief AI Officers, Allianz offers AI education programs for their employees, and Mercedes-Benz has established corporate AI guidelines (Allianz SE 2025; Mercedes-Benz 2025; Wilkinson 2024). Thus, an AI orientation captures firms' strategies to internally address AI's transformative impact, which is important as AI is heralded as a societal engine for productivity and innovation. However, low aggregate productivity gains and the limited productive adoption of AI create fears that AI's impact may be overhyped (Babina et al. 2024). Thus, examining whether there are firms at the cusp of using AI productively helps to understand whether AI's impact is indeed partially a hype but also, if not, which firms are likely to soon exhibit competitive advantage. Developing strategic AI orientation is particularly useful in this regard, as strategic orientations enable the conceptualization and measurement of multidimensional strategic choices across firms and contexts (Venkatraman 1989), especially in the context of innovation (Spanjol et al. 2011). As a result, our study answers calls for empirical research on the relationship between firms' competitive advantage and their development of specialized assets, capabilities, as well as situated agency for AI (Berg et al. 2023; Helfat et al. 2023; Kemp 2024; Krakowski et al. 2023).

The purpose of this article is to answer two connected research questions by employing a sequential explore and test design in two studies (Wellman et al. 2023). In an exploratory **Study I**, we qualitatively explore managerial perceptions of firms' AI orientation to improve our grasp of the concept, asking: *How do firms establish a strategic AI orientation?* We conducted expert interviews with 42 corporate AI managers from different firms in Europe and the United States (US) with a focus on the prevalence of a strategic AI orientation in relation to innovation outcomes. We use the resulting qualitative evidence on AI orientation as a starting point to deductively develop hypotheses for a quantitative **Study II** (Venkatesh et al. 2013; Wellman et al. 2023), asking: *To what extent does a firm's strategic AI orientation affect its technological innovation outcomes?*

Study I reveals that managerial attention to AI is a key enabler for firms' AI orientation and that managers perceive AI orientation to be positively related to firms' technological innovation. Thus, our hypotheses in Study II are guided by the attention-based view (Ocasio 1997) and its insights into managerial orientations and associated innovation outcomes. We hypothesize that a firm's degree of AI orientation is positively related to its technological innovation outcomes. Since the focus of managerial attention depends on managers' experiences (Hambrick and Mason 1984), we also expect a positive moderating effect of the Chief Executive Officer's (CEO) IT experience, a supportive factor for innovation in the digital era (Choi et al. 2021). To test our hypotheses, we use natural language processing to develop a longitudinal, textual measure of firms' AI orientation that captures firms' attention to AI in their annual 10-K filings. Extensive validation, such as expert assessments, a keyword-in-context analysis, and a comparison of algorithmic and manual coding ensures the reliability of the measure. We combine this measure with patent data of the S&P 500 firms between 2012 and 2021. We find that a firm's degree of AI orientation is positively related to its technological innovation output and that a CEO's IT education strengthens this link.

Based on these insights, we contribute to the literature on AI and innovation in two ways. First, we unveil the relevance of the information systems construct AI orientation for the innovation management literature. We use a framework that was intended to guide scholars (managers) in the management of AI (J. Li, Li, Wang, and Thatcher 2021) and validate whether managers perceive it to exist and to be relevant. Validating the construct, our findings lead us to extend it with a particular focus on managerial attention (Ocasio 1997). While AI orientation is originally abstract, we concretize how managerial attention to several building blocks (i.e., top management support, infrastructure, capabilities, organizational artifacts, cooperations, and strategy) acts as a mechanism that connects strategic AI orientation and technological innovation. Thereby, we address calls to disentangle the mechanisms underlying the AI-competitive advantage relationship (Helfat et al. 2023; Kemp 2024). This creates a starting point of inquiry for scholars who study the antecedents of AI use from interdisciplinary perspectives touching innovation, technology, and strategy. Second, we establish a positive AI-innovation relationship from a strategic perspective. This is crucial as AI research is still debating whether AI use fosters or hinders innovation. AI can either enhance it, overcoming humans' cognitive limitations (Eicke et al. 2025), or restrict it, increasing reliance on historical data without the contextual understanding of humans (Choudhury et al. 2020). We contribute to this debate, showing that for strategic AI orientation, the positive influence of AI outweighs its drawbacks. As managerial orientation toward AI as general-purpose technology increases, firms' patent more across technology domains. This insight deepens our understanding of the outcomes of strategic AI orientation and enhances the external validity of AI-innovation research by extending our knowledge beyond single use cases or specific AI technologies (Lou and Wu 2021; Rammer et al. 2022). In doing so, we contribute to more generalizable evidence for conditions under which firms obtain sustained competitive advantage through AI (Helfat et al. 2023). These theoretical contributions offer a starting point for firm-level, strategic AI research.

2 | AI as a Strategic Choice

AI technologies are the most transformative digital technologies of our time, encompassing algorithms that build mostly on machine learning approaches to identify, generalize, and transfer probability structures in datasets (LeCun et al. 2015). As a result, AI technologies classify data points into clusters (discriminative AI), predict potential future outcomes from historical data (predictive AI), and generate textual, graphical, or auditory artifacts (generative AI).

As these AI technologies advance, their use cases evolve from routine- to exploratory tasks (Raisch and Fomina 2025). On the one hand, discriminative and predictive AI assist decision-makers in improving choices in routine tasks (Choudhary et al. 2025). For example, they recommend investments or predict medical treatment options (Burak 2024). On the other hand, predictive and generative AI augment humans in solving complex problems and thus innovating (Eicke et al. 2025; Raisch and Fomina 2025). For instance, predictive and generative AI enabled personalized shoes (Nike 2024) and novel drugs (Callaway 2023). Given this innovative potential, productively using AI enables (technological) innovation (Rammer et al. 2022), that is, to develop and implement new ideas/technology that create value (Damanpour 1991).

Prior work on AI and innovation confirms the positive impact of AI resources on research and development, revealing that they enhance pharmaceutical product development (Lou and Wu 2021). Relatedly, studies highlight AI's value in broadening idea generation, given AI algorithms' ability to discover novel patterns from existing data (e.g., Bouschery et al. 2023; Eicke et al. 2025; Verganti et al. 2020). More concretely, Rammer et al. (2022) focus on firms' use of specific AI technologies, such as image recognition and natural language processing, and find that they positively affect product and process innovation. In contrast, AI may also constrain innovation due to its input incompleteness, its reliance on historical data, and the restriction of background knowledge and routines (Balasubramanian et al. 2022; Choudhury et al. 2020). Given these inconsistent predictions, our understanding of the AI-innovation link remains incomplete.

Foundational to the arguments underlying the AI-innovation link is the assumption that firms productively use AI. However, most firms have not yet used AI productively (McElheran et al. 2024). As a result, scholars have started to focus on the strategic orientation that firms have toward AI (J. Li, Li, Wang, and Thatcher 2021). However, what this perspective encompasses remains mostly opaque.

In general, firm-level orientations reflect firms' foci that steer their activities (Gatignon and Xuereb 1997). Across all foci, such orientations exhibit two features: They direct firm and employee behavior (Y. Li et al. 2010) and help to achieve and sustain competitive advantage as they direct decision-makers' attention to value-adding activities (Spanjol et al. 2011). Hence, firms' degree of AI orientation guides firms' decisions and activities related to AI and is thus likely to affect firm-level outcomes. As such, firms' AI orientation is distinct from an externally oriented market orientation (Noble et al. 2002) or an internally oriented but generic strategic orientation (Venkatraman 1989). It also differs from technological orientation—a firm's general proclivity to use technologies (Gatignon and Xuereb 1997)—since AI's impact differs from prior technologies. AI is distinct as it addresses cognitive tasks previously only attributed to human cognition, which elevate it from a mere tool to an active collaborator (Anthony et al. 2023). Also, in practice, AI receives distinct attention, often in AI departments that operate beside IT departments, which are absent for most other IT, such as blockchain or the metaverse (van Giffen and Ludwig 2023).

Despite scholars' and practitioners' growing interest in the strategic relevance of AI (Raisch and Krakowski 2021), our knowledge of AI as a strategic choice and its consequences for innovation remains limited. Therefore, this study aims to clearly demarcate how firms establish a strategic AI orientation and to what extent it affects firms' technological innovation outcomes. This extends prior studies that take a strategic view but limit their generalizability to a single industry (e.g., Lou and Wu 2021). We offer a conceptualization that spans industries and functions. Further, we extend prior studies that focus on the productive use of AI only (e.g., Igna and Venturini 2023; Rammer et al. 2022; Verganti et al. 2020) by examining the precursor of productive use, the strategic orientation toward AI. Table 1 sets our study in relation to prior research on AI and innovation.

3 | Empirical Studies

3.1 | Research Design Across Studies

Using an explore and test approach (Wellman et al. 2023), we develop an understanding of the construct AI orientation through insights generated from qualitative and quantitative methods in two phases, while adhering to rigorous quality criteria for mixed-methods studies (Park and Ho 2025). First, we conducted a qualitative pre-study based on exploratory interviews with 42 senior AI managers in 41 firms in the US, Germany, Switzerland, the Netherlands, and Spain to ascertain whether firms' AI orientation is perceived as a distinct construct, especially in relation to innovation outcomes. Second, based on the exploratory interviews, which enable us to develop a concrete definition of strategic AI orientation and an intuition of potential relationships between AI orientation and technological innovation outputs, we deductively develop testable hypotheses.

Following the interviewees' emphasis on the key role of top management attention toward AI, these hypotheses are guided by the attention-based view (Ocasio 1997) and its insights into managerial orientations and associated innovation outcomes. Taken together, the interviews help us to understand the phenomenon, establish boundary conditions for the construct, and inform the subsequent hypothesis development on the link

TABLE 1 | Literature on AI and innovation at the firm level.

Study	Methodological approach	Perspective(s)	Measurement of AI	Main finding/reasoning
Babina et al. (2024)	• Quantitative • Secondary data (2010–2018) • ~1700 US firms	Strategic notion	AI employees and AI job postings	Firm-level AI investments increase firm performance through the mechanism of product innovation growth.
Igna and Venturini (2023)	• Quantitative • Secondary data (1995–2016) • ~20,000 European firms	Productive use of AI	AI patents	Firms' experience in the domain of information and communication technology drives innovations in AI.
G. Li, Li, and Sethi (2021)	• Quantitative • Secondary data (2010–2017) • ~1600 Chinese firms	Productive use of AI	AI patents	AI innovation and corporate social responsibility are imperfect substitutes with regard to firm's idiosyncratic risk.
Lou and Wu (2021)	• Quantitative • Secondary data (2010–2019) • ~2000 global firms	Productive use of AI and strategic notion	AI patents and AI job postings	Firms' AI innovation capability enhances the discovery of novel drugs.
Rammer et al. (2022)	• Quantitative • Cross-sectional (2018) • ~6500 German firms	Productive use of AI	Implemented AI methods	The deployment of AI methods positively influences firms' product and process innovations.
Verganti et al. (2020)	• Qualitative • Case studies of 4 US firms	Productive use of AI	Case studies on AI use	AI boosts innovation within firms by enhancing design thinking.
This study	• Quantitative • Secondary data (2012–2021) • US S&P 500	Strategic notion	AI orientation in news articles and shareholder information	AI orientation enhances firms' technological innovation outcomes due to shifts in managerial attention.

between AI orientation and firms' technological innovation. Such a triangulation generates a deep conceptual understanding of the construct and enables an informed interpretation of empirical results (Turner et al. 2017). The following sections describe our research design for both the qualitative (Study I) and quantitative study (Study II).

3.2 | Qualitative Pre-Study I

3.2.1 | Research Approach

We conducted an explorative qualitative study based on expert interviews to understand the core constructs and their relationships (Turner et al. 2017); that is, *how firms establish a strategic AI orientation*, especially in relation to innovation outcomes. Following Goffin et al. (2019), we designed a robust qualitative study to examine the construct strategic AI orientation, with the study being deliberately exploratory. Such an exploratory case study is warranted as the construct of strategic AI orientation has not been theoretically validated, leaving scholars with an incomplete understanding of what it entails. Further, it is not clear to what extent managers see a strategic AI orientation as related to a firm's innovation outcomes. Thus, an exploratory case study is suitable to build new theory or generate a new link to existing theory (Edmondson and McManus 2007). Therefore, we leverage expert interviews as a pre-study for our quantitative follow-on study (Venkatesh et al. 2013), similar to pilot studies in fully qualitative research (Goffin et al. 2019).

Beyond ventures who provide AI for certain tasks as their main business, AI has mostly been used by large, mature firms that have the resources for its deployment (Babina et al. 2024; Rammer et al. 2022). Thus, we chose to sample interviewees from large (multi-)national firms.[1] We chose our interviewees within such firms based on their experience with AI, as firms without dedicated AI roles are unlikely to have experienced a strategic AI orientation and its associated outcomes. We also chose interviewees who are senior so that they are close to the firm's strategy development. Given different hierarchical structures across firms, we use the reporting level to the CEO to compare positions. Our interviewees are between CEO-1 (e.g., vice president) and CEO-4 (e.g., team lead) in firms across 17 sectors (Table 2).[2] Triangulating insights from interviews with managers across firms and sectors ensures a strong substantiation of constructs and hypotheses that apply to a broad range of firms (Eisenhardt 1989; Goffin et al. 2019). Taken together, this theoretical sampling ensures that we can generate adequate theoretical insights (Eisenhardt 1989).

To ensure comparability between interviews while allowing for rich narratives, we developed an interview guide with open-ended questions for the semi-structured interviews. For instance, we asked about the AI managers' responsibilities, the presence or absence of, and triggers of a strategic perspective on AI, intended outcomes, and success factors for the management and adoption of AI. We refined this interview guide after the first five interviews to consistently address emerging themes. The final sample size of 42 interviews emerged from a point of theoretical saturation; that is, additional interviews no longer provided additional insights. All 42 interviews were carried out via the online meeting tool Zoom and lasted between 23 and 81 min (Table 2), resulting in over 400 pages of verbatim transcripts. To avoid researcher bias, two AI scholars who were not involved in the interviews reviewed these transcripts.

To increase rigor, one co-author and one postgraduate research assistant independently analyzed the interviews (Goffin et al. 2019). Consistent with the exploratory nature of Study I, we opted for a robust but flexible analysis approach similar to the methodology suggested by Gioia et al. (2013). In a first step, we iteratively reviewed the transcripts and coded emerging concepts which were grounded in, but not limited to, latent concepts like objectives, structures, and strategies addressed in the interview guide (Mayring 2015). The emerging first-order concepts closely reflect our interviewees' expressions and work realities. In a second step, we abstracted these findings into higher-level second-order themes. To this end, we compared concepts and statements across informants, derived commonalities, captured the commonalities' nature, and assigned them to overarching, exploratory themes (Gioia et al. 2013). We discussed such emerging themes and the assignment of first-order concepts until we reached common conclusions. We further condensed the second-order themes into aggregate dimensions that provide a high-level overview of how firms establish a strategic AI orientation. Appendix S1 illustrates the data structure.

3.2.2 | Findings of Study I

Throughout the interviews, AI managers consistently stressed the strategic relevance of AI. For example, one interviewee exposed that *"[t]here is already [...] a strategy that has defined this [AI] as one of the cornerstones for future existence and growth*," which goes beyond AI technology: *[A]* "*company-wide AI strategy is [...] about business, about organization, about technology, about people, and about responsibility.*" Also, our interviewees stressed the relevance of technological infrastructure, capability building, cooperations, and top management support. Table 3 provides an overview of the technology-, capability-, and governance-related dimensions that define strategic AI orientation, their associated exploratory themes and emergent concepts, and shows illustrative quotes. For a visual summary of the dimensions, see Figure 1. Appendix S3 offers more details. The derived dimensions are anchored in existing conceptualizations of AI orientation (J. Li, Li, Wang, and Thatcher 2021) and AI innovation capability (Lou and Wu 2021) that emphasize AI resources and strategic embeddings.

Drawing on the synthesis and abstraction of these insights, we define strategic AI orientation as firms' *degree of strategically dedicating managerial attention to orchestrating complementary AI-related resources and capabilities with the aim of adding value by deploying AI technologies*. This deepens the definition by J. Li, Li, Wang, and Thatcher (2021), which focuses on strategic directions for AI. First, we specify the necessity of directing managerial attention to AI to ensure strategic priority, as AI-related goals risk becoming marginalized without it. Second,

TABLE 2 | Interview sample.

No.	Position	Industry	Duration (minutes)
1	Manager	Telecommunication	40
2	Team lead	Food	35
3	Partner	Sports	35
4	Department head	Pharma	61
5	Department head	Pharma	55
6	Department head	Financial services	78
7	Department head	Chemistry	81
8	Director	Automotive	55
9	Manager	Aviation	70
10	Department head	Consulting	31
11	Director	Manufacturing	54
12	Director	Chemistry	67
13	Director	Insurance	57
14	Manager	Sports	51
15	Department head	Telecommunication	56
16	Team lead	Insurance	54
17	Director	Sports	70
18	Department head	Insurance	53
19	Department head	Pharma	66
20	Team lead	Financial services	37
21	Vice president	Media	43
22	Director	Pharma	70
23	Director	Medical technology	53
24	Team lead	Medical technology	60
25	Department head	Consumer research	49
26	Department head	Insurance	54
27	Manager	Insurance	43
28	Department head	Insurance	28
29	Department head	Telecommunication	36
30	Team lead	Financial services	34
31	Department head	Technology	44
32	Manager	Technology	44
33	Department head	Insurance	23
34	Department head	Financial services	37
35	Team lead	Telecommunication	43
36	Director	Financial services	42
37	Partner	Auditing	40
38	Department head	Construction	41
39	Director	Chemistry	36
40	Manager	Consulting	35
41	Department head	Automotive	40
42	Manager	Technology	49

we introduce the orchestration of complementary resources and capabilities, as a strategic AI orientation is broader than its technological facet.

Foundational to AI orientation is its strategic notion that extends beyond isolated use cases. While specific AI technologies such as large language models benefit particular use cases such as idea generation in new product development (Bouschery et al. 2023), firms must embed the wealth of AI use cases and related AI technologies they envision in an overarching context. A strategic AI orientation provides a guiding framework for this. As an interviewee from the automotive industry underlines, companies focusing on AI develop "*strategic capabilities that are more long-term, that is 2-3 years. We know that we need specific capabilities to address market needs and trends but how the specific product will look like afterwards is not yet clear.*" In line with this forward-looking perspective, a strategic AI orientation captures firms' future-oriented attention to AI and differs from backward-looking concepts such as AI maturity (Igna and Venturini 2023).

Further, interviewees discuss the clear link between AI and firm innovativeness. An interviewee from a manufacturing firm states that "*Efficiency and product innovation are, I think, the two big drivers. [...] Many firms use AI for efficiency. But you have to be careful that you don't lose sight of [...] product innovation. [...] [It] can be a huge competitive advantage.*" Similarly, an interviewee from a medical technology firm stresses AI's innovation potential to "*open up new business areas.*" These intended outcomes match prior research, highlighting AI's efficiency-improving (e.g., Czarnitzki et al. 2023) and innovation-promoting potential (e.g., Lou and Wu 2021). While efficiency gains are common as firms realize quick wins (Benbya et al. 2020), recent work emphasizes that innovation- rather than efficiency gains drive firms' value creation from AI (Babina et al. 2024).

Taken together, Study I enables us to generate a clearly demarcated definition of strategic AI orientation and a starting point to hypothesize about a direct relationship between the construct and firms' technological innovation outcomes. As a result, we increase our confidence in construct validity and internal validity (Gibbert and Ruigrok 2010), setting up Study II. Regarding external validity, we want to clarify that our assertions are most likely to be generalizable to large, mature firms across industries but may not extend to small firms that do not have dedicated AI resources and shallow resource pools.

TABLE 3 | Dimensions of AI orientation.

Dimension	Exploratory theme	Emergent concept	Definition	Illustrative quote from AI manager
Technology	Technical infrastructure	Data assets	*Quality and quantity of (codified) knowledge and its access*	*"Data quality is a very important aspect, because depending on the data I put in, the result may turn out accordingly" (insurance)*
		Coding and software development	*Development, selection, and integration of technical models and algorithms*	*"I am responsible for a software development team, which is focused on developing software based on machine learning or simply integrating machine learning capabilities" (media)*
		Platforms	*Development and maintenance of centralized information storage for knowledge management*	*"So that you can work with a platform, so to speak, cloud-based platform, where you also centralize all these use cases" (insurance)*
Capabilities	Capability building	Recruitment of AI specialists	*Hiring of professionals with formal education and/or experience valuable for developing and deploying AI technologies*	*"There were initial attempts [...] but they were not data scientists, because the difference is the following, my team are all people who learned this in their studies. So, they really did an education in the field of AI, machine learning" (construction)*
		Upskilling	*Training employees across hierarchical levels to enhance AI-related competencies*	*"There is an AI Education Strategy as well. So, we try to have training on all levels regarding AI" (automotive)*
		Multiplicators	*Establishment of roles to share AI-related knowledge and provide contact persons for centralized AI departments in divisions*	*"AI ambassadors were also created" (automotive)*
		AI business translators	*Training/hiring of professionals who facilitate alignment between technical AI teams and business units to ensure that AI solutions meet business needs*	*"The Analytics Translator is particularly about generating as many ideas as possible together with the business by taking them along on this journey" (telecommunications)*
	Cooperation	Inside the firm	*Facilitation of firm-internal collaboration on AI-related topics across hierarchies/departments*	*"We have a Data Science Community of Practice within our company, where we bring people together across the various organizational units" (sports)*
		Outside the firm	*Engaging with external partners to collaboratively develop/buy technological expertise/systems*	*"In strong interaction with our technology partners, [...]*, i.e., *a Google, a Microsoft, an Open AI" (financial services)*

(Continues)

TABLE 3 | (Continued)

Dimension	Exploratory theme	Emergent concept	Definition	Illustrative quote from AI manager
Governance	Organizational artifacts	AI departments	*Establishment of a centralized, corporate unit specialized in steering and monitoring AI adoption within the firm*	*"The top management has decided that it makes sense to establish a center of excellence around artificial intelligence" (automotive)*
		AI budget	*Allocation of financial and human resources to enhance AI development and adoption*	*"There were, of course, simply major investments made, and I don't think that would have happened if it hadn't been such a strategic priority" (sports)*
		Code of conduct	*Agreement on regulatory/ethical guidelines for the development and adoption of AI technologies*	*"We put out an AI ethics report" (pharma)*
	Top management support	Top management attention	*Company leaders' allocation of time and cognitive resources to AI-related topics and entities within the organization*	*"Attention from the management. I think that's the most important thing of all. If we didn't have that, we wouldn't have got as far as we have" (insurance)*
		Initiation by CEO	*Active, directional intervention by the board of directors, especially the chairperson, to focus on AI-related issues*	*"Our new CEO joined us and made it very clear that our goal was to get into this area [AI], and that's where we made significant investments" (financial services)*
	Strategy	Strategic manifestation	*Development of a (codified) overarching plan regarding the adoption of AI in the firm*	*"So, the AI strategy was commissioned by the corporate strategy because the topic of artificial intelligence is seen as a strategic topic" (aviation)*

FIGURE 1 | Visualization of the findings of study I.

Thus, Study II also tests our assertions with data on large, public firms.

3.3 | Quantitative Study II

3.3.1 | Theory and Hypotheses

In line with our interviewees' emphasis on the top management's attention to AI as a key enabler, we use theories of managerial attention—the extent to which a manager dedicates attention to a specific topic (Ocasio 1997)—to examine the concept of AI orientation. As managerial attention is limited (Ocasio 1997), intensifying the focus on one domain reduces attention to others, thereby indicating priority differences within firms. Against the backdrop of information overload, the allocation of managerial attention is a central strategic decision. Thus, firms demonstrate higher levels of AI orientation if managers direct increased attention toward AI and initiate processes to guide AI adoption (J. Li, Li, Wang, and Thatcher 2021; Y. Li et al. 2010). Considering that managerial attention steers firm behavior (Ocasio 1997), increased managerial attention toward AI orientation likely shapes firms' technological innovation outcomes.

We draw on the attention-based view (Ocasio 1997) to analyze how managing AI relates to technological innovation. Ocasio (1997, 189) characterized attention as "*the noticing, encoding, interpreting, and focusing of time and effort by organizational decision-makers*." The *focus of managerial attention* captures to which elements managers dedicate their awareness so that these elements enter into their consciousness (Ocasio 1997). As managers make strategic choices, their focus of attention steers firm outcomes (Narayan et al. 2021). Also, research on the attention-based view emphasizes AI's potential "*to transcend existing human limits to attention and to address complex interdependencies that humans may not envisage*" (Joseph et al. 2024, 13). Accordingly, we argue that firms' AI orientation goes along with shifts in managerial attention that affect firms' technological innovation. Three arguments support this reasoning.

First, managers who take a forward-looking view on the development of AI-related resources create an environment conducive to innovation. As AI orientation covers strategic directions (J. Li, Li, Wang, and Thatcher 2021), managers develop more long-term goals without expecting immediate returns on investment. Such future orientation amplifies firms' innovation in technologically dynamic settings (Nadkarni and Chen 2014). Simultaneously, managerial focus on AI orientation enables firms to embrace the change required for innovating. By initiating interdepartmental teamwork to create a firm-wide understanding of AI, AI-oriented firms release silo structures and enable idea exchanges. The resulting

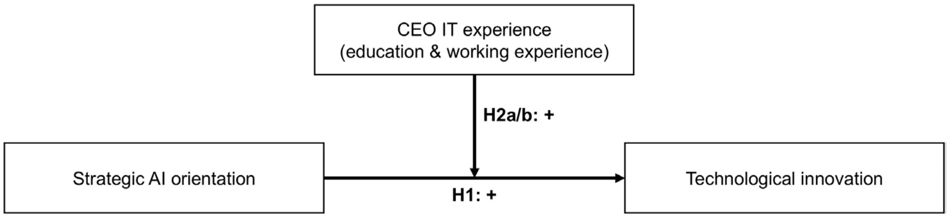

FIGURE 2 | Research model.

collaboration of diverse agents fosters innovation (Miller and Triana 2009).

Second, AI-oriented firms provide a set-up to experiment with AI. Based on the ability of AI technologies to recognize patterns that are hidden to humans (LeCun et al. 2015), using AI allows employees to overcome cognitive impediments in information-rich settings and to discover new insights (Garbuio and Lin 2021). Thus, firm-wide experimentation with AI allows firms to identify novel knowledge and business opportunities. Examples of such innovation-enhancing potential are manifold, covering the detection of novel drugs (Callaway 2023) and the anticipation of successful new TV series like House of Cards (Verganti et al. 2020). Thus, a stronger focus on AI orientation broadens access to innovative opportunities that strengthen firms' technological innovation.

Third, AI-oriented firms' optimized allocation of cognitive resources fosters innovation. As AI applications automate repetitive tasks, managers have more attentional capacity available for time- and attention-intensive activities like fostering innovation. Camuffo et al. (2023) echo this, stating that the AI-driven automation of high-frequency/low-impact decisions frees up attention for low-frequency/high-impact decisions such as innovation. Similarly, psychological mechanisms such as managers' mind-wandering allow for imagination and future simulation (Dane 2018). Such future-oriented thinking and acting promote innovation (Danneels and Sethi 2011), reiterating our assertion that firms' focus on AI enhances innovativeness through a future-oriented, strategic view. Hence, AI orientation enhances firms' allocation of managerial attention to innovation.

To conclude, we argue that a firm's AI orientation increases technological innovation through three mechanisms: establishing an environment conducive to innovation, identifying innovative opportunities, and releasing cognitive resources. This reasoning is consistent with prior work revealing that executives' attention to emerging technology accelerates and intensifies firms' entry into technology-related product markets (Eggers and Kaplan 2009). Thus, we hypothesize:

H1. *A greater degree of strategic AI orientation increases firms' technological innovation.*

Given that managers' choices are a function of their prior experiences (Hambrick and Mason 1984), we investigate the role of individual experiences in transforming a firm's AI orientation into technological innovation outcomes. In general, experiences guide managers' focus of attention and thus their decision-making (Cho and Hambrick 2006). Focusing on the CEO as the most powerful member of the top management team, we suggest that CEOs' IT experience strengthens the link between AI orientation and technological innovation by directing managerial attention toward AI.

CEOs' IT experience covers the dimensions of education and working experience (Choi et al. 2021). IT education reflects a CEO's interest in and knowledge of the technical component of IT (cf. Hambrick and Mason 1984), while IT working experience provides a CEO with an understanding of IT industry dynamics (Kor 2003). Although demographic attributes have limited expressive power regarding CEOs' psychological characteristics, they are suited to study CEOs' experience in a specific functional area such as IT (Choi et al. 2021).

CEOs' IT experience indicates that the CEO has directed her attention to technological issues earlier in her career. This is important as CEOs direct attention to their areas of expertise (Lo et al. 2022). Accordingly, we argue that IT-experienced CEOs experience less attentional friction losses when directing their attention to AI. Thus, IT-experienced CEOs are more likely to focus on AI and—given their expertise with IT—can better convert a firm's AI orientation into innovation by initiating necessary changes. Consistent with our reasoning, CEOs' IT experience strengthens the link between CEO risk-taking and IT innovation, as IT-experienced CEOs are more motivated and self-confident to take IT-related risks (Choi et al. 2021). In summary, the reduction of attentional friction losses gives IT-experienced CEOs an advantage in identifying and leveraging innovative opportunities based on their firms' AI orientation when compared with CEOs without IT experience.

Relatedly, we argue that IT-experienced CEOs orchestrate IT-related resources effectively, strengthening the link between AI orientation and technological innovation. Based on experience, CEOs develop heuristics that direct attention to value-adding resource orchestration activities. Similarly, marketing-specialized CEOs leverage their customer-centricity to identify opportunities and allocate resources effectively (Buyl et al. 2011). This complements work revealing that executives' functional experience enables them to build a climate of support for IT initiatives and favors firms' progressive use of IT (Jarvenpaa and Ives 1991). In summary, IT experience builds expertise in technology-driven innovation such that IT-experienced CEOs strengthen the link between AI orientation and technological innovation. Figure 2 depicts this study's research model.

H2a/b. *The CEO's IT experience in terms of* (*a*) *education and* (*b*) *working experience strengthens the relationship* *between a firm's degree of AI orientation and its technological innovation.*

3.3.2 | Data and Sample

We test our hypotheses using panel data of US listed firms in the S&P 500 between 2012 and 2021. We combine data from text analysis with patent data from USPTO, and firm data from Compustat, BoardEx, and ExecuComp. Further, we use hand-collected data on CEOs' demographics from their official biographies and professional social network profiles (Bendig et al. 2023). Like previous work, we exclude firms without SIC code, non-classifiable firms (SIC 9900–9999), governmental entities (SIC 9100–9199), and financial firms (SIC 6000–6999), as well as those with assets below USD 10 million and an R&D intensity above 1 (Kim and Bettis 2014). Similar to prior work on patents, we aggregate data to parent firms (Arora et al. 2021). The final sample covers 1514 firm-year observations, corresponding to 262 parent firms, from 2012 to 2021. We start our analysis in 2012, as this marks a period when firms began to pay increased attention to AI, triggered by IBM's AI system Watson winning the TV game show Jeopardy due to improved deep learning algorithms (Ferrucci 2012). Besides, 2012 marked a shift in the hardware used for most AI software, using the graphics processing unit (GPU) to run neural network code (The Economist 2024). This setup is generally used today and has led to the rise of Nvidia, supporting the sampling timeframe.

3.3.3 | Measures

3.3.3.1 | Dependent Variable. Firms' technological innovation is commonly measured through patent data, mainly through patent counts (Savage et al. 2020). Thus, we measure technological innovation as the number of granted patents applied for by a firm in a specific year.[3] While patent counts are a common measure for technological innovation, they may fall short of capturing the nuance in innovation. We thus run robustness checks based on firms' technological breadth, that is, patenting in new technology classes, in line with prior work (e.g., Kang and Kim 2020; Wirsich et al. 2016).

3.3.3.2 | Independent Variable. Firm-level data on AI is rare (Raj and Seamans 2019). Despite a recent notable exception (Babina et al. 2024), existing AI measurements are very sample-specific and cannot address strategic AI orientation. For instance, cross-sectional survey data (Rammer et al. 2022) neglect the longitudinal effects of AI orientation. AI patents (Igna and Venturini 2023; Miric et al. 2023), publications at AI conferences (Hartmann and Henkel 2020), and deep AI knowledge on websites (Dahlke et al. 2024) offer a backward-looking view that measures AI maturity instead of AI orientation. While online job postings (Goldfarb et al. 2023) and the acquisition of AI firms (Hartmann and Henkel 2020) offer a strategic view, they are hardly accessible or difficult to scale to large samples. Building a more accessible and scalable measure, J. Li, Li, Wang, and Thatcher (2021) relied on keywords originating from a Forbes article to assess firms' textual data. However, the lack of a comprehensive dictionary and its validation questions this measure's reliability and validity.

Given these shortcomings, we develop and validate a longitudinal, large-scale, and continuous measure of firms' strategic AI orientation. Our measure is replicable and scalable as it relies on publicly accessible data: firms' 10-K filings and news articles. We refine a prior measurement by applying a computer-aided textual analysis (CATA) to 10-K's to build a continuous variable.[4] Through CATA, scholars develop and validate dictionaries consisting of keywords that capture a construct (Matthews et al. 2022). If and how often such keywords appear in text corpora offers valuable information on hard-to-operationalize constructs such as firm behavior and orientation (e.g., Matthews et al. 2022; Schäper et al. 2023). Consistently, the textual measurement of IT-related concepts becomes common (e.g., Engelen et al. 2022). Thus, we develop and validate a dictionary for CATA to grasp a firm's strategic AI orientation. Appendix S4 includes a detailed step-by-step explanation of the measurement creation and its validation.

First, we create an AI orientation dictionary of academic literature based on unsupervised topic modeling, following the approach of Schäper et al. (2023). Topic modeling is "*a text mining approach for automated content analysis developed to identify hidden and latent topic structures in large, machine-readable text corpora*" (Antons et al. 2016, 729). We first establish the text bodies used for topic modeling by searching for research on the management of AI published in management and information systems journals between 2000 and 2022. We identify 335 articles, containing about 3.4 million words. Yet, scholarly articles may overlook topics relevant to firms. Thus, we add 196 consulting reports on the corporate use of AI, capturing strategic questions and use cases, from five leading consulting firms. These reports contain about 600,000 words.

In a second step, we extract the most frequent words using an unsupervised machine learning algorithm for topic modeling (Hannigan et al. 2019). Similar to prior work (e.g., Schäper et al. 2023), the algorithm calculates word frequencies and co-occurrences, based on which it identifies key concepts within the input data. As machine-based text analysis lacks contextual knowledge, we perform manual checks (Pollach 2011), that is, remove words unrelated to the management of AI such as "journal." Finally, we end up with a list of 239 potential keywords.

To avoid measurement errors, extensive manual checks and validation are required (McKenny et al. 2018). We perform three content validation steps to ensure that the keywords reflect the construct: expert assessment, keyword-in-context analysis, and manual coding (Belderbos et al. 2017). First, three AI scholars from computer science, information systems, and management, and three AI practitioners individually assessed our keyword list. If at least four out of six experts rate a keyword as suitable, it remains in the dictionary. This threshold of 67% aligns with validation practices (Belderbos et al. 2017; Matthews et al. 2022) and ensures that at least one scholarly and practical rater agreed to keep the keyword. Second, a keyword-in-context analysis ensures that all keywords unambiguously reflect the construct in the text body of the 10-K's (Belderbos et al. 2017; Krippendorff 2004). Following prior work (Belderbos et al. 2017; Matthews et al. 2022), we manually check 20 randomly selected contextual text snippets per keyword. If the keyword in the original context reflects our construct in at least 60% of all text snippets, we retain it. If this threshold is not reached, we drop the keyword from the dictionary (e.g., the abbreviation ML referred too often to milliliters instead of machine learning). Appendix S4 provides further examples. Third, three trained postgraduate research assistants manually coded 350 annual reports for AI orientation to check whether the dictionary correctly reflects the construct. Their ratings reflect an adequate interrater agreement—intraclass correlation coefficient = 0.917, $\alpha = 0.766$ (Bliese 2000; Krippendorff 2004)—and correspond to the algorithmic classification of firms' AI orientation. These results offer confidence in the constructs' validity. The resulting final dictionary comprises 49 keywords in eight clusters (Table 4). Appendix S4 further provides a sample of keywords within their original context and elaborates on further validity types, including sampling validity, correlational validity, predictive validity, and external validity of our measure.

To measure firms' AI orientation, we analyze firm-specific, textual data. We apply the AI orientation dictionary to 10-K filings from 2012 to 2021 through CATA. Traditionally, CATA-based analyses take the sum of keyword occurrences as proxies (e.g., Becker et al. 2022; Junge et al. 2023). Yet, this includes negatively connotated occurrences that reduce rather than increase the measure, for example, when firms posit AI as a threat to their business. Thus, we perform a sentiment analysis to distinguish between positively, neutrally, and negatively connotated sentences.

Our final proxy, the *AI orientation score*, consists of the sum of positively and neutrally connotated sentences containing keywords from the AI orientation dictionary. Aligned with our theorizing and prior research, the keyword frequency reflects the strategic attention a firm dedicates to a topic (e.g., Junge et al. 2023; Narayan et al. 2021). Controlling for 10-K length, we scale AI orientation as the relative attention a firm devotes to AI throughout the 10-K report. As the attention may vary, we calculate an AI orientation score for each firm-year combination, representing the attention that managers devote to the strategic embedding of AI in a specific year. Consistent with the increasing awareness around AI over time, our variable shows a steady increase, both regarding the mean value of the strategic AI orientation score and regarding the percentage of firms that pay attention to AI as compared with those that do not (from 12% of the sample in 2012 to 50% in 2021).

Since many firms in our sample have not yet adopted an AI orientation, we test our hypotheses using three operationalizations of AI orientation to accommodate this distribution: binary (=1 if any AI orientation keyword), categorical (=3 if top 5%, =2 if < top 5% but > 0 keywords, =1 if 0 keywords), and continuous. This ensures comparability with the existing binary measure of AI orientation (J. Li, Li, Wang, and Thatcher 2021) while still exploiting the richness that our continuous measure offers.

3.3.3.3 | Moderators. Using CEOs' official biographies from annual reports and definitive proxy statements, complemented with data from professional social network profiles and firm websites, we measure CEOs' IT-related education as a binary variable. This variable equals one if the CEO has a university degree in computer science or information systems (Choi et al. 2021). The binary variable of CEOs' IT-related functional working experience is one if she is currently or has formerly served on the board of IT firms and zero otherwise (Bendig et al. 2023; Choi et al. 2021). We classify IT firms based on their presence in high-tech industries (Yu et al. 2019).

3.3.3.4 | Control Variables. As larger firms possess more resources, we control for *firm size* as the natural logarithm of total assets (AT; Compustat denotations). We include *leverage* (DT/AT) as it relates to firms' risk-taking tendency (Boyallian and Ruiz-Verdú 2018). We add *firm profitability* (NI/AT) and *potential slack* (DT/TEQ) as investments in technologies and innovation depend on financial performance and slack resources (Greve 2003). *R&D intensity* (XRD/SALE) controls for firms' tendency to innovate. Like Kim and Bettis (2014), we set missing values of R&D expenditures to zero. We control for *knowledge intensity* (INTAN/AT) and *capital intensity* (REVT/AT) to capture a firm's resources for investing in AI and innovation. We include *industry profitability* (firms' average ROA in the focal firm's industry) to control for the possibility of building slack resources (George 2005). We control for *industry competition* (Herfindahl–Hirschman index of SALE), since competitive pressure affects corporate innovation (Jansen et al. 2006) and for *market turbulence* as the ratio of administrative expenses and sales of firms in the same industry (Saboo et al. 2016), as it captures dynamic customer preferences, potentially driving AI orientation and innovation. Finally, we include the natural logarithm of total words in a firm's 10-K to set the AI orientation score in relation to *document length*. Including document length is common for CATA-based measurements, as longer texts may inherently contain more relevant keywords (Vagnani 2015).

3.3.3.5 | Model Specifications. We forward the dependent variable by 1 year to compare AI orientation to patent filings in the following year. This is justified as firms require time to leverage the benefits of IT. A one-year lag aligns with the time strategic decisions need to influence business value (Taylor and Vithayathil 2018) and reflects the time it takes firms to benefit from IT commitments in terms of innovativeness (e.g., Karhade and Dong 2021). The lag further allows us to exclude AI orientation scores after 2020 to omit pandemic-related issues, potentially biasing text-based measures. As patents are a count variable with solely nonnegative integer values, we run a count-specific panel Poisson regression with firm- and year-fixed effects and robust standard errors.[5] Firm-fixed effects establish a fit between our theorizing and empirical analyses as we analyze how technological innovation differs *within* a firm regarding the firm's strategic AI orientation.

3.3.4 | Results of Study II

Table 5 reports descriptive statistics and correlations. As we include one AI measure per model, high correlations between them are unproblematic. Multicollinearity is no concern with variance inflation factors (VIF) below 5 and an average VIF of 1.60 (Hair et al. 2014). Yet, recent work calls the relevance of VIF into question (Kalnins and Praitis Hill 2025). We follow Kalnins (2018), displaying full correlation and stepwise

TABLE 4 | AI orientation dictionary.

AI orientation dictionary				
Artificial intelligence and machine learning (general)	ai artificial_intelligence augmented_intelligence	cognitive_technology deep_learning human-machine_interaction	intelligent_machine learning_algorithm machine_intelligence	machine_learning ML_model ML_system
Data analytics and business intelligence	advanced_analytics big_data_analytics cognitive_analytics	cognitive_computing data_analytics data_literacy	data_mining data_science data_strategy	
Natural language processing	natural_language_processing	sentiment_analysis	speech_recognition	text_mining
Computer vision	image_recognition	machine_vision		
Predictive AI technologies	prediction_model	predictive_analytics	predictive_maintenance	predictive_modeling
Internet of things and smart systems	autonomous_vehicle intelligent_agent	intelligent_assistant intelligent_automation	internet_of_things IOT	smart_manufacturing
AI algorithms	input_layer generative_adversarial_network knowledge_engineering	knowledge_graph neural_network neuromorphic	output_layer pattern_recognition reinforcement_learning	
Advanced computing	high-performance_computing	quantum_computing		

Note: All permutations of these keywords are included.

TABLE 5 | Descriptive statistics and bivariate correlations.

	Variables	*N*	Mean	SD	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	Technological innovation	1547	231.6	701.6	0	9459	1.00															
2	AI orientation (binary)	1547	0.298	0.458	0	1	*0.22*	1.00														
3	AI orientation (categorical)	1547	1.362	0.599	1	3	*0.25*	*0.93*	1.00													
4	AI orientation (continuous)	1547	1.438	4.870	0	61	*0.25*	*0.47*	*0.67*	1.00												
5	CEO IT experience (education)	1547	0.059	0.235	0	1	*0.33*	*0.15*	*0.20*	*0.21*	1.00											
6	CEO IT experience (work)	1547	0.650	0.477	0	1	*0.18*	*0.27*	*0.29*	*0.22*	*0.17*	1.00										
7	Document length	1547	31,237	14,784	50	98,117	*−0.05*	*0.10*	*0.09*	0.04	0.02	−0.01	1.00									
8	Firm size	1547	9.759	1.098	7.104	12.840	*0.27*	*0.04*	*0.05*	*0.05*	*0.14*	0.01	0.03	1.00								
9	Firm profitability	1547	0.071	0.073	−0.464	0.368	−0.00	*0.07*	*0.06*	*0.07*	−0.02	*0.17*	*−0.09*	*−0.07*	1.00							
10	Potential slack	1547	1.164	16.770	−283.4	383.5	0.01	0.01	0.01	0.00	−0.01	−0.02	−0.01	−0.02	0.02	1.00						
11	Industry profitability	1547	0.057	0.052	−0.317	0.368	−0.04	0.01	0.01	0.00	−0.04	0.03	−0.03	*−0.08*	*0.61*	0.01	1.00					
12	R&D intensity	1547	0.057	0.092	0	0.965	*0.08*	*0.16*	*0.19*	*0.20*	*0.16*	*0.28*	*0.22*	*−0.14*	0.01	0.01	0.02	1.00				
13	Leverage	1547	−1.392	0.811	−13.26	0.139	−0.01	*−0.05*	*−0.08*	*−0.06*	−0.03	*−0.05*	0.00	*0.16*	*−0.14*	0.00	−0.03	*−0.19*	1.00			
14	Industry competition	1547	0.556	0.295	0.088	1	−0.02	−0.04	*−0.06*	*−0.09*	−0.03	*−0.24*	*−0.05*	*0.16*	*−0.07*	0.02	0.01	*−0.36*	*0.09*	1.00		
15	Knowledge intensity	1547	−1.791	1.747	−10.28	−0.117	−0.02	*0.13*	*0.12*	*0.06*	0.04	*0.12*	*0.05*	−0.03	0.02	0.01	*0.11*	0.00	*0.13*	−0.03	1.00	
16	Capital intensity	1547	−0.352	0.573	−2.030	1.714	−0.02	*−0.06*	*−0.07*	*−0.05*	−0.05	*−0.18*	*−0.20*	*−0.16*	*0.21*	0.04	*0.20*	*−0.25*	*−0.08*	*0.28*	*−0.05*	1.00
17	Market turbulence	1547	−1.728	0.864	−7.127	−0.135	*0.07*	*0.12*	*0.15*	*0.12*	*0.10*	*0.26*	*0.12*	*−0.29*	*0.13*	0.02	*0.11*	*0.39*	*−0.07*	*−0.24*	*0.20*	*−0.25*
	Number of parent firms	303																				

Note: All significant bivariate correlation coefficients are displayed in italics ($p < 0.05$). The variables size, leverage, knowledge intensity, capital intensity, and market turbulence are logarithmized.
Abbreviations: Max, maximum; Min, minimum; *N*, observations; SD, standard deviation.

regression tables to examine both closely. No independent variable exceeds a correlation of much larger than |0.3| with any other variable, mitigating multicollinearity concerns (Kalnins 2018). Also, correlations between independent and dependent variables are of the same sign as the β coefficients, reducing concerns (Kalnins 2018).[6]

Table 6 shows the regression results. The first model for each measure of the independent variable, that is, binary (Model 1, $\beta = 0.485$, $p = 0.055$), categorical (Model 4, $\beta_{\text{categorical}=2} = 0.461$, $p = 0.060$; $\beta_{\text{categorical}=3} = 0.706$, $p = 0.020$), and continuous (Model 7, $\beta = 0.023$, $p = 0.015$), provides evidence for H1 as AI orientation is significantly positively related to technological innovation. The continuous measure of AI orientation picks up nuances in firms' strategic AI orientation. In contrast, the coefficients of the binary and categorical measures are largest and least conservative with a slightly weaker significance level. This may mean that binary and categorical measures are too coarse to detect nuances in firms' strategic AI orientation. In terms of economic significance, firms that have a strategic AI orientation when compared with those that do not (Model 1, binary) exhibit a 62% increase in granted patents. Using the continuous variable (Model 7), an increase in AI orientation by two standard deviations (SD) is associated with a 25% increase ($\exp(\beta \times 2SD) - 1$) in granted patents (Wooldridge 2013). Given a median market price for a patent of $225,000 (Bloomberg Law 2020), this increase corresponds to $56,250. This multiplies for high-tech firms that rely on patents for intellectual property protection and exhibit a high degree of AI orientation: Firms scoring high in AI orientation can face potential market gains of up to $530 million.[7]

Our results partially confirm the moderating effect of CEO IT experience. In general, the results support a positive moderating effect of CEO IT education. The interaction terms between the binary (Model 2, $\beta = 1.425$, $p = 0.017$), categorical (Model 5, $\beta_{\text{categorical}=2} = 1.369$, $p = 0.027$; $\beta_{\text{categorical}=3} = 1.511$, $p = 0.005$), and continuous variables (Model 8, $\beta = 0.037$, $p < 0.001$) of AI orientation and CEO IT education are significantly positive. However, there are inconsistencies in the strength of the moderating effect of CEOs' IT working experience. These inconsistencies seem to follow our prior discussions about the appropriateness of measuring strategic AI orientation with binary and categorical variables. On the one hand, the interaction term between AI orientation (binary) and CEO IT working experience (Model 3, $\beta = 0.564$, $p = 0.123$) and the interaction term between the categorical variable AI orientation (2nd category) and CEO IT working experience (Model 6, $\beta = 0.487$, $p = 0.204$) are insignificant. On the other hand, the interaction term between AI orientation (categorical, 3rd category) and CEO IT working experience (Model 6, $\beta = 0.691$, $p = 0.028$) and the interaction term between AI orientation (continuous) and CEO IT working experience (Model 9, $\beta = 0.023$, $p < 0.001$) become more nuanced and significant. Taken together, these results indicate that the association between firms' AI orientation and technological innovation is stronger for firms whose CEO has IT-related knowledge in the form of IT education. This effect seems to be weaker for IT-related working experience. Figure 3 illustrates the moderating effects. There are many reasons why IT-related education may be different from IT-related working experience. One difference may be that education for most executives generally predates working experience and thus creates stronger imprints on behavior and technological capabilities (Dalziel and Basir 2024).

3.3.5 | Robustness Checks

We conduct robustness tests of our findings (Table 7) for which we vary the (1) operationalization of the independent variable, (2) dependent variable, and (3) sample. This ensures that our assertions are not driven by unique empirical choices but are generalizable to different measures and samples.

We first test the robustness of our AI orientation measure. First, we winsorize the continuous AI orientation measure and rerun the regressions because a small group of highly AI-oriented firms may drive our findings. This is not the case, and the results hold (Models 1–3). Second, we include negatively connotated sentences with AI keywords, as firms may treat AI strategically by stating risks in their 10-K or by commenting negatively on their competitors' AI-related efforts. Our results hold (Model 4). Third, we address the concern that 10-Ks may be biased to create an advantageous impression. Since firms cannot directly influence media coverage, we rerun our analyses with a measure of AI orientation based on 200,000 news articles from renowned publishers accessed via Factiva. Our results hold (Models 5–7). Fourth, we replace the text-based measure of AI orientation with a continuous measure of firms' stock of AI employees, that is, the number of employees with AI-related job profiles, previously established by Babina et al. (2024). The results provide additional confidence in our findings (Models 8–10). Finally, we replace AI orientation with *explorative* AI orientation. In line with measuring exploration vs. exploitation focus dichotomously (Uotila et al. 2009), this analysis classifies positively or neutrally connotated sentences with at least one keyword from the AI orientation dictionary as exploratively AI-oriented if the respective sentence contains more keywords from an existing exploration than from an exploitation dictionary (Matthews et al. 2022). Such explorative AI orientation is significantly positively related to firms' technological innovation (Model 11), strengthening our findings.

Subsequently, we test the robustness of our dependent variable, technological innovation. First, we replace patent counts with a measure of firms' breadth in technological innovation. Breadth is operationalized as the yearly number of patent filings within technology classes (Cooperative Patent Classification system) that a firm did not explore within the past 5 years (Kang and Kim 2020). Our results hold for breadth (Model 12). Second, we address a potential truncation bias, as patents filed at the end of the sampling period are not yet granted and are thus omitted in the data. Following the suggestion of Lerner and Seru (2022), we test for the robustness of our findings by (1) excluding the last years of the sample, limiting our analyses to the years 2012–2018 to account for delays in patent granting, and (2) omitting the computer, electronics, and chemical industries as these exhibit a disproportionately high patenting propensity. Our results hold for all checks (Models 13–14). Finally, even though patents are a widely accepted innovation measure (Savage et al. 2020), we check whether AI orientation is equally related to alternative

TABLE 6 | Panel Poisson regression results.

DV: Tech. inno.	Binary AI orientation			Categorical AI orientation			Continuous AI orientation		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AI orientation	**0.485†**	0.012	0.146				**0.023***	−0.003	0.001
	(1.92)	(0.18)	(1.40)				(2.44)	(−0.53)	(0.09)
CEO IT education		−1.296*			−1.319*			−0.349**	
		(−2.40)			(−2.48)			(−2.63)	
AI orientation × education		**1.425***						**0.037*****	
		(2.39)						(4.97)	
CEO IT work			−0.449†			−0.434†			−0.212
			(−1.87)			(−1.78)			(−1.57)
AI orientation × work			**0.564**						**0.023*****
			(1.54)						(3.48)
AI orientation (categorical = 2)				**0.461†**	0.013	0.171†			
				(1.88)	(0.22)	(1.72)			
AI orientation (categorical = 3)				**0.706***	0.131	0.169			
				(2.33)	(1.03)	(1.33)			
AI orientation (=2) × education					**1.369***				
					(2.21)				
AI orientation (=3) × education					**1.511****				
					(2.81)				
AI orientation (=2) × work						**0.487**			
						(1.27)			
AI orientation (=3) × work						**0.691***			
						(2.20)			
Firm size	−0.318	−0.194	−0.262	−0.289	−0.148	−0.246	−0.248	0.067	−0.220
	(−1.38)	(−1.00)	(−1.20)	(−1.25)	(−0.75)	(−1.12)	(−0.99)	(0.33)	(−0.92)
Firm profitability	−0.238	−1.119**	−0.080	−0.188	−1.020***	0.003	−0.195	−0.590†	0.160
	(−0.56)	(−3.13)	(−0.18)	(−0.46)	(−3.37)	(0.01)	(−0.48)	(−1.67)	(−0.40)
Firm potential slack	−0.000	0.001	0.000	−0.000	0.001	−0.000	−0.000	0.001	−0.000
	(−0.04)	(1.30)	(−0.36)	(−0.19)	(1.19)	(−0.43)	(−0.61)	(0.86)	(−0.65)
Industry profitability	0.626	1.269†	0.317	0.509	1.152†	0.187	0.182	0.359	0.083
	(1.15)	(1.78)	(0.70)	(0.98)	(1.77)	(0.41)	(0.43)	(0.84)	(0.20)
Firm R&D intensity	0.706	−0.237	0.768	0.691	−0.101	0.833	1.509	1.913	1.684
	(0.46)	(−0.22)	(0.46)	(0.45)	(−0.09)	(0.51)	(0.83)	(1.34)	(0.94)
Firm leverage	−0.055	0.012	−0.069†	−0.059	0.001	−0.070†	−0.103*	−0.082	−0.102*
	(−1.27)	(0.21)	(−1.75)	(−1.36)	(0.02)	(−1.80)	(−2.22)	(−1.29)	(−2.33)
Industry competition	0.315	0.029	0.191	0.325	0.028	0.191	0.087	−0.195	0.055
	(0.87)	(0.15)	(0.70)	(0.91)	(0.14)	(0.69)	(0.35)	(−0.68)	(0.23)
Firm knowledge intensity	0.028	0.104	0.004	0.031	0.097	−0.000	0.069	0.049	0.064
	(0.35)	(1.37)	(−0.05)	(0.39)	(1.23)	(0.00)	(0.71)	(0.54)	(0.66)

(Continues)

TABLE 6 | (Continued)

DV: Tech. inno.	Binary AI orientation			Categorical AI orientation			Continuous AI orientation		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Firm capital intensity	−0.433*	0.090	−0.388†	−0.343	0.182	−0.347†	−0.339	0.189	−0.350
	(−1.96)	(0.63)	(−1.90)	(−1.60)	(1.25)	(−1.66)	(−1.52)	(0.93)	(−1.64)
Market turbulence	0.389	0.219	0.434	0.422	0.282	0.444	0.551	0.872*	0.530
	(1.33)	(1.00)	(1.45)	(1.41)	(1.20)	(1.48)	(1.47)	(2.17)	(1.45)
Document length	−0.000***	−0.000***	−0.000***	−0.000***	−0.000*	−0.000***	−0.000*	−0.000	−0.000†
	(−3.60)	(−3.33)	(−4.63)	(−3.58)	(−2.49)	(−3.23)	(−2.10)	(−0.74)	(−1.88)
Year and firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log pseudolik.	−23,322	−13,730	−22,143	−22,967	−13,517	−21,962	−24,479	−18,690	−24,252
Wald Chi^2	268.20	453.44	201.40	246.84	821.73	379.71	426.93	764.88	445.47
Pseudo R^2	0.324	0.594	0.357	0.330	0.600	0.362	0.292	0.456	0.299
Firm-year obs.	1514	1188	1514	1514	1188	1514	1514	1188	1514
Firms	262	222	262	262	222	262	262	222	262

Note: The *t* statistics in parentheses. $^{\dagger}p<0.10$, $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$. Size, leverage, knowledge intensity, capital intensity, and market turbulence are logarithmized. We use McFadden's Pseudo R^2, calculated as $1-\frac{\text{loglikelihood of full model (Poisson)}}{\text{loglikelihood of constant only model (Poisson)}}$. Pseudo R^2 using deviances easily reach values of 0.3 (Mittlböck and Waldhör 2000) and are thus to be interpreted with caution.
Abbreviations: DV, dependent variable; FE, fixed effects; obs, observations; pseudolik, pseudolikelihood.

innovation measures: the propensity of new technological product introductions (Bendig et al. 2023), the scope of markets that a firm operates in (Hoberg and Phillips 2025), the market value of patents (Kogan et al. 2017), and sales growth ($\text{sales}_t/\text{sales}_{t-1}$) (Schulz et al. 2023). We find that firms' AI orientation is positively associated with all these outcomes (Models 15–18), supporting our findings.

Finally, we probe the robustness of our findings to sample changes. Following our theorization, our results should be pronounced in the high-tech sector. Focusing on high-tech firms shows that our results hold with mostly larger coefficients (Models 19–21). Further, AI orientation also relates positively to technological innovation in a larger sample of S&P 1500 firms (Model 22).

Taken together, we provide a wide array of robustness checks that increase the reliability of our findings. Nevertheless, bias may be present. To assess the likelihood of such bias, we probe the sensitivity of our main estimates to omitted variables. Using the robustness of inference to replacement approach (Frank et al. 2013), we find that 18.41% (binary), 20.47% (categorical), and 29.85% (continuous) of our observations would need to be replaced with zero-effect observations to invalidate our results (Xu et al. 2019). Thus, omitted variables are unlikely to bias our results.[8]

3.3.6 | Accounting for Endogeneity in Terms of Simultaneous Causality

We posit that a firm's degree of AI orientation increases its technological innovation. Yet, this relationship may also suffer from reverse causality, as technologically innovative firms may be more likely to use AI since they take technological risks. Thus, our independent variable would be correlated with the error term of the dependent variable, introducing a bias to our results. To address this endogeneity concern, we use an instrumental variable approach, two-stage least squares (2SLS), as it is particularly suited for addressing reverse causality concerns (Hill et al. 2021).

For a 2SLS, the instrument must be strongly related to the endogenous variable AI orientation (relevance condition) and unrelated to the error term (exogeneity condition), which means only predicting technological innovation through a firm's AI orientation (Kennedy 2008). We use the prevalence of dedicated data analytics or AI managers in a firm's industry (four-digit SIC codes) as an instrument. We measure such prevalence through the sum of dedicated management roles within the industry excluding the focal firm. Similar to prior work (e.g., Bendig et al. 2023; Nath and Bharadwaj 2020), we hand-collect data on firms' data analytics or AI managers from firm websites, extensive web searches, and professional social network profiles.

Our instrument is relevant as firms set goals based on their peers' behavior (Cyert and March 1963). Also, the Cragg and Donald (1993) F-test rejects the null hypothesis of a weak instrument. Further, we expect our instrument to be exogenous. While firms likely monitor their peers' strategic decisions, firms cannot directly influence their peers' decision to employ AI managers. We perform a 2SLS for the binary, categorical, and continuous measures (Table 8). The *F*-statistics of 21.87 (Model 2), 38.22 (Model 4), and 38.62 (Model 6) exceed the critical threshold of 10 and the Stock and Yogo (2005) weak identification test's critical value of 10%. In all tests, the coefficient of our instrumental variable is significantly positive in the first stage (Models 1, 3, and 5) and AI orientation remains significantly positively related to technological innovation

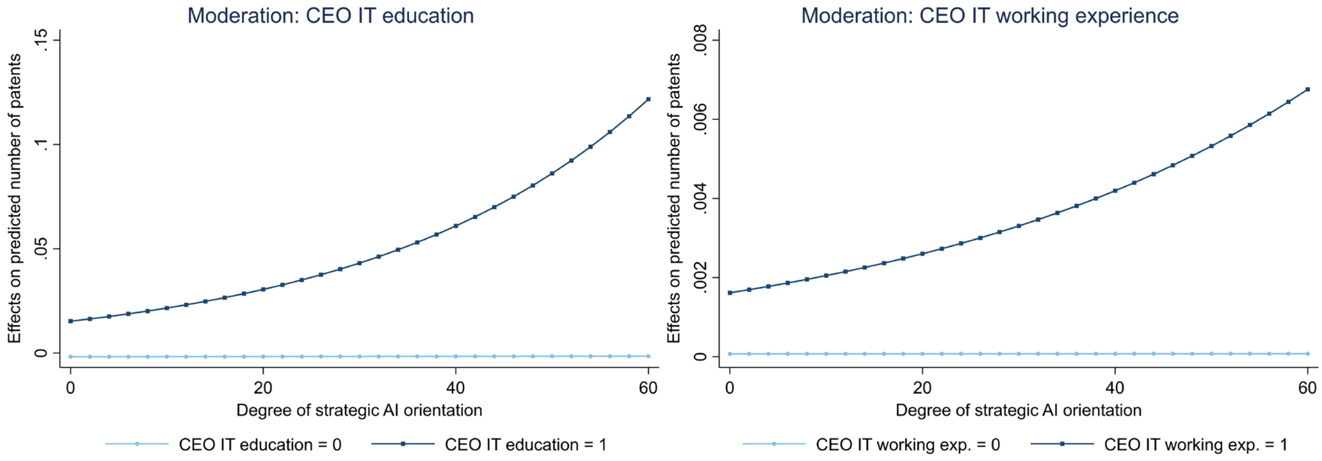

FIGURE 3 | Interaction plots. The figure illustrates the predictive margins of the interaction between the continuous measure of AI orientation and CEO IT education (Table 6, Model 8) and CEO IT working experience (Table 6, Model 9).

(Models 2, 4, and 6). This mitigates concerns of reverse causality and also addresses potential concerns of multicollinearity (Kalnins and Praitis Hill 2025) and omitted variables (Hill et al. 2021).

4 | Discussion and Implications

4.1 | Discussion of Research Findings

Inspired by the transformative potential of AI for firms (Raisch and Krakowski 2021), we asked two research questions: *How do firms establish a strategic AI orientation? To what extent does a firm's strategic AI orientation affect its technological innovation outcomes?* Using a sequential explore and test design with a qualitative pre-study and a quantitative main study, we further develop the construct of strategic AI orientation. Taken together, both studies indicate the presence of a strategic AI orientation in large, mature firms and its positive association with technological innovation through the mechanism of managerial attention.

First, our qualitative pre-study indicates that managerial attention to AI is expanding, covering both the technology itself and, more recently, also the overarching strategic management of AI. According to our interviewees, this is largely driven by the top management's focus on AI. Answering a recent call for research on how to capture value from AI (Berg et al. 2023), our focus on managerial attention offers a valuable perspective to understand why the sole availability of complementary resources is insufficient to create value from AI. Instead, managerial attention to AI ensures a targeted orchestration of complementary resources to achieve AI-related strategic goals. Thus, the perspective of managerial attention substantiates that technology is not limited to the operational level but is also a strategic choice (e.g., Gatignon and Xuereb 1997; Guo et al. 2020).

Second, our quantitative main study indicates that greater AI orientation positively relates to a firm's technological innovation output *across* technological domains. Extending the view of AI as a general-purpose technology (Goldfarb et al. 2023), our finding shows that firms' strategic AI orientation functions as a broad enabler of technological innovation, potentially enhancing firms' agility and learning. This is intriguing as it contrasts with the impact of productively using AI as a substitute for humans, which jeopardizes learning by reducing routine and background knowledge diversity (Balasubramanian et al. 2022). In contrast, our empirical evidence suggests that a firm-wide AI orientation enhances cross-domain collaboration, enabled by managerial oversight.

Third, we find that CEOs' IT education, as a proxy for understanding the technical component of AI, strengthens the relationship between strategic AI orientation and technological innovation. Interestingly, CEOs' prior IT working experience does not consistently strengthen the relationship. This is interesting, as IT working experience is often seen as a proxy for the knowledge of industry dynamics and thus as knowledge about the orchestration of complementary resources to create value from technology. However, IT working experience might be less impactful due to AI's recent emergence in firms' day-to-day use and its clear differentiation from previous digital technologies (McElheran et al. 2024). Thus, CEOs may lack sufficient long-term experience with industry dynamics in the AI era. Besides, education precedes working experience and thus leaves stronger cognitive and behavioral imprints (e.g., Dalziel and Basir 2024). As a result, IT education rather than working experience seems to enable CEOs to navigate the AI transformation. We elaborate on the theoretical contributions that arise from these findings in the next chapter.

4.2 | Theoretical Contributions

Scholarly interest at the intersection of technology and innovation management has increased exponentially given digital technologies' disruptive role for innovation (e.g., Benbya et al. 2024; Wetzels 2021). The increasing relevance of AI, accelerated through the development of generative AI, works like a prism, opening more diverse unanswered questions at the nexus of AI and innovation management (Bouschery et al. 2023). Particularly, firm-level research on AI's role for innovation outcomes has many unanswered questions, mainly due to a lack

TABLE 7 | Robustness checks.

	Robustness of findings to changes in the operationalization of the independent variable										
	Winsorized			Sentiment	News articles			AI employees			Explorative AI
DV: Tech. inno.	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**
AI orientation	0.035*	−0.002	0.002	0.014*	0.001*	−0.000	0.000**	0.000*	0.000	0.000***	0.060***
	(2.57)	(−0.15)	(0.19)	(2.08)	(2.14)	(−1.39)	(2.80)	(2.11)	(0.05)	(3.65)	(3.30)
CEO IT education		−0.418*				−0.340			−0.254		
		(−2.57)				(−1.65)			(−1.53)		
AI orientation × IT education		0.050***				0.001*			0.000*		
		(3.42)				(2.23)			(2.30)		
CEO IT work			−0.255†				−0.075			−0.004	
			(−1.79)				(−0.89)			(−0.05)	
AI orientation × IT work			0.035***				0.001*			0.001**	
			(4.36)				(2.05)			(2.85)	
Full controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log pseudolik.	−24,374	−18,641	−23,967	−24,805	−16,457	−13,949	−14,879	−18,235	−15,555	−15,069	−25,090
Wald Chi^2	287.72	498.39	268.04	193.96	503.36	593.06	7878.05	527.22	822.05	7507.28	1358.41
Pseudo R^2	0.295	0.457	0.307	0.283	0.525	0.597	0.569	0.468	0.545	0.556	0.275
Regression type	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson
Firm-year obs.	1514	1188	1514	1514	819	681	819	1381	1116	1381	1514
Firms	262	222	262	262	165	142	165	244	210	244	262

	Robustness of findings to changes in the operationalization of the dependent variable							Robustness of findings to sample changes			
	Breadth	Until 2018	Exclude industries	Tech products	Firm scope	Patent value	Sales growth	High-tech firms			S&P 1500
DV: Tech. inno.	**(12)**	**(13)**	**(14)**	**(15)**	**(16)**	**(17)**	**(18)**	**(19)**	**(20)**	**(21)**	**(22)**
AI orientation	0.026***	0.029*	0.035***	0.039**	0.092*	770.362*	0.003†	0.024**	0.002	−0.001	0.023*
	(4.31)	(2.59)	(3.87)	(3.08)	(2.13)	(2.11)	(1.83)	(2.77)	(0.37)	(−0.11)	(2.50)
CEO IT education									−0.361*		
									(−2.57)		

(Continues)

TABLE 7 | (Continued)

	Robustness of findings to changes in the operationalization of the dependent variable							Robustness of findings to sample changes			
	Breadth	**Until 2018**	**Exclude industries**	**Tech products**	**Firm scope**	**Patent value**	**Sales growth**	**High-tech firms**			**S&P 1500**
DV: Tech. inno.	**(12)**	**(13)**	**(14)**	**(15)**	**(16)**	**(17)**	**(18)**	**(19)**	**(20)**	**(21)**	**(22)**
AI orientation × IT education									0.034***		
									(4.34)		
CEO IT work										−0.148	
										(−1.35)	
AI orientation × IT work										0.027***	
										(4.18)	
Full controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log pseudolik.	−4859	−21,145	−17,445	—	—	—	—	−19,141	−15,571	−18,943	−29,195
Wald Chi^2/F	892.91	347.52	742.22	71.43	2.14	4.31	16.99	626.53	1024.46	893.51	362.08
Pseudo R^2	0.342	0.292	0.409	0.037	0.058	0.160	0.285	0.363	0.480	0.369	0.291
Regression type	Poisson	Poisson	Poisson	GEE	OLS	OLS	OLS	Poisson	Poisson	Poisson	Poisson
Firm-year obs.	1531	1315	1219	1049	1555	1327	1559	894	673	894	2859
Firms	266	253	210	208	294	233	294	149	123	149	529

Note: The t statistics in parentheses. Year- and firm-FE included. $^{\dagger}p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.
Abbreviations: GEE, generalized estimating equations; OLS, ordinary least squares.

TABLE 8 | Instrumental variable regression.

	Binary AI orientation		Categorical AI orientation		Continuous AI orientation	
	(1) First stage (DV = AI)	**(2) Second stage (DV = Tech. inno.)**	**(3) First stage (DV = AI)**	**(4) Second stage (DV = Tech. inno.)**	**(5) First stage (DV = AI)**	**(6) Second stage (DV = Tech. inno.)**
AI orientation		2103.996***		1300.136***		152.855***
		(4.29)		(5.35)		(5.65)
Industry AI manager prevalence	0.047***		0.075***		0.641***	
	(4.68)		(6.18)		(6.21)	
Cragg–Donald Wald *F* statistic		21.87***		38.22***		38.62***
Stock–Yogo critical values (10% max. IV size)		16.38		16.38		16.38
Firm-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Full controls included	Yes	Yes	Yes	Yes	Yes	Yes
Firm-year observations	1531	1531	1531	1531	1531	1531
Firms	266	266	266	266	266	266

Note: The t statistics in parentheses. $^{\dagger}p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.
Abbreviation: DV, dependent variable.

of firm-level AI data. We address the need for more research in this area by (1) unveiling the relevance of the information systems construct AI orientation for the innovation management literature and by concretizing its mechanisms as well as (2) establishing AI orientation's relationship with firms' technological innovation outcomes. We outline the relevance of these contributions for different audiences in management research below.

First, we contribute to innovation management research by unveiling the relevance of the information systems construct AI orientation, including refining it by establishing its building blocks and highlighting its importance for innovation and strategy research. While AI orientation was intended as a framework that guides scholars (managers) in examining how firms invest in, manage, and apply AI (J. Li, Li, Wang, and Thatcher 2021), it has not been studied whether managers perceive it to exist, ascribe a strategic relevance to it, and how firms develop such a strategic AI orientation. Thus, we validate the construct with a qualitative study and extend the construct and its definition with a particular emphasis on managerial attention. While the original definition focuses on a firm's strategic direction in a more abstract way, we highlight that such a direction is contingent on managerial attention to several building blocks: technical infrastructure, capability building, organizational artifacts, cooperations, top management support, and strategy (Table 3). As a result, our study is useful for innovation and technology management scholars who seek more in-depth insight into the concrete steps firms take to embed AI strategically. Highlighting these mechanisms through which strategic AI orientation and competitive advantage are linked ultimately addresses calls for empirical research on the relationship between firms' competitive advantage and their development of specialized assets, capabilities, as well as situated agency for AI (Berg et al. 2023; Helfat et al. 2023; Kemp 2024). Further, we also address a call for research on the changing nature of organizing and the attention-based view (Joseph et al. 2024). While we know much about large hierarchical firms, our qualitative pre-study shows, in addition, how large firms establish completely new topics, such as AI, within their established structures by focusing on multiple but related dimensions, such as technology, capabilities, and governance. Taken together, we provide novel insights at the intersection of innovation, technology, and strategy that extend our understanding of the construct strategic AI orientation and establish mechanisms through which it affects firms' competitive advantage.

Second, we establish a positive link between AI and innovation from a strategic perspective. This is vital, as AI scholarship is still debating whether firms' AI use may foster or hinder innovation. On the one hand, deploying AI could enhance innovation by overcoming humans' cognitive limitations, identifying data patterns, and enabling humans to focus on complex tasks (Eicke et al. 2025; Jia et al. 2023; Sturm et al. 2021). On the other hand, its input incompleteness, reliance on historical data, and the restriction of organizational background knowledge may inhibit innovation (Balasubramanian et al. 2022; Choudhury et al. 2020). We take a stance in this debate by highlighting the positive effects of a strategic orientation toward AI that increases firms' patenting outcomes across technology domains. Our article reveals that for strategic AI orientation, the positive influence of AI seems to outweigh its drawbacks, as managers' attention to the strategic embedding of AI enhances their firms' technological innovativeness. This is important in two ways. First, prior research on strategic AI orientation had not examined its relationship with technological innovation outcomes. By establishing this link, we deepen the understanding of the consequences of firms' strategic AI orientation. Second, prior work on AI use and innovation had only focused on a subset of firms that have productively integrated AI in their product and service offerings (e.g., Igna and Venturini 2023; Rammer et al. 2022; Verganti et al. 2020). However, focusing only on firms with a mature use of AI limits the external validity of studies, as it compels scholars to focus on specific use cases (Verganti et al. 2020) or types of AI technologies such as image recognition or natural language processing (Rammer et al. 2022). Although important, this limits the generalizability to other use cases and AI technologies. We enhance the external validity by taking the reality of most firms into account, which are preparing for the AI transformation but are far from intensively integrating AI into their products and services. As such, we position a holistic strategic perspective on AI simultaneously as a prerequisite and continuous facilitator of productive AI use. Importantly, our findings also strengthen the internal validity of AI and innovation research. Studying the link between strategic AI orientation and multiple facets of firms' innovativeness, as well as firm growth and scope in robustness tests (Tables 6 and 7), we validate AI's theoretical impact as general purpose technology. Enhancing the internal validity in such ways is key to accumulating a body of research that provides nuanced insights which ultimately allow us to infer under which conditions firms obtain sustained competitive advantage through AI (Helfat et al. 2023). Overall, these contributions enhance innovation and strategy research in times of AI.

4.3 | Practical Implications

AI has a more transformative impact on firms than most other technologies as it greatly affects firms' knowledge creation. However, we show that firms only obtain such benefits with managerial focus, adapting organizational structures, governance mechanisms, and resources. Drawing on the qualitative results (Table 3), our general managerial recommendation is to think about AI holistically; that means not only about the technological capabilities but also about the necessary concomitant changes to firm strategies and operations, which are the enablers of innovation benefits from AI. This overarching recommendation can also be segmented into steps.

First, consider people as much as technology. Hiring and training employees with measurable AI literacy is vital to leverage AI's full potential in terms of innovativeness while avoiding unprofitable investments from undirected AI use. Importantly, managers must understand AI's transformative potential and ensure its strategic embedding. Consistently, we find that CEOs with formalized IT education can better convert an AI strategy into technological innovation outcomes. Hence, appointing tech-savvy managers is key to unlocking AI's potential. Second, managers should adjust the firms' structure to enable specialization and interdepartmental collaboration simultaneously. Interviews with senior AI managers reveal the value of specialized AI departments to maintain an overview, while AI business translators and multiplicators spread AI-related knowledge and AI impact cases within the firm. Third, managers should leverage AI's innovative potential. We show that a greater AI orientation increases firms' innovativeness across technological domains. By leveraging this innovation potential, a greater AI orientation not only supports firms' existing business and technology strategies but can redefine them.

4.4 | Limitations and Future Research

Despite careful theorizing and extensive analyses, our study is not without its limitations. First, although our reasoning is thoroughly embedded in the attention-based view, we do not explicitly test a mediating effect of managers' focus of attention, as such a focus in large samples is generally also measured through CATA (Zhong et al. 2021) just as AI orientation. Thus, a mediation analysis would examine the link between keyword sets, having limited expressive power. Hence, we use an extensive qualitative pre-study to provide initial support for this mechanism as interviewees stress their firm's strategic orientation toward AI. This opens opportunities for future research that we could not address in our design. For instance, future studies may examine through which channels firms develop managerial attention toward AI and how they internalize related knowledge, such as through acquisitions of AI startups, hiring of AI managers, or alliances with specialized AI firms.

Second, according to our results, an AI orientation relates positively to firms' technological innovation across technological domains. However, we currently do not study *how* a strategic AI orientation may span domains. Thus, future studies may investigate the technological innovation trajectories associated with greater AI orientation. For instance, whether firms transition incrementally across domains or jump discontinuously (see also Kang and Kim 2020).

Third, AI technologies and how firms use them are going to change in the future, raising questions about the longevity of the construct strategic AI orientation and its relationship to innovation. While AI is likely to enable lasting business changes (Goldman Sachs 2023), AI applications will evolve and firms' strategic AI orientation will adapt. This creates opportunities to examine the development of firms' AI orientation over time, for example, regarding its speed and rhythm. Similarly, future studies may examine whether an AI orientation leads to sustained competitive advantage over time or whether it only enables first-mover advantages. Further, despite the rapid development of new AI technologies, only a very limited number of firms are steering this development (IBM 2024) and have acquired AI-related employees at scale (Babina et al. 2024). To better understand this "AI divide" (McElheran et al. 2024, 375), we encourage scholars to examine drivers of AI orientation, such as top management behaviors or industry dynamics.

Fourth, beyond exploring why firms differ in their AI orientation, research may provide insights into the conditions under

TABLE 9 | Avenues for further research.

Future research directions	
Consequences of AI orientation	• To what extent does a strategic AI orientation enhance organizational learning and firms' agility? • To what extent do firms with a stronger AI orientation engage in the internalization of AI-related knowledge, e.g., through acquisitions of technology startups or through hiring?
AI orientation and trajectories of technological innovation	• To what extent does a strategic AI orientation enhance technological innovation differently across domains? Are those domains clustered, e.g., by their vicinity to prior innovations of a firm? • To what extent does a strategic AI orientation lead to discontinuous radical innovation or incremental innovation?
AI orientation over time	• How is a firm's AI orientation developing over time, e.g., regarding the speed or rhythm of development? • To what extent do certain events disproportionately increase firms' strategic AI orientation?
AI divide	• Why do firms differ in their degree of strategic AI orientation? To what extent do top management team characteristics, competitors' behavior, and environmental dynamics explain this AI divide?
Dimensions of AI orientation	• How do adjacent research domains like information systems, human resources, or organizational behavior inform our understanding of the dimensions of AI orientation? • How does a strategic AI orientation reshape technical processes, skill requirements, and the nature of network ties?
AI orientation and organizational design	• Which organizational designs, such as structures or incentive systems, strengthen the relationship between strategic AI orientation and firms' value creation? • To what extent does a firm's AI orientation change corporate structures?
Strategic perspectives on technology	• When do firms exhibit strategic perspectives on other technologies? • To what extent do strategic perspectives on other technologies explain behaviors or performance that are not explainable by the quantity or quality of productively using these technologies?

which firms can create disproportionate value from AI deployment. We currently know little about the organizational structures and incentive systems that are best suited to enhance firms' value creation from AI. Interestingly, Valentine et al. (2024) show that AI may reorganize firms' structures, warranting a more nuanced exploration of the interplay between AI and organizational design. Along the same lines, the dimensions of AI orientation outlined in Table 3 offer various avenues for further research that can expand the boundaries of innovation management research by integrating insights from domains such as information systems, organizational behavior, or human resource management. For instance, the theme technical infrastructure sparks questions on how AI redefines firms' IT processes and which role platforms play in this development (Gregory et al. 2021). The emerging role of business translators warrants further exploration of the emergence and volatility of skills in the AI era (Felten et al. 2021; Strich et al. 2021), while studying cooperation mechanisms for AI orientation can advance the understanding of network ties (Soluk et al. 2025).

Finally, taking a strategic orientation perspective on AI raises the question of whether and with what outcomes firms (do not) exhibit strategic perspectives on other technologies such as blockchain, quantum computing, or the metaverse. Future research could replicate our approach for numerous other promising technologies that might become general-purpose technologies. Table 9 summarizes the avenues for future research, of which we hope that they inspire and provoke further research in the emerging algorithmic era.

5 | Conclusion

Despite burgeoning research at the AI-innovation-nexus, we have limited insights into AI's impact on firms' innovation outcomes. While initial research advances our insights into the productive use of AI and its consequences for innovation, this excludes most firms in practice, as they are far from having used AI productively. Instead, firms currently build strategic AI orientations by directing managerial attention to AI and by developing AI strategies. Combining qualitative and quantitative work, we find that managers perceive a strategic AI orientation as present and valuable, which is reflected in our quantitative study as firms with a strategic AI orientation have a greater innovative output. These insights extend current knowledge by unveiling the importance of the construct AI orientation for innovation research, integrating prior ambiguous predictions on the relationship between AI and innovation. Thereby, we offer a starting point for firm-level strategic AI research.

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Ethics Statement

The authors have read and agreed to the Committee on Publication Ethics (COPE) international standards for authors.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available through commercial licenses from third party vendors. Sharing is restricted through the vendor.

Endnotes

[1] In addition, focusing on mature firms is appropriate as they do not change their strategic trajectories, as in our case strategic AI orientation, too frequently. In contrast, young firms are often prone to pivoting their strategy which makes long-term planning and the development of strategic orientations unfeasible.

[2] More descriptive information about the interviewees can be found in Appendix S1.

[3] To merge patent and firm data, we address ambiguous firm names (identifiers) and complex ownership structures. Like Arora et al. (2021), we first use an exact name match, then standardize names and legal entities to match again. We perform a fuzzy match with manual checks for the remaining firms. We aggregate data on the parent firm level, using ownership data from Osiris. This is vital as authorities assign patents to subsidiaries and parent firms, biasing the analysis if overlooking subsidiaries' patents (Arora et al. 2021).

[4] We extend J. Li, Li, Wang, and Thatcher's (2021) binary measure of AI orientation, which is based on 19 AI keywords from a news article, text mining in annual reports based on these words, and the manual expert validation of this approach.

[5] We chose a Poisson instead of a negative binomial panel regression since negative binomial panel regressions with fixed effects tend to state incorrect confidence intervals (Allison and Waterman 2002).

[6] As concerns may emerge regarding R&D intensity and industry profitability, we rerun our regressions without them and find similar results in terms of significance and magnitude. Thus, we do not see multicollinearity as a major concern for our estimation.

[7] Calculations show that a 25% increase in patents would equal about USD 183 million for Microsoft (3248 patents in 2019 × USD 56,250). For IBM, an increase would equal USD 532 million (9459 patents in 2019 × USD 56,250).

[8] We also conducted more general robustness tests (Appendix S5), such as varying the model specification (random effects, more controls) or dropping observations with short annual reports (< 2000 words).

References

Allianz SE. 2025. "Building a Future-Ready Workforce." https://www.allianz.com/en/mediacenter/news/articles/250225-ai-at-allianz-building-a-future-ready-workforce.html.

Allison, P. D., and R. P. Waterman. 2002. "Fixed-Effects Negative Binomial Regression Models." *Sociological Methodology* 32, no. 1: 247–265.

Anthony, C., B. A. Bechky, and A.-L. Fayard. 2023. "'Collaborating' With AI: Taking a System View to Explore the Future of Work." *Organization Science* 34, no. 5: 1672–1694.

Antons, D., R. Kleer, and T. O. Salge. 2016. "Mapping the Topic Landscape of JPIM 1984–2013: In Search of Hidden Structures and Development Trajectories." *Journal of Product Innovation Management* 33, no. 6: 726–749.

Arora, A., S. Belenzon, and L. Sheer. 2021. "Matching Patents to Compustat Firms, 1980–2015: Dynamic Reassignment, Name Changes, and Ownership Structures." *Research Policy* 50, no. 5: 104217.

Babina, T., A. Fedyk, A. He, and J. Hodson. 2024. "Artificial Intelligence, Firm Growth, and Product Innovation." *Journal of Financial Economics* 151: 103745.

Balasubramanian, N., Y. Ye, and M. Xu. 2022. "Substituting Human Decision-Making With Machine Learning: Implications for Organizational Learning." *Academy of Management Review* 47, no. 3: 448–465.

Becker, L., K. Coussement, M. Büttgen, and E. Weber. 2022. "Leadership in Innovation Communities: The Impact of Transformational Leadership Language on Member Participation." *Journal of Product Innovation Management* 39, no. 3: 371–393.

Belderbos, R., M. Grabowska, B. Leten, S. Kelchtermans, and N. Ugur. 2017. "On the Use of Computer-Aided Text Analysis in International Business Research." *Global Strategy Journal* 7, no. 3: 312–331.

Benbya, H., T. H. Davenport, and S. Pachidi. 2020. "Artificial Intelligence in Organizations: Current State and Future Opportunities." *MIS Quarterly Executive* 19, no. 4: 4.

Benbya, H., F. Strich, and T. Tamm. 2024. "Navigating Generative AI Promises and Perils for Knowledge and Creative Work." *Journal of the Association for Information Systems* 25, no. 1: 23–36.

Bendig, D., R. Wagner, E. P. Piening, and J. N. Foege. 2023. "Attention to Digital Innovation: Exploring the Impact of a Chief Information Officer in the Top Management Team." *MIS Quarterly* 47, no. 4: 1487–1516.

Berg, J., M. Raj, and R. Seamans. 2023. "Capturing Value From Artificial Intelligence." *Academy of Management Discoveries* 9, no. 4: 424–428.

Bliese, P. D. 2000. "Within-Group Agreement, Non-Independence, and Reliability: Implications for Data Aggregation and Analysis." In *Multilevel Theory, Research, and Methods in Organizations: Foundations, Extensions, and New Directions*, edited by K. J. Klein and S. W. Kozlowski, 349–381. Wiley.

Bloomberg Law. 2020. "IP Transactions, Professional Perspective – Patent Valuations Across Transaction and Licensing Markets." https://www.bloomberglaw.com/external/document/XEOIEER4000000.

Bouschery, S. G., V. Blazevic, and F. T. Piller. 2023. "Augmenting Human Innovation Teams With Artificial Intelligence: Exploring

Transformer-Based Language Models." *Journal of Product Innovation Management* 40, no. 2: 139–153.

Boyallian, P., and P. Ruiz-Verdú. 2018. "Leverage, CEO Risk-Taking Incentives, and Bank Failure During the 2007–10 Financial Crisis." *Review of Finance* 22, no. 5: 1763–1805.

Burak, A. 2024. "Generative AI vs Predictive AI: Which One Dominates the AI Revolution?" https://relevant.software/blog/generative-ai-vs-predictive-ai/#Applications_of_Predictive_AI.

Buyl, T., C. Boone, W. Hendriks, and P. Matthyssens. 2011. "Top Management Team Functional Diversity and Firm Performance: The Moderating Role of CEO Characteristics." *Journal of Management Studies* 48, no. 1: 151–177.

Callaway, E. 2023. "How Generative AI is Building Better Antibodies." *Nature* 617: 235.

Camuffo, A., A. Gambardella, and A. Pignataro. 2023. "Framing Strategic Decisions in a Digital World." *Strategic Management Review* 4, no. 2: 127–160.

Cho, T. S., and D. C. Hambrick. 2006. "Attention as the Mediator Between Top Management Team Characteristics and Strategic Change: The Case of Airline Deregulation." *Organization Science* 17, no. 4: 453–469.

Choi, I., S. Chung, K. Han, and A. Pinsonneault. 2021. "CEO Risk-Taking Incentives and IT Innovation: The Moderating Role of a CEO's IT-Related Human Capital." *MIS Quarterly* 45, no. 4: 2175–2192.

Choudhary, V., A. Marchetti, Y. R. Shrestha, and P. Puranam. 2025. "Human and AI Ensembles: When Can They Work?" *Journal of Management* 51, no. 2: 536–569.

Choudhury, P., E. Starr, and R. Agarwal. 2020. "Machine Learning and Human Capital Complementarities: Experimental Evidence on Bias Mitigation." *Strategic Management Journal* 41, no. 8: 1381–1411.

Cragg, J. G., and S. G. Donald. 1993. "Testing Identifiability and Specification in Instrumental Variable Models." *Econometric Theory* 9, no. 2: 222–240.

Cyert, R. M., and J. G. March. 1963. *A Behavioral Theory of the Firm*. Prentice Hall.

Czarnitzki, D., G. P. Fernández, and C. Rammer. 2023. "Artificial Intelligence and Firm-Level Productivity." *Journal of Economic Behavior & Organization* 211: 188–205.

Dahlke, J., M. Beck, J. Kinne, et al. 2024. "Epidemic Effects in the Diffusion of Emerging Digital Technologies: Evidence From Artificial Intelligence Adoption." *Research Policy* 53, no. 2: 104917.

Dalziel, M., and N. Basir. 2024. "The Technological Imprinting of Educational Experiences on Student Startups." *Research Policy* 53, no. 2: 104940.

Damanpour, F. 1991. "Organizational Innovation: A Meta-Analysis of Effects of Determinants and Moderators." *Academy of Management Journal* 34, no. 3: 555–590.

Dane, E. 2018. "Where is My Mind? Theorizing Mind Wandering and Its Performance-Related Consequences in Organizations." *Academy of Management Review* 43, no. 2: 179–197.

Danneels, E., and R. Sethi. 2011. "New Product Exploration Under Environmental Turbulence." *Organization Science* 22, no. 4: 1026–1039.

Edmondson, A. C., and S. E. McManus. 2007. "Methodological Fit in Management Field Research." *Academy of Management Review* 32, no. 4: 1246–1264.

Eggers, J. P., and S. Kaplan. 2009. "Cognition and Renewal: Comparing CEO and Organizational Effects on Incumbent Adaptation to Technical Change." *Organization Science* 20, no. 2: 461–477.

Eicke, A.-K., J. N. Foege, and S. Nüesch. 2025. "Iterative Alternative Evaluation Within Human–Artificial Intelligence Problem-Solving: An Extension to Raisch and Fomina's 'Combining Human and Artificial Intelligence'." *Academy of Management Review* 50, no. 2: 480–481.

Eisenhardt, K. M. 1989. "Building Theories From Case Study Research." *Academy of Management Review* 14, no. 4: 532–550.

Engelen, A., V. Rieger, M. Wehner, and F. Heidemann. 2022. "Is Organizational Commitment to IT Good for Employees? The Role of Industry Dynamism and Concentration." *MIS Quarterly* 46, no. 4: 2387–2404.

Felten, E., M. Raj, and R. Seamans. 2021. "Occupational, Industry, and Geographic Exposure to Artificial Intelligence: A Novel Dataset and Its Potential Uses." *Strategic Management Journal* 42, no. 12: 2195–2217.

Ferrucci, D. A. 2012. "Introduction to 'This is Watson'." *IBM Journal of Research and Development* 56, no. 3.4: 1:1–1:15.

Frank, K., S. J. Maroulis, M. Q. Duong, and B. M. Kelcey. 2013. "What Would It Take to Change an Inference? Using Rubin's Causal Model to Interpret the Robustness of Causal Inferences." *Educational Evaluation and Policy Analysis* 35, no. 4: 437–460.

Freisinger, E., M. Unfried, and S. Schneider. 2024. "The AI-Augmented Crowd: How Human Crowdvoters Adopt AI (Or Not)." *Journal of Product Innovation Management* 41, no. 4: 865–889.

Gama, F., and S. Magistretti. 2025. "Artificial Intelligence in Innovation Management: A Review of Innovation Capabilities and a Taxonomy of AI Applications." *Journal of Product Innovation Management* 42, no. 1: 76–111.

Garbuio, M., and N. Lin. 2021. "Innovative Idea Generation in Problem Finding: Abductive Reasoning, Cognitive Impediments, and the Promise of Artificial Intelligence." *Journal of Product Innovation Management* 38, no. 6: 701–725.

Gatignon, H., and J.-M. Xuereb. 1997. "Strategic Orientation of the Firm and New Product Performance." *Journal of Marketing Research* 34, no. 1: 77–90.

George, G. 2005. "Slack Resources and the Performance of Privately Held Firms." *Academy of Management Journal* 48, no. 4: 661–676.

Gibbert, M., and W. Ruigrok. 2010. "The 'What' and 'How' of Case Study Rigor: Three Strategies Based on Published Work." *Organizational Research Methods* 13, no. 4: 710–737.

Gioia, D. A., K. G. Corley, and A. L. Hamilton. 2013. "Seeking Qualitative Rigor in Inductive Research: Notes on the Gioia Methodology." *Organizational Research Methods* 16, no. 1: 15–31.

Goffin, K., P. Åhlström, M. Bianchi, and A. Richtnér. 2019. "Perspective: State-of-the-Art: The Quality of Case Study Research in Innovation Management." *Journal of Product Innovation Management* 36, no. 5: 586–615.

Goldfarb, A., B. Taska, and F. Teodoridis. 2023. "Could Machine Learning be a General Purpose Technology? A Comparison of Emerging Technologies Using Data From Online Job Postings." *Research Policy* 52, no. 1: 104653.

Goldman Sachs. 2023. "The Generative World Order: AI, Geopolitics, and Power." www.goldmansachs.com/insights/articles/the-generative-world-order-ai-geopolitics-and-power.

Gregory, R. W., O. Henfridsson, E. Kaganer, and H. Kyriakou. 2021. "The Role of Artificial Intelligence and Data Network Effects for Creating User Value." *Academy of Management Review* 46, no. 3: 534–551.

Greve, H. R. 2003. "A Behavioral Theory of R&D Expenditures and Innovations: Evidence From Shipbuilding." *Academy of Management Journal* 46, no. 6: 685–702.

Guo, H., C. Wang, Z. Su, and D. Wang. 2020. "Technology Push or Market Pull? Strategic Orientation in Business Model Design and Digital Start-Up Performance." *Journal of Product Innovation Management* 37, no. 4: 352–372.

Hair, J. F., W. C. Black, B. J. Babin, and R. E. Anderson. 2014. *Multivariate Data Analysis*. Pearson Education Limited.

Hambrick, D. C., and P. A. Mason. 1984. "Upper Echelons: The Organization as a Reflection of Its Top Managers." *Academy of Management Review* 9, no. 2: 193–206.

Hannigan, T. R., R. F. J. Haans, K. Vakili, et al. 2019. "Topic Modeling in Management Research: Rendering New Theory From Textual Data." *Academy of Management Annals* 13, no. 2: 586–632.

Hartmann, P., and J. Henkel. 2020. "The Rise of Corporate Science in AI: Data as a Strategic Resource." *Academy of Management Discoveries* 6, no. 3: 359–381.

Helfat, C. E., A. Kaul, D. J. Ketchen, J. B. Barney, O. Chatain, and H. Singh. 2023. "Renewing the Resource-Based View: New Contexts, New Concepts, and New Methods." *Strategic Management Journal* 44, no. 6: 1357–1390.

Hill, A. D., S. G. Johnson, L. M. Greco, E. H. O'Boyle, and S. L. Walter. 2021. "Endogeneity: A Review and Agenda for the Methodology-Practice Divide Affecting Micro and Macro Research." *Journal of Management* 47, no. 1: 105–143.

Hoberg, G., and G. M. Phillips. 2025. "Scope, Scale, and Concentration: The 21st-Century Firm." *Journal of Finance* 80, no. 1: 415–466.

IBM. 2024. "Data Suggests Growth in Enterprise Adoption of AI is due to Widespread Deployment by Early Adopters, but Barriers Keep 40% in the Exploration and Experimentation Phases." https://www.multivu.com/players/English/9240059-ibm-2023-global-ai-adoption-index-report/.

Igna, I., and F. Venturini. 2023. "The Determinants of AI Innovation Across European Firms." *Research Policy* 52, no. 2: 104661.

Jansen, J. J. P., F. A. J. van den Bosch, and H. W. Volberda. 2006. "Exploratory Innovation, Exploitative Innovation, and Performance: Effects of Organizational Antecedents and Environmental Moderators." *Management Science* 52, no. 11: 1661–1674.

Jarvenpaa, S. L., and B. Ives. 1991. "Executive Involvement and Participation in the Management of Information Technology." *MIS Quarterly* 15, no. 2: 205–227.

Jia, N., X. Luo, Z. Fang, and C. Liao. 2023. "When and How Artificial Intelligence Augments Employee Creativity." *Academy of Management Journal* 64, no. 1: 5–32.

Joseph, J., D. Laureiro-Martinez, A. Nigam, W. Ocasio, and C. Rerup. 2024. "Research Frontiers on the Attention-Based View of the Firm." *Strategic Organization* 22, no. 1: 6–17.

Junge, S., J. Luger, and J. Mammen. 2023. "The Role of Organizational Structure in Senior Managers' Selective Information Processing." *Journal of Management Studies* 60, no. 5: 1178–1204.

Kalnins, A. 2018. "Multicollinearity: How Common Factors Cause Type 1 Errors in Multivariate Regression." *Strategic Management Journal* 39, no. 8: 2362–2385.

Kalnins, A., and K. Praitis Hill. 2025. "The VIF Score. What is It Good for? Absolutely Nothing." *Organizational Research Methods* 28, no. 1: 58–75.

Kang, J., and S.-J. Kim. 2020. "Performance Implications of Incremental Transition and Discontinuous Jump Between Exploration and Exploitation." *Strategic Management Journal* 41, no. 6: 1083–1111.

Karhade, P., and J. Q. Dong. 2021. "Information Technology Investment and Commercialized Innovation Performance: Dynamic Adjustment Costs and Curvilinear Impacts." *MIS Quarterly* 45, no. 3: 1007–1024.

Kemp, A. 2024. "Competitive Advantages Through Artificial Intelligence: Toward a Theory of Situated AI." *Academy of Management Review* 49, no. 3: 618–635.

Kennedy, P. 2008. *A Guide to Econometrics*. Blackwell.

Kim, C., and R. A. Bettis. 2014. "Cash is Surprisingly Valuable as a Strategic Asset." *Strategic Management Journal* 35, no. 13: 2053–2063.

Kogan, L., D. Papanikolaou, A. Seru, and N. Stoffman. 2017. "Technological Innovation, Resource Allocation, and Growth." *Quarterly Journal of Economics* 132, no. 2: 665–712.

Kor, Y. Y. 2003. "Experience-Based Top Management Team Competence and Sustained Growth." *Organization Science* 14, no. 6: 707–719.

Krakowski, S., J. Luger, and S. Raisch. 2023. "Artificial Intelligence and the Changing Sources of Competitive Advantage." *Strategic Management Journal* 44, no. 6: 1425–1452.

Krippendorff, K. 2004. "Reliability in Content Analysis: Some Common Misconceptions and Recommendations." *Human Communication Research* 30, no. 3: 411–433.

LeCun, Y., Y. Bengio, and G. Hinton. 2015. "Deep Learning." *Nature* 521, no. 7553: 436–444.

Lerner, J., and A. Seru. 2022. "The Use and Misuse of Patent Data: Issues for Finance and Beyond." *Review of Financial Studies* 35, no. 6: 2667–2704.

Li, G., N. Li, and S. P. Sethi. 2021. "Does CSR Reduce Idiosyncratic Risk? Roles of Operational Efficiency and AI Innovation." *Production and Operations Management* 30, no. 7: 2027–2045.

Li, J., M. Li, X. Wang, and J. Thatcher. 2021. "Strategic Directions for AI: The Role of CIOs and Boards of Directors." *MIS Quarterly* 45, no. 3: 1603–1643.

Li, Y., Z. Wei, and Y. Liu. 2010. "Strategic Orientations, Knowledge Acquisition, and Firm Performance: The Perspective of the Vendor in Cross-Border Outsourcing." *Journal of Management Studies* 47, no. 8: 1457–1482.

Lo, D., F. Brahm, W. Dessein, and C. Minami. 2022. "Managing With Style? Microevidence on the Allocation of Managerial Attention." *Management Science* 68, no. 11: 8261–8285.

Lou, B., and L. Wu. 2021. "AI on Drugs: Can Artificial Intelligence Accelerate Drug Development? Evidence From a Large-Scale Examination of Bio-Pharma Firms." *MIS Quarterly* 45, no. 3: 1451–1482.

Matthews, L., M. L. M. Heyden, and D. Zhou. 2022. "Paradoxical Transparency? Capital Market Responses to Exploration and Exploitation Disclosure." *Research Policy* 51, no. 1: 104396.

Mayring, P. 2015. "Qualitative Content Analysis: Theoretical Background and Procedures." In *Approaches to Qualitative Research in Mathematics Education*, edited by A. Bikner-Ahsbahs, C. Knipping, and N. Presmeg, 365–380. Springer.

McElheran, K., J. F. Li, E. Brynjolfsson, et al. 2024. "AI Adoption in America: Who, What, and Where." *Journal of Economics and Management Strategy* 33, no. 2: 375–415.

McKenny, A. F., H. Aguinis, J. C. Short, and A. H. Anglin. 2018. "What Doesn't Get Measured Does Exist: Improving the Accuracy of Computer-Aided Text Analysis." *Journal of Management* 44, no. 7: 2909–2933.

Mercedes-Benz. 2025. "Two Letters and Four Principles." https://group.mercedes-benz.com/sustainability/digital-trust/ai/ai-guidelines.html.

Miller, T., and M. D. C. Triana. 2009. "Demographic Diversity in the Boardroom: Mediators of the Board Diversity–Firm Performance Relationship." *Journal of Management Studies* 46, no. 5: 755–786.

Miric, M., N. Jia, and K. G. Huang. 2023. "Using Supervised Machine Learning for Large-Scale Classification in Management Research: The Case for Identifying Artificial Intelligence Patents." *Strategic Management Journal* 44, no. 2: 491–519.

Mittlböck, M., and T. Waldhör. 2000. "Adjustments for R2-Measures for Poisson Regression Models." *Computational Statistics & Data Analysis* 34, no. 4: 461–472.

Nadkarni, S., and J. Chen. 2014. "Bridging Yesterday, Today, and Tomorrow: CEO Temporal Focus, Environmental Dynamism, and Rate of New Product Introduction." *Academy of Management Journal* 57, no. 6: 1810–1833.

Narayan, S., J. S. Sidhu, and H. W. Volberda. 2021. "From Attention to Action: The Influence of Cognitive and Ideological Diversity in Top Management Teams on Business Model Innovation." *Journal of Management Studies* 58, no. 8: 2082–2110.

Nath, P., and N. Bharadwaj. 2020. "Chief Marketing Officer Presence and Firm Performance: Assessing Conditions Under Which the Presence of Other C-Level Functional Executives Matters." *Journal of the Academy of Marketing Science* 48: 670–694.

Nike. 2024. "Creating the Unreal: How Nike Made Its Wildest Air Footwear Yet." https://about.nike.com/en-GB/stories/creating-the-unreal-how-nike-made-its-wildest-air-footwear-yet.

Noble, C. H., R. K. Sinha, and A. Kumar. 2002. "Market Orientation and Alternative Strategic Orientations: A Longitudinal Assessment of Performance Implications." *Journal of Marketing* 66, no. 4: 25–39.

Ocasio, W. 1997. "Towards an Attention-Based View of the Firm." *Strategic Management Journal* 18: 187–206.

Park, T., and J.-Y. Ho. 2025. "Mixed Methods Research in Technology and Innovation Management (TIM): A Review of Three Leading TIM Journals and Recommendations for Moving Forward." *Research Policy* 54, no. 6: 105256.

Pollach, I. 2011. "Software Review: Wordstat 5.0." *Organizational Research Methods* 14, no. 4: 741–744.

Raisch, S., and K. Fomina. 2025. "Combining Human and Artificial Intelligence: Hybrid Problem-Solving in Organizations." *Academy of Management Review* 50, no. 2: 441–464.

Raisch, S., and S. Krakowski. 2021. "Artificial Intelligence and Management: The Automation-Augmentation Paradox." *Academy of Management Review* 46, no. 1: 192–210.

Raj, M., and R. Seamans. 2019. "Primer on Artificial Intelligence and Robotics." *Journal of Organization Design* 8, no. 1: 1–14.

Rammer, C., G. P. Fernández, and D. Czarnitzki. 2022. "Artificial Intelligence and Industrial Innovation: Evidence From German Firm-Level Data." *Research Policy* 51, no. 7: 104555.

Saboo, A. R., A. Chakravarty, and R. Grewal. 2016. "Organizational Debut on the Public Stage: Marketing Myopia and Initial Public Offerings." *Marketing Science* 35, no. 4: 656–675.

Savage, J. P., M. Li, S. F. Turner, D. E. Hatfield, and L. B. Cardinal. 2020. "Mapping Patent Usage in Management Research: The State of Prior Art." *Journal of Management* 46, no. 6: 1121–1155.

Schäper, T., C. Jung, J. N. Foege, M. Bogers, S. Fainshmidt, and S. Nüesch. 2023. "The S-Shaped Relationship Between Open Innovation and Financial Performance: A Longitudinal Perspective Using a Novel Text-Based Measure." *Research Policy* 52, no. 6: 104764.

Schulz, C., S. Kortmann, F. T. Piller, and P. Pollok. 2023. "Growing With Smart Products: Why Customization Capabilities Matter for Manufacturing Firms." *Journal of Product Innovation Management* 40, no. 6: 794–816.

Soluk, J., I. Miroshnychenko, and S. Nambisan. 2025. "AI Adoption in Family Firms: A Mixed-Methods Study on the Paradoxical Roles of Passive and Active Family Involvement." *Journal of Product Innovation Management*.

Spanjol, J., and C. H. Noble. 2023. "From the Editors: Engaging With Generative Artificial Intelligence Technologies in Innovation Management Research—Some Answers and More Questions." *Journal of Product Innovation Management* 40, no. 4: 383–390.

Spanjol, J., W. J. Qualls, and J. A. Rosa. 2011. "How Many and What Kind? The Role of Strategic Orientation in New Product Ideation." *Journal of Product Innovation Management* 28, no. 2: 236–250.

Stock, J. H., and M. Yogo. 2005. "Testing for Weak Instruments in Linear IV Regression." In *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg*, edited by D. Andrews and J. Stock, 80–108. Cambridge University Press.

Strich, F., A.-S. Mayer, and M. Fiedler. 2021. "What Do I Do in a World of Artificial Intelligence? Investigating the Impact of Substitutive Decision-Making AI Systems on Employees' Professional Role Identity." *Journal of the Association for Information Systems* 22, no. 2: 304–324.

Sturm, T., J. Gerlach, L. Pumplun, et al. 2021. "Coordinating Human and Machine Learning for Effective Organizational Learning." *MIS Quarterly* 45, no. 3b: 1581–1602.

Symrise. 2024. "The Most Inspiring Perfumers Combined With the Most Powerful AI Fragrance Tool – Makes Perfect Scents." https://www.symrise.com/scent-and-care/competence-platforms/philyra/.

Taylor, J., and J. Vithayathil. 2018. "Who Delivers the Bigger Bang for the Buck: CMO or CIO?" *Journal of Strategic Information Systems* 27, no. 3: 207–220.

The Economist. 2024. "A Short History of AI." https://www.economist.com/schools-brief/2024/07/16/a-short-history-of-ai.

Turner, S. F., L. B. Cardinal, and R. M. Burton. 2017. "Research Design for Mixed Methods: A Triangulation-Based Framework and Roadmap." *Organizational Research Methods* 20, no. 2: 243–267.

Uotila, J., M. Maula, T. Keil, and S. A. Zahra. 2009. "Exploration, Exploitation, and Financial Performance: Analysis of S&P 500 Corporations." *Strategic Management Journal* 30, no. 2: 221–231.

Vagnani, G. 2015. "Exploration and Long-Run Organizational Performance: The Moderating Role of Technological Interdependence." *Journal of Management* 41, no. 6: 1651–1676.

Valentine, M. A., A. L. Pratt, R. Hinds, and M. S. Bernstein. 2024. "The Algorithm and the Org Chart: How Algorithms Can Conflict With Organizational Structures." *Proceedings of the ACM on Human-Computer Interaction* 8: 364.

van Giffen, B., and H. Ludwig. 2023. "How Siemens Democratized Artificial Intelligence." *MIS Quarterly Executive* 22, no. 1: 3.

Venkatesh, V., S. A. Brown, and H. Bala. 2013. "Bridging the Qualitative-Quantitative Divide: Guidelines for Conducting Mixed Methods Research in Information Systems." *MIS Quarterly* 37, no. 1: 21–54.

Venkatraman, N. 1989. "Strategic Orientation of Business Enterprises: The Construct, Dimensionality, and Measurement." *Management Science* 35, no. 8: 942–962.

Verganti, R., L. Vendraminelli, and M. Iansiti. 2020. "Innovation and Design in the Age of Artificial Intelligence." *Journal of Product Innovation Management* 37, no. 3: 212–227.

Wellman, N., C. Tröster, M. Grimes, Q. Roberson, F. Rink, and M. Gruber. 2023. "Publishing Multimethod Research in AMJ: A Review and Best-Practice Recommendations." *Academy of Management Journal* 66, no. 4: 1007–1015.

Wetzels, M. 2021. "The Road Ahead is Digital for Innovation Management and There is No Way Back." *Journal of Product Innovation Management* 38, no. 2: 245–247.

Wilkinson, L. 2024. "Pfizer Appoints AI Chief to Boost Its Digital Leadership Team." https://www.ciodive.com/news/pfizer-chief-ai-officer-digital-leadership-team/724139/.

Wirsich, A., A. Kock, C. Strumann, and C. Schultz. 2016. "Effects of University–Industry Collaboration on Technological Newness of Firms." *Journal of Product Innovation Management* 33, no. 6: 708–725.

Wooldridge, J. M. 2013. *Introductory Econometrics: A Modern Approach*. Cengage Learning.

Xu, R., K. A. Frank, S. J. Maroulis, and J. M. Rosenberg. 2019. "Konfound: Command to Quantify Robustness of Causal Inferences." *Stata Journal* 19, no. 3: 523–550.

Yu, W., M. Minniti, and R. Nason. 2019. "Underperformance Duration and Innovative Search: Evidence From the High-Tech Manufacturing Industry." *Strategic Management Journal* 40, no. 5: 836–861.

Zhong, W., Z. Ma, T. W. Tong, Y. Zhang, and L. Xie. 2021. "Customer Concentration, Executive Attention, and Firm Search Behavior." *Academy of Management Journal* 64, no. 5: 1625–1647.

Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Data S1:** Supporting Information.