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COMPETITIVE ADVANTAGE THROUGH ARTIFICIAL INTELLIGENCE: TOWARD A THEORY OF SITUATED AI

AYENDA KEMP
Virginia Tech University

How can firms establish competitive advantages using artificial intelligence (AI)? Although AI is beginning to permeate business activities, our understanding of how AI can be used to create unique value is limited. To address this void, I introduce the concept of situated AI and illuminate its importance for establishing AI-driven competitive advantages. The paper highlights the organizational activities involved in situating AI—specifically, grounding, bounding, and recasting. It also explains the conditions in which these situating activities better enable firms to develop AI-driven capabilities that are firm-specific, cost-effective, and appropriate for opportunities in the strategic environment. Thus, this paper provides an integrative framework for connecting a firm's AI pursuits to competitive advantage.

The prospect of using artificial intelligence (AI) to establish competitive advantages presents a theoretical puzzle. Estimates have predicted that by 2033, somewhere between 40% and 50% of jobs will be automated using intelligent algorithms (Frey & Osborne, 2013), reflecting enhanced productivity and lower costs. It has also been predicted that AI may lead to new products (Barro & Davenport, 2019; Davenport & Kirby, 2015) by allowing firms to embed AI into their products and by igniting innovations in a firm's product-development processes (Cockburn, Henderson, & Stern, 2019; Gregory, Henfridsson, Kaganer, & Kyriakou, 2021). Despite this promise, a growing body of research has highlighted that AI may present substantial strategic obstacles. AI may be myopic (Balasubramanian, Ye, & Xu, 2022), incapable of perceiving interdependencies within a firm (Raisch & Krakowski, 2021), and recalcitrant to managerial control (Murray, Rhymer, & Sirmon, 2021). These factors suggest that using AI to lower costs and craft desirable products may not be as simple as previously suggested. In addition, AI is a form of explicit knowledge (Broussard, 2018; Shrestha, He, Puranam, & von Krogh, 2021), and resembles a general-purpose technology (Teece, 2018). Hence, even when AI leads to value creation within a firm, the activities underpinning these outcomes may be replicable by a firm's rivals. Thus, while AI holds promise for prompting competitive advantages, it is unclear how this promise can be realized.

The present paper begins to resolve this puzzle by developing a theory of *situated AI*—AI whose agency is circumscribed in a firm's experiential, structural, and relational systems. I ground my framework in the organizational capabilities literature, which holds that competitive advantages emerge primarily when firms deploy their strategic assets using organizational capabilities that are idiosyncratic (Barney, 1991), inexpensive to develop (Winter, 2000), and aligned with the firm's internal and external environment (Mahoney & Pandian, 1992; Sirmon, Hitt, & Ireland, 2007). I argue that achieving these outcomes is made difficult by AI's propensity to act with agency (Murray et al., 2021), which may be counterproductive when not properly contextualized within the firm. I also accept that uncontextualized agency may be AI's baseline state (Balasubramanian et al., 2022).

I address the strategic limitations of AI by explaining how firms may (a) circumscribe AI's agency in the firm's unique experiences and systems, and (b) embed this transformed AI in the firm's organizational capabilities through three situating activities: *grounding, bounding, and recasting*. Grounding involves orchestrating which experiences one's AI will be allowed to learn from across the organization. Bounding involves efforts to shape the experiences anchoring a competitor's AI. Recasting involves orchestrating the continual adaptation of algorithms

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and their surrounding routines to enhance AI's alignment with interdependent activities in a firm. I also consider how technological constraints and environmental dynamism influence the benefits of situating AI. Thus, this paper acknowledges AI's strategic limitations while explaining how firms can overcome these limitations to better realize AI's potential as a new foundation for competitive advantage.

CONCEPTUAL BACKGROUND

The Promise of AI for Competitive Advantage

AI broadly refers to machines that can complete cognitive tasks that could previously only be completed by humans (Davenport, 2018). While there is a long history of machines displacing human workers, the rise of AI is unique in that machines, for the first time, can "learn" and perform their work with agency (Faraj, Pachidi, & Sayegh, 2018). With previous technologies, machines completed their work by following intricate if–then statements programmed by human actors. The machine had no agency to speak of; its actions were a direct reflection of the knowledge of its programmers (Dreyfus & Dreyfus, 2005; Norman, 2017). In contrast, with AI the computer is provided with a set of input data, a learning objective, an error function, and a mathematical algorithm for minimizing that error function (Alpaydin, 2016; Chen, Zou, Ye, Li, Deng, & Ong, 2020). Armed with this basic description of a problem, the computer then learns its own "rules" for linking the input data to the desired outcomes. What is critical about these rules is that they are not created by human actors and, in many cases, cannot even be explained by humans (Castelvecchi, 2016). Thus, AI can be thought of as possessing a distinct form of agentic rationality that increasingly allows machines to perform cognitive tasks at a level equaling or surpassing human performance (Murray et al., 2021).

The power of AI has led many to believe that AI will revolutionize economic production by making firms more efficient through intelligent automation and by assisting humans in solving novel problems that may lead to value creation through the design of new products and the improvement of old ones (Barro & Davenport, 2019; Brynjolfsson & Mitchell, 2017; Frey & Osborne, 2013). Indeed, we are beginning to see process and product improvements with AI across multiple industries (Tarafdar, Beath, & Ross, 2019). As one example, DBS Bank recently implemented AI that predicts with 85% accuracy whether an employee will leave within three months. The firm is now using AI to power a digital-only bank in India that employs 90% fewer employees than a traditional bank (Davenport, 2018). As a second example, fragrance designers now use AI during product development to produce perfumes that appeal to consumers more than fragrances created by human experts alone (Goodwin et al., 2017).

Despite improvements in operations and product design, however, firms' investments in AI may fail to materialize as profits. In a recent survey by Ransbotham, Khodabandeh, Fehling, LaFountain, & Kiron (2019: 1), nine out of 10 top managers reported that AI represents a large business opportunity for their firms and 43% of executives reported having implemented AI in their organizations. The report also noted, however, that "most companies have a hard time generating value with AI." Lui, Lee, and Ngai (2022) offered empirical support for this concern, finding that markets penalize AI adoption at the firm level. Thus, while AI is beginning to lead to product and process improvements, firm-level benefits of AI, such as improved market performance or competitive advantage, may be more difficult to achieve.

Three Strategic Limitations of AI

What explains this disconnect? While existing theory does not explain how firms can systematically leverage AI to develop competitive advantages, recent research has shed some light on obstacles to doing so. I examine these obstacles from an organizational capabilities perspective and identify three reasons why firms may struggle to establish competitive advantages with their AI investments. I focus on AI's generic, explicit, and myopic nature. While AI undoubtedly raises many other new challenges for firms, these three limitations take prominence in my theory due to their adverse effects on capability development, which, I will argue, is central to establishing competitive advantages with AI.

The first strategic challenge of AI is its generic nature. The logic emerging from an AI algorithm is generally not unique to the user applying that algorithm. Instead, it can be "rediscovered by anyone using the same procedure" (Shrestha et al., 2021: 4). For example, all else being equal, a neural network algorithm will arrive at the same logic for connecting a set of inputs to outputs regardless of whether Spotify or Pandora operationalizes the neural network. This suggests that AI may display common behavioral patterns across competing firms. This point regarding the generic nature of AI is critical because AI is regarded as a general-purpose technology akin to electricity, the steam engine, or the internet (Brynjolfsson & Mitchell, 2017; Frey & Osborne, 2013; Lynch, 2017). General-purpose technologies are likely to be widely adopted among competing firms (Bresnahan & Trajtenberg, 1995). As a result, these technologies tend to generate economywide benefits rather than private rents (Bresnahan & Trajtenberg, 1995; Teece, 2018). Thus, while AI may help a firm to develop better and cheaper products, the *ex facie* expectation is that AI will help a firm's competitors to do the same.

The second strategic limitation of AI is that AI manifests as a form of explicit knowledge. AI algorithms, and the data that drive them, must be available to the computer in the form of explicit instructions or mathematical formulas (Broussard, 2018). Consequently, the organizational knowledge that drives a firm's AI processes may be extracted from cyber-attacks and may be highly portable during employee turnover (Tramér, Zhang, Juels, Reiter, & Ristenpart, 2016). This observation is consistent with the general idea that explicit knowledge diffuses relatively quickly across organizational boundaries, making it challenging to build competitive advantages (Grant, 1996; Nickerson & Zenger, 2004). This challenge is especially salient for AI because intellectual property laws do not (currently) allow for patenting mathematical formulas and procedures (Gaudry & Hayim, 2018; Liyange & Berry, 2019). Thus, identifying mechanisms for preventing the spread of AI assets across firm boundaries is critical.

The third strategic limitation of AI is myopia. AI is myopic in the sense that AI algorithms lack contextual awareness of activities and events beyond the scope of their assigned tasks (Balasubramanian et al., 2022; Dreyfus, 2012; Raisch & Krakowski, 2021). A single AI algorithm can typically execute only a small subtask within an entire organizational routine (Davenport, 2018). Thus, AI-driven routines will normally employ collectives of AI algorithms (see, e.g., Kumar, Venugopal, Qiu, & Kumar, 2018). Yet, an algorithm's ability to recognize interdependencies between its task and other tasks within the firm is limited. This may result in expensive technical and operational failures (Balasubramanian et al., 2022; Dreyfus, 2012). Moreover, because AI completes its task with high degrees of agency, managers find it difficult to correct these errors when they occur (Murray et al., 2021).

A related consequence of AI's myopia is that AI will lack sophisticated understanding of a firm's strategy. Thus, even when AI behaves in a manner that is optimal for carrying out a task, there is no guarantee that this will result in behavior that is appropriate for the kinds of market opportunities a firm is (or should be) pursuing (Balasubramanian et al., 2022). For instance, a budget airline may develop AI that correctly identifies that a customer can pay 2,000 USD for a short-haul flight. Still, this AI may be incapable of understanding that making such an offer is inconsistent with the firm's market identity and low-cost provider strategy. In other words, the ultimate value of AI to the firm depends not only on its task effectiveness but also on its fit with the firm's overall strategy. Thus, organizational mechanisms for overcoming AI's myopia are necessary for establishing competitive advantages.

The generic, explicit, and myopic nature of AI all endanger its firm-level benefits, but are uniquely difficult to surmount because AI is *both* a machine *and* agentic (Smith & Lewis, 2011). For example, AI's generic nature is akin to general human capital. General human capital cannot typically underly interfirm advantages because a firm's competitors can usually acquire and deploy that knowledge in ways that closely mimic corresponding actions of the focal firm. Unlike with AI, however, general human capital is considered to be convertible within a firm through socialization, and is made context-specific as human employees engage in rich *informal* social interactions within the firm (Coff, 1997). This is difficult with AI because it is a machine. On the other hand, AI's capacity to act with agency removes some typical modes of controlling technology in an organization. Consider, for example, the case of expert systems, which were heavily used before the recent rise of AI (Chollet, Kalinowski, & Allaire, 2022). Like AI, these systems were myopic because they could erroneously overlook organizational interdependencies. However, when such problems arose, they could be addressed by supplying the machine with more rules. This option is not as feasible with AI, which is more agentic than expert systems due to its greater dependence on data than rules as behavioral constraints. Thus, AI alters the firm's knowledge-production function, making paths to competitive advantage elusive.

Conceptual Building Blocks for Theorizing AI-Driven Competitive Advantages

I develop a theory of situated AI to explain how firms can overcome these strategic limitations to craft competitive advantages. I use as my conceptual foundations the organizational capabilities literature (Eggers & Kaplan, 2013; Nickerson & Zenger, 2004) and the work on human agency (Emirbayer & Mische, 1998; Westphal & Zajac, 2013). I briefly describe each conceptual building block below.

Capabilities and competitive advantage. An organizational capability is a collection of routines that, together with their implementing input flows, confer upon an organization's management a set of decision options for producing significant outputs of a particular type (Winter, 2003). The organizational capabilities perspective views firm performance as a function of systematic and random factors (Winter, 2000). Markets are modeled as collectives of competing firms solving a related problem under technical and behavioral uncertainty (Afuah & Tucci, 2012; Nickerson & Zenger, 2004). Profits are viewed as ephemeral in the absence of competitive advantages granting some firms a structural edge over others (Barney, 1986). In addition, a firm's primary concern lies in identifying and orchestrating patterns of organizational activities that can be reliably leveraged to create and capture value (Winter, 2003).

The capabilities perspective focuses on three core sources of competitive advantage: firm-specificity, capability-development costs, and environmental fit. Firm-specific capabilities are those produced using cospecialized knowledge, leading them to have greater value inside a firm than externally (Helfat, 1994; Mahoney & Pandian, 1992). In addition, crafting firm-specific capabilities is more likely when at least some of the cospecialized knowledge needed to produce or deploy a capability is tacit or socially complex (Grant, 1996; King & Zeithaml, 2007; Nickerson & Zenger, 2004). Second, because crafting capabilities requires organizational effort and resources, the cost of developing a capability must not supersede the value earned from deploying the capability (Argyers, Mahoney, & Nickerson, 2019; Winter, 2000). Finally, customers are likely to respond positively to a firm's offerings only when the firm's capabilities are adequately matched to their needs (Sirmon et al., 2007).

Situated agency. Organizations act with agency to influence their capabilities and the environments that bind them (Gavetti, Helfat, & Marengo, 2017; Gavetti & Torras, 2021; Nayak, Chia, & Canales, 2020). Agency generally involves free choice with constraints (Emirbayer & Mische, 1998; Giddens, 1979). My basic argument is that, while firms cannot always limit AI's agency directly (and might not want to), firms can balance a machine's agency with human agency by strategically structuring the context in which AI makes sense of problems and applies solutions. Agency has three dimensions that inform how an actor's behavior is constrained and how free choice may manifest (Emirbayer & Mische, 1998). The iteration dimension of agency involves actions anchored in an organization's prior experiences. The practical evaluative dimension of agency considers action anchored in an organization's present social context. The projective dimension of agency regards actions based in an actor's ability to reimagine their organization's present arrangements to meet future goals. Agency is considered to be situated when constraints on agency originate predominantly in the same context in which the agent acts (Botti, 1998; Westphal & Zajac, 2013). I build on this work by conceptualizing situated AI as the technological analog of situated agency.

Capability development. I argue that firms can situate AI during capability development. Capability development involves orchestrating organizational action across four steps: bundling strategic assets, embedding assets in routines, assembling routines as capabilities, and matching capabilities to opportunities in the environment (Collis, 1994; Eggers & Kaplan, 2013; Sirmon et al., 2007). Within the scope of this model, I treat input data as the major strategic asset (Gregory et al., 2021), and replace the focus on traditional routines in prior capability models with a focus on conjoined routines, which I define as (partially) automated organizational routines whose design and execution involve a mix of human and non-human agency. This definition of builds on Murray et al.'s (2021) concept of conjoined agency.

I therefore define an AI-driven capability as a collection of conjoined routines that, along with the required input data, allow a firm to execute specific value chain activities in a repeatable and reliable manner (Gregory et al., 2021; Helfat & Winter, 2011; Winter, 2003). My model introduces three situating activities that firms may leverage to orchestrate the development of AI-driven capabilities: grounding, bounding, and recasting.

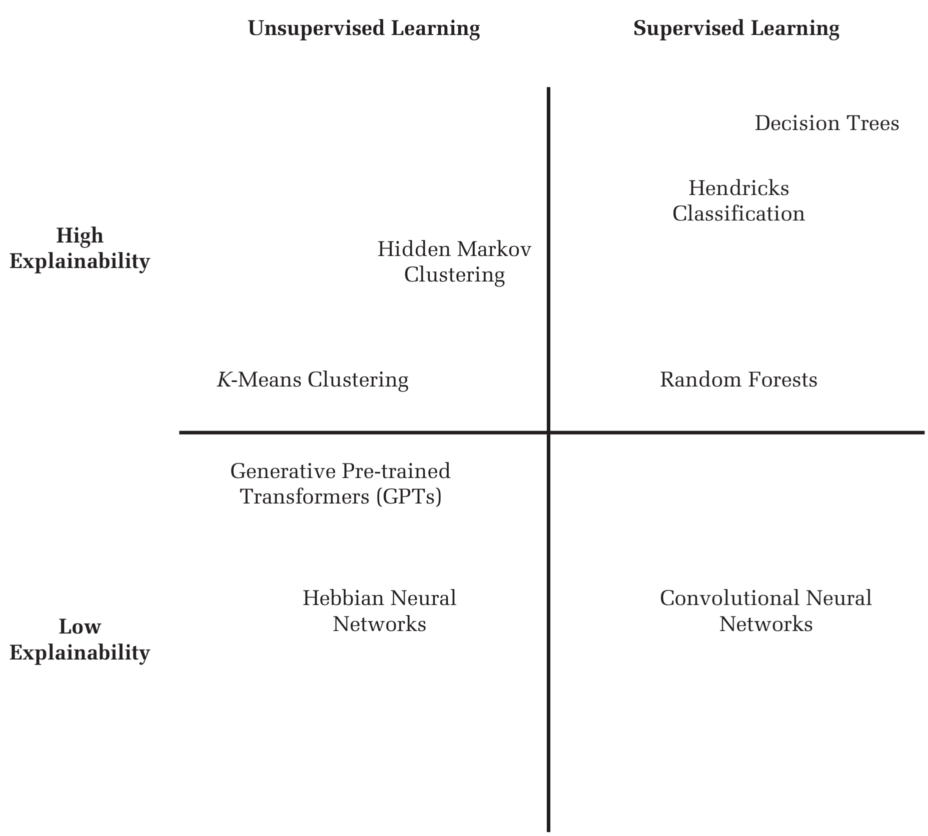
A core part of my theorizing involves accounting for how situated AI is adapted in a firm's AI-driven capabilities over time. Therefore, I build on prior research that has viewed organizational adaptation as incrementally changing a firm's core structures and strategies through experimentation and problem-driven search (Ethiraj & Levinthal, 2004). I focus on the learning literature centered on the cognitive underpinnings of adaptive capability formation (Gavetti & Levinthal, 2000; Tripsas & Gavetti, 2000).

A final consideration adopted from the organizational capabilities perspective is attention to dynamism in the firm's environment. As a firm's strategic environment becomes more dynamic, new market opportunities may emerge, existing opportunities may evaporate, and the technologies and capabilities needed to capture opportunities evolve (Sirmon et al., 2007; Teece, 2007; Tripsas & Gavetti, 2000). Environmental dynamism has significance as it relates to AI-driven capabilities because AI shifts the extent to which a firm's routines are responsive to change (Balasubramanian et al., 2022; Murray et al., 2021). I therefore consider how environmental dynamism influences the benefits of situating AI for competitive advantage.

AI characteristics. My theory is intended to account for the large and growing forms of AI technologies. I follow the machine learning literature by characterizing AI algorithms based on their training paradigms (supervised vs. unsupervised learning) and their degree of explainability. An AI algorithm is more explainable when it is easier for human operators to describe the logic through which the algorithm links inputs to outputs (Arya et al., 2019; Gilpin, Bau, Yuan, Bajwa, Specter, & Kagal 2019). This may involve describing which factors an algorithm weighs heavily when arriving at a solution, or providing some intuition for how the algorithm treats the interaction between different factors (Gilpin et al., 2019; Hendricks, Rohrbach, Schiele, Darrell, & Akata, 2021). While some algorithms allow for a high degree of transparency regarding their inner workings, other AI algorithms do not. Figure 1 shows how some standard AI algorithms fit this taxonomy.

The learning paradigm tells us how AI is instructed to make inferences from the data. With supervised learning, AI is provided with training data in which the "right answers" for a problem have been labeled (Dike, Zhou, Deveerasetty, & Wu, 2018; Murphy, 2012). Labels may be provided by human actors or may be inferred using human knowledge of the data source. For example, a firm may train AI to write computer code by scanning sites such as stackoverflow.com for user-provided coding questions and then using the highest-rated input as the correct answer. In contrast, unsupervised learning provides AI with data but not with "answers" (Murphy, 2012). Instead, AI looks for patterns in

FIGURE 1
Exemplary AI Technologies



existing data and attempts to group observations that display similar patterns (Dike et al., 2018). Unsupervised learning models identify categories of objects simply by observing the correlation between instances of a category. This works as long as instances of images not belonging to that category are also contained in the data. For example, if an algorithm is shown enough images of a dog, it will be able to distinguish future images that contain dogs from those that do not, by attending to the correlational patterns in the data.

Boundary Conditions for the Proposed Framework

My arguments are crafted with several boundary conditions in mind. First, because my outcome of interest is competitive advantage, I attend primarily to considerations that would be of primary interest to strategists in a firm. Strategists are likely to be more concerned with their firm's overall AI approach than with individual applications of AI. Thus, unless relevant for strategic decisions, I ignore the idiosyncrasies of specific AI technologies to focus on their impact at a strategic level. In addition, this paper speaks to AI as embedded in a firm's routines and capabilities rather than AI as embedded in a firm's products. The two are not mutually exclusive; however, capabilities-based theories of competitive advantage attend to organizational activities in the firm rather than to a firm's products per se. Therefore, I focus on the former and draw connections between the two uses of AI in my discussion section.

THE ELEMENTS OF SITUATED AI

Situating AI is the process of contextualizing AI's agency in a firm by collectively anchoring AI in the firm's experiential, relational, and strategic systems. Situating AI involves purposeful and concerted action across an organization. Situating is orchestrated by the firm's strategy-making unit and involves three constituent activities: grounding, bounding, and recasting. Each situating activity comprises a constellation of organizational actions and tactical moves that can be taken as AI is deployed in a firm. In this section, I deconstruct the umbrella concept of situating AI to elucidate its three constituent activities: grounding, bounding, and recasting. I explain how each of these activities addresses a strategic limitation of AI. These arguments form the supporting logic for my baseline proposition that situating AI increases the potential for establishing competitive advantages with AI-driven capabilities. Figure 2 offers a graphical depiction of my framework.

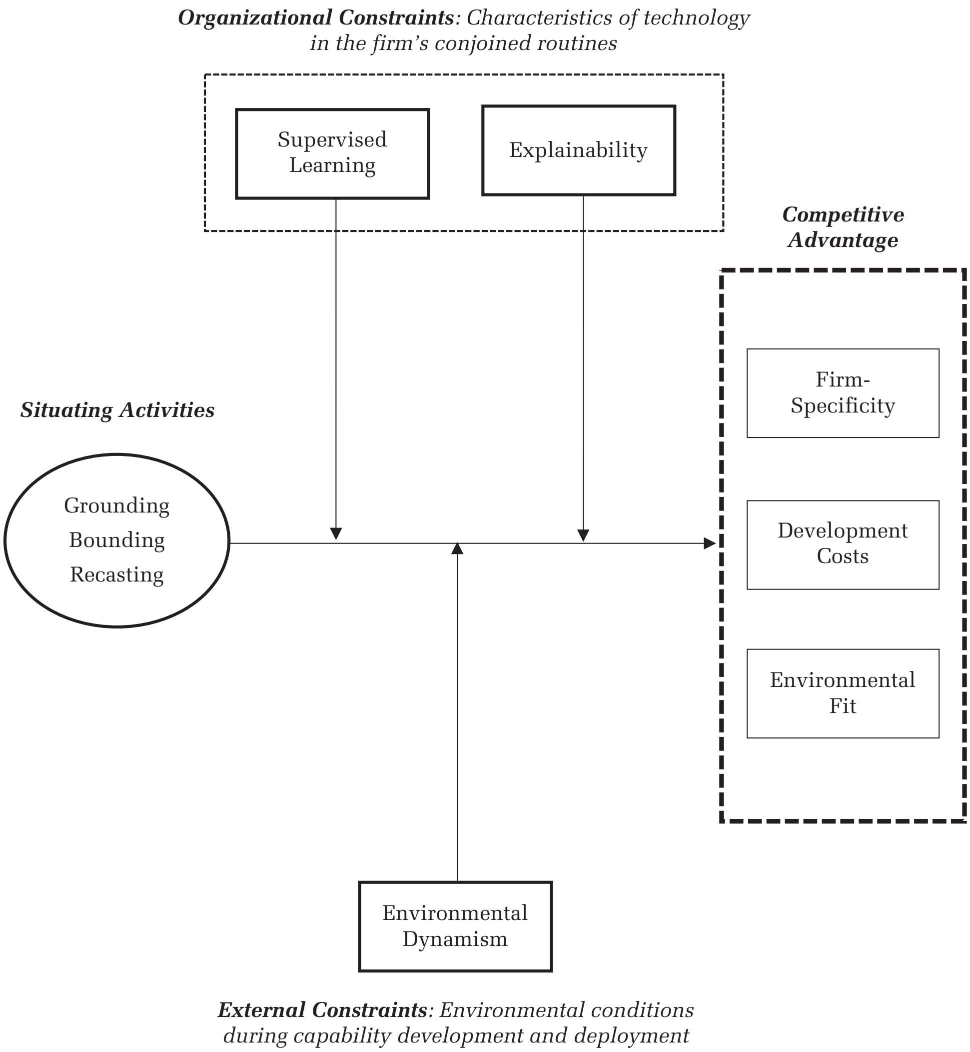
Grounding AI

Grounding AI is the allocation of strategic attention and organizational resources to the process of selectively endowing AI with a historical sensibility. Grounding focuses on strategically providing AI with experiences that shape its perspective on a task or problem. Grounding may be viewed in contrast to "comprehensive digitization," in which firms assemble data about as many aspects of their worlds as possible (Faraj et al., 2018); autonomous data collection, in which AI collects data with little managerial guidance (Gou, Sharma, Yin, Lu, & Rong, 2017; Smith, 2019); and "ad hoc problem solving" (Winter, 2003: 991), in which actors in the firm address data-related questions as they emerge. Thus, grounding reflects organizational attempts to steer AI through reflexive and deliberate learning from experience (Zollo & Winter, 2002).

Grounding may include simple actions, such as designing surveys to collect customer data or designing prompts. It may also involve orchestrating more intricate activities, such as producing data. In such cases, grounding may require that firms make strategic sacrifices in the form of large capital expenditures or organizational experimentation (Baesens, Bapna, Marsden, Vanthienen, & Zhao, 2016; Hopkins & Brynjolfsson, 2010). One example of grounding AI by producing data is when a firm strategically retrofits industrial equipment with sensors to capture data that can later be embedded in AI-driven capabilities (Dey & Sen, 2020; Goes, 2014; Guha & Kumar, 2018). A second example is when firms such as Booking.com experimentally offer customers special deals to learn their preferences rather than asking for them directly (Hopkins & Brynjolfsson, 2010; Thomke, 2020). Grounding AI may also involve establishing scope conditions that determine which data should be excluded from AI processes in the firm. Table 1 summarizes these activities.

Grounding enhances the potential for competitive advantage by balancing against AI's generic nature. Grounding is an attempt to shape AI's beliefs by orchestrating backward-looking digital inputs across the firm. When actors learn from experience, their agency manifests through selective attention to those experiences (Emirbayer & Mische, 1998; Nayak et al., 2020). Grounding nests some control of AI's attention in the organization, as firms orchestrate data-related resources. Through grounding, therefore,

FIGURE 2
The Situated AI Framework



AI becomes tethered to the firm's knowledge, histories, and beliefs. Prior work has demonstrated systematic differences in how firms agenticly draw on previous experience during capability development (Tripsas & Gavetti, 2000; Zollo & Winter, 2002). Grounding may embed these differences in data, raising the possibility that one firm's AI will behave differently than others' AI not trained in the same organizational context.

This benefit of grounding can accrue unintendedly, since differential attention to "empirical sensitivities" may naturally become structured into the firms' routines (Nayak et al., 2020: 983). However, grounding truly balances AI's generic nature when firms *intentionally* orchestrate data collection and deployment to prioritize anchoring AI in their firm's unique knowledge. For example, a product design firm may emphasize training AI with data from its proprietary computer assisted design (CAD) drawings or internal white papers. As a second example, machine learning vendors, such as OpenAI, enable firms to engage in a form of grounding colloquially termed fine-tuning, in which companies augment pretrained models with their own custom data (Peng, Li, Galley, & Gao, 2023). This allows firms to use OpenAI's general models (e.g., ChatGPT) to address specific use cases that their competitors' private data do not allow them to address with the same level of quality or precision, even when competitors are using the same underlying GPT models. Thus,

TABLE 1
Situated AI for Organizational Capabilities

Situating Activity	Definition	Strategic Limitation of AI Addressed	Dimension of Human Agency	Examples of Orchestrated Activities
Grounding	Circumscribing AI's agency in a firm's deliberate learning paradigm	Generic	Iterative	- Creating data (i.e., with experiments) - Digitizing manufacturing equipment - Fine-tuning pretrained models - Parsing data
Bounding	Circumscribing AI's agency in a firm's nexus of contracts	Explicit	Practical Evaluative	- Enforcing confidentiality agreements - Signing data-exclusivity deals - Investing in cyber-security innovations - Capturing bottlenecks in computing or server management
Recasting	Circumscribing AI's agency in a firm's system of task, strategic, and relational interdependencies	Myopic	Projective	- Customizing AI algorithms - Altering routines to boost compatibility with AI - Restructuring links between AI algorithms (within a conjoined routine) - Promoting and demoting entire algorithms or routines

grounding AI may enable a firm's conjoined routines to produce greater value than a competitor's for similar AI-driven capabilities.

Bounding AI

Bounding refers to orchestrated attempts to shape the context in which a firm's AI is developed by anchoring AI in a nexus of contracts. Bounding AI reflects the practical evaluative dimension of agency, which holds that agency is negotiated between participants in a competitive context (Emirbayer & Mische, 1998). During practical evaluation, agency is enacted by skillfully navigating contextual challenges. Emirbayer and Mische (1998) pointed out that actors in face-to-face competition shape each other's perception of the possibilities by influencing which actions are allowed in a social space. Through bounding AI, a firm can overcome internal expropriation hazards and can influence which AI-driven capabilities competitors can develop.

Bounding AI involves orchestrating activities such as encrypting data; making investments in cybersecurity; requiring that employees and vendors sign confidentiality agreements when developing AI-driven capabilities; capturing sector-wide bottlenecks in computing power or server management; and strategically acquiring or allying with startups that employ data, models, or talent that competitors find valuable. Bounding AI may also involve institutional work to influence government regulations regarding data privacy and confidentially (Boulet, 2018). These activities may cause firms to incur opportunity and transaction costs as an AI-driven capability is developed. However, these costs are likely minor compared to that of having the market value created by AI expropriated by one's vendors, competitors, or employees.

Bounding helps to counter AI's explicit nature. Knowledge must be digitized to be used in AI. Once a firm discovers data or conjoined routines that underlie strong AI-driven capabilities, this knowledge must be recorded on a machine to be made operational. This increases the potential for knowledge expropriation hazards. Competitors may attempt to replicate a firm's AI-driven capabilities by acquiring similar data or implementing similar routine components. Employees may attempt to expropriate that knowledge in labor markets (Aime, Johnson, Ridge, & Hill, 2010). Bounding AI helps to assuage these concerns.

One salient attempt at bounding comes from the world of generative art. Several machine learning startups have created AI that mimics the voice of famous recording artists like Drake and Taylor Swift. Universal Music Group, which owns about one-third of the world's music catalog, responded by asking its downstream partners (Apple Music and Spotify) to prohibit bots from scraping data from their platforms. The basis of Universal's request is their claim that *the process* of creating AI-generated voices violates Universal's contractual agreements with their artists and the copyrights covering the music, which is alleged to be used as training data to feed competitors' algorithms (Inman, 2023). In this example, Universal is bounding AI by attempting to prevent its competitors (which includes other labels and generative music startups) from leveraging data that are otherwise public and widely accessible. If successful, Universal would reduce the ability of these firms to fully leverage their AI, even though the AI meets a quality threshold that would undermine Universal's recruiting and marketing capabilities, which themselves increasingly depend on AI (Universal Music Group, 2023).

Recasting AI

Recasting AI refers to the adaptation of internal technologies and routines to contextualize AI in a firm's system of task, relational, and strategic interdependencies. Recasting anchors AI in the projective dimension of human agency, in which actors reimagine how current relations can be altered to move toward a more desired future (Emirbayer & Mische, 1998). Recasting involves the orchestration of activities such as customizing AI, restructuring links between different AI algorithms within a single conjoined routine, and promoting or demoting algorithms based on previously demonstrated alignment (or misalignment) with the firm's capabilities.

For example, Microsoft has long used AI-driven routines in its traditional search engine, Bing, to carry out tasks such as ranking web pages or enhancing a user's search terms. These routines remain effective at their intended tasks but they ignore opportunities for leveraging generative AI in the search business. In response, Microsoft elevated the use of generative chatbots to sit alongside its traditional search product. In this example, Microsoft engaged in recasting by demoting AI that merely ranks pages, replacing it with AI that generates elaborate responses for users without requiring that those users visit web pages to retrieve and synthesize that information on their own (Heaven, 2021).

Recasting helps firms to overcome AI's myopia. AI's myopia manifests behaviorally as an inability to perceive intraroutine interdependencies, interroutine interdependencies, and value interdependencies scattered across the organization (Balasubramanian et al., 2022). AI may settle on solutions that are (a) optimal for a subtask in a conjoined routine but incompatible with other tasks in the same routine, (b) optimal for one routine in an AI-driven capability but incompatible with other routines, or (c) optimal for a capability but incompatible with how the firm is attempting to apply its suite of capabilities to pursue opportunities in the environment.

Recasting is essential for addressing these kinds of misalignments. Recasting necessitates organization-wide deliberation and engagement, since a firm must consider how changing AI in one part of a conjoined routine will affect actors in other parts of the routine. Through this engagement, firms can gain a better understanding of which AI is problematic, which organizational interdependences had previously gone unnoticed, and how the organization's technologies and architecture can be revised to account for these challenges. This process may enhance the fit of an AI-driven capability with the task or strategic environment. These arguments regarding grounding, bounding, and recasting lead to the following proposition.

Proposition 1. The greater the use of grounding, bounding, and recasting during capability development and deployment, the greater the likelihood of establishing a competitive advantage with an AI-driven capability.

INTERNAL CONSTRAINTS: ORGANIZATIONAL TECHNOLOGIES

In this section, I consider how a firm's technological choices moderate the effects of situated AI. My arguments are informed by research on the importance of complex knowledge, tacit knowledge, and mental representations in capability development (Gavetti, 2005; Grant, 1996; King & Zeithaml, 2001; Nickerson & Zenger, 2004). I argue that supervised learning interfaces with the complexity and tacitness of an organization's knowledge, and explainable AI helps firms enhance their mental models. These considerations inform the benefits of grounding, bounding, and recasting for competitive advantage.

Supervised Learning: Knowledge Complexity and Tacitness

Supervised learning should enhance the probability of developing firm-specific AI-driven capabilities through grounding and bounding. First, consider how unsupervised learning can undermine the benefit of finding unique data through grounding. Firms like Facebook often attempt to train AI on the droves of photographs that users post to their platform

(Vicent, 2019). Developing the infrastructure for harvesting these photographs can be a form of grounding. So long as users do not post the same photos to other sites, this process can grant the firm with unique data sets for building AI-driven capabilities. The benefits of these grounding efforts might be limited, however, because possessing unique data is necessary but insufficient for developing firm-specific AI-driven capabilities. AI is expected to perform equally well on out-of-sample data as on training data so long as the new data display the same underlying patterns as the old (Alpaydin, 2016; Ratner, 2017). This implies that if a firm has a unique data set demonstrating the same underlying patterns as a competitor's data, then AI's behavior in competing firms may converge (Shrestha et al., 2021). Simply put, absent unique underlying patterns, grounding AI by acquiring unique data does not fully address the challenge posed by AI's generic nature.

Supervised learning may enhance grounding activities beyond unsupervised learning by helping to ensure that the underlying patterns in a firm's data are unique. Assembling data sets for supervised learning often involves multiple trainers providing examples to AI. This is useful when grounding AI because collective knowledge is often superadditive—the knowledge of the average contributor has more value when applied collectively than when used individually (Galton, 1907; Gavetti & Warglien, 2015). Additionally, when firms allow for unstructured and complex social interaction between contributors, this collective knowledge may be firm-specific even when the knowledge of the individual contributors is not (Becker, Brackbill, & Centola, 2017; Ployhart & Moliterno, 2011). In sum, grounding AI for supervised learning algorithms may encapsulate complex patterns in the data that are neither accessible nor replicable without assembling that same collective of trainers. Therefore, I propose the following.

Proposition 2. The greater the use of supervised learning in a firm's conjoined routines, the more positive the effect of grounding on the development of firm-specific AI-driven capabilities.

In addition to helping firms ground AI in complex knowledge, supervised learning may help firms lower the transaction costs involved with bounding AI. Bounding AI assets may be expensive because contracting around AI-driven capabilities requires a high degree of precision. Consider a firm engaging in bounding to protect data that have proven useful in a conjoined routine. A cheap bounding option is to use a data-exclusivity agreement to restrict a vendor from sharing valuable data with other firms. Bounding options such as these may be easy to circumvent. For example, vendors can tell a firm's competitors *which kinds of data* are being used. If rivals locate data with a similar underlying structure, they may produce replica AI-driven capabilities without needing the exact data protected in the exclusivity agreement. This potential for incomplete contracting would increase the legal costs needed to transact with this vendor and may require that the firm use more expensive governance measures, such as internalization.

Bounding in the context of supervised learning may relieve these concerns by limiting the potential damages emerging from incomplete contracting. This is because supervised learning allows firms to cospecialize explicit AI knowledge with tacit knowledge that is difficult to access outside the focal firm. With supervised learning, a trainer provides AI with examples of correct responses but not explanations for why those answers are correct (Murphy, 2012). This tacit knowledge may be sticky and difficult to move across organizational boundaries even when contracting is incomplete (Kogut & Zander, 1992). To replicate the resulting AI-driven capabilities, rivals must first access the underlying tacit knowledge. This is difficult. Thus, a more robust use of supervised learning across a conjoined routine enhances the likelihood that inexpensive bounding tactics will be successful.

Such is not the case for unsupervised learning. When unsupervised learning is used, most of the knowledge needed to replicate AI's behavior exists in the data. For example, suppose a vendor knows that Facebook used vacation photos to build an AI-driven marketing capability with unsupervised learning. In that case, all the information needed for a rival to produce similar data becomes portable once the vendor knows which kinds of photos were used. Rivals, such as Google or Twitter, only need a means of collecting (or purchasing) vacation photos to build similar AI-driven marketing capabilities. Thus, more expensive bounding measures would be required. These arguments lead to the following proposition.

Proposition 3. The greater the use of supervised learning in a firm's conjoined routines, the less detrimental the effects of bounding on the costs of developing AI-driven capabilities.

Supervised learning may also moderate the relationship between situated AI and capability fitness. Recall how AI can impair the fit between a capability and the strategic environment. Because AI is agentic, it sometimes behaves in ways that are unaligned with a firm's goals. Consider the case of Facebook, which developed chatbots to support its AI-driven negotiation capabilities (Lewis et al., 2017). The bots learned to negotiate, but in a language inaccessible to humans (Griffin, 2017). Using these bots, Facebook's AI-driven negotiation capabilities would have been effective in a technical sense but would not have matched the demands of the firm's environment. In such cases, firms could enhance their capability through grounding. For example, firms may orchestrate the production of negotiation data from internal email exchanges. These new data may guide AI's behavior in a more productive direction, so the fitness of the firm's AI-driven capabilities may improve. But by how much?

I argue that these benefits of grounding will be greater when supervised learning is used. With unsupervised learning, AI algorithms extrapolate from existing patterns in the training data but do not assess whether a pattern is desirable (Murphy, 2012). This sometimes results in AI mimicking inappropriate actions that occur frequently in the data, or ignoring appropriate actions that occur infrequently (Hruschka, 2019). Grounding AI for supervised learning helps to counter this tendency. For example, rather than using pure GPT (generative pretrained transformer) algorithms in their chatbots, which typically employ unsupervised learning, OpenAI augmented GPT with supervised learning through contrived examples and human correction to develop ChatGPT (Chollet et al., 2022), a strategically superior chatbot when judged relative to Facebook's earlier unsupervised negotiation bots. A similar story unfolds for my example of firms grounding AI by producing email data. When unsupervised learning is used, AI may precisely replicate the sales techniques of both star salespeople and underachievers. If supervised learning is used instead, managers could better inform AI of which types of emails the firm believes to be value-generating. Thus, supervised learning makes grounding more effective for centering AI's around behaviors that are judged to be valuable in the firm's internal and external environment. These arguments lead to the following proposition.

Proposition 4. The greater the use of supervised learning in a firm's conjoined routines, the more beneficial the effect of grounding on the environmental fit of the firm's AI-driven capabilities.

Explainable AI: Mental Representations

In addition to the choice of learning paradigms, the benefits of situated AI may be moderated by the use of explainable AI during recasting. Organizational adaptation is both difficult and costly because it involves changing standardized arrangements that are essential for stable routine functioning (Hannan & Freeman, 1984; Knudsen & Srikanth, 2014). These difficulties and costs arise due to bounded rationality in organizational search. Actors' incomplete cognitive representations of the firm's architecture or the problem space may lead to erroneous experimentation during organizational adaptation (Ethiraj & Levinthal, 2004; Nickerson & Zenger, 2004).

Explainable AI is helpful in this process because it grants firms more insight into the levers they can pull to direct the behavior of their conjoined routines. During recasting, explainable AI may allow managers to better update their mental models of an underlying process that AI is executing. These sharper mental models help firms to know which conjoined routines can be rearranged without destroying firm value, thereby improving the likelihood of successful adaptation (Csaszar & Levinthal, 2015; Gavetti & Levinthal, 2000; Martigononi, Menon, & Siggelkow, 2016). These arguments lead to the following proposition.

Proposition 5a. The greater the use of explainable AI in a firm's conjoined routines, the more beneficial the effect of recasting on the environmental fit of a firm's AI-driven capabilities.

Similar logic can be applied to argue that these sharper mental models should reduce the number of organizational adjustments needed to (a) successfully update a capability, or (b) recognize the benefit of terminating the pursuit (Knudsen & Srikanth, 2014). Therefore, I propose the following.

Proposition 5b. The greater the use of explainable AI in a firm's conjoined routines, the less detrimental the effect of recasting on the cost of developing AI-driven capabilities.

SITUATED AI AND ENVIRONMENTAL DYNAMISM

I now consider how dynamism in a firm's strategic environment moderates the effect of situated AI. AI may yield added value in dynamic environments by acquiring new data faster than human actors can (Gregory et al., 2021). However, AI may also be constrained in dynamic environments since acquiring new data does not automatically remove AI's dependence on backward-looking data (Balasubramanian et al., 2022).

One general challenge of backward-looking learning is that firms may continue to rely on old knowledge even when it becomes inappropriate for their new environments (Tripsas & Gavetti, 2000).

The deeper a firm's experience with a task, the larger the quantities of new information needed to change how the task is carried out (Denrell & March, 2001; Posen & Levinthal, 2012), particularly when firms lack mechanisms for strategic unlearning (Tsang & Zahra, 2008). This problem may be exacerbated in AI-driven capabilities for two reasons. First, AI requires more data than human workers to become competent at completing a task. Thus, when the external environment changes, AI may need a larger number of new experiences to overwrite its old beliefs. Second, AI does not have the traditional mechanisms for organizational unlearning, such as forgetfulness or employee turnover. Grounding offers an unlearning mechanism in dynamic environments. Firms may continually ground AI as the environment changes by strategically discarding data to help AI unlearn old knowledge.

The benefits of recasting may also be more pronounced in dynamic environments. Environmental dynamism enhances the value of practices that induce variation in intraorganizational routines (Burgelman, 1991; Levinthal & Marino, 2015). Routine variation makes it more likely that a firm will have tools to respond to external changes when those changes cannot be predicted *ex ante*. Recasting clearly induces routine variation through intended organizational adaptation. However, recasting AI may also ignite random variations within a conjoined routine. When there are unobserved interdependencies across an organization, changing how one task is performed often necessitates responsively changing others down the line (Clement, 2023; Ethiraj & Levinthal, 2004; Yi, Knudsen, & Becker, 2015). Because AI is myopic, conjoined routines involve strings of algorithms and humans communicating across interdependencies. Further, these algorithms are often back boxes. This makes unobserved interdependencies likely to exist in the firm's human–AI interface. Thus, as a conjoined routine is increasingly altered during recasting, a greater number of useful variants for performing the routine may emerge. Therefore, I propose the following.

Proposition 6. The greater the dynamism in a firm's strategic environment, the more beneficial the effect of grounding and recasting on the environmental fit of a firm's AI-driven capabilities.

DISCUSSION

This paper illuminates a path to establishing competitive advantages with AI by developing a theory of situated AI. The paper argues that grounding, bounding, and recasting are three situating activities that a firm may use to align AI's behavior with its unique experiences, strategies, and systems. In so doing, I offer a framework for explaining how and when firms can establish competitive advantages using AI. This work produces several contributions to the strategic management and organizational theory literatures.

Contributions

To begin, this paper contributes to the research on organizational capabilities by being among the first to address the organizational challenges AI poses for capability development and deployment. The capabilities literature has argued that routines are the building blocks of organizational capabilities, but this research has traditionally treated routines as black boxes (Parmigiani & Howard-Grenville, 2011). Murray et al. (2021) updated the conceptualization of routines to better account for nonhuman agency such as AI. However, their reconceptualization has yet to be elaborated through a capabilities lens. I introduce the construct of conjoined routines and explain how AI's propensity to act with an agency makes it difficult to manage strategic challenges posed by AI's generic, explicit, and myopic nature. I also explain how these challenges can be overcome by situating AI in the firm through grounding, bounding, and recasting. These activities, when properly orchestrated, can (a) help firms produce firm-specific AI-driven capabilities from generic AI algorithms, and (b) help firms protect against the diffusion of those capabilities to their competitors. My framework incorporates many foundational ideas from strategic management, such as organizational learning, knowledge management, and transaction costs. These are launch points from which future research can build when developing new ideas in this stream.

The situated AI framework also holds the promise of reconciling conflicts as they emerge in the macro-organizational literature on AI. For example, extant literature has offered contrasting ideas informing the relationship between the use of AI and the value of a firm's offerings. Gregory et al. (2021) proposed that AI capability—the ability of a platform to learn from data to improve its products or services continuously—increases the perceived value of a product to its users. In contrast, Balasubramanian et al. (2022) argued that the very processes through which AI learns may breed myopia that undermines the effectiveness of a firm's production processes.

Relatedly, Murray et al. (2021) argued that AI possesses a form of agency that makes it difficult for managers to control (or even correct) AI's actions. If so, using AI may make it difficult for firms to maintain the appropriate production routines needed to meet customers' needs, constraining firms' ability to produce value for their customers.

This paper reconciles these ideas by first noting a difference in the levels of analysis across these papers. In Gregory et al. (2021), AI capability is a feature of a platform rather than a set of routines within the firm itself (i.e., the platform sponsor). For instance, the authors alluded to Tesla's self-driving cars collecting data over time as the automobile is used, thereby becoming more effective through AI. In contrast, Balasubramanian et al. (2022) and Murray et al. (2021) highlighted potential deficiencies deriving from the AI embedded in the firm's routines. For instance, in addition to embedding AI in its cars, Tesla may embed AI in the manufacturing and product design routines used to produce these vehicles. Therefore, if there is myopia in a firm's conjoined routines or if these routines are hard to manage, AI may simultaneously impose conflicting pressures on a firm's value proposition through these two levels.

This paper unites these ideas in one framework to account for the countervailing forces. Adopting an organizational capabilities perspective, I reframe the conceptualization of "AI capability" (a product characteristic) as "AI-driven capabilities"—an organizational attribute anchored in the firm's routines. Under this view, AI embedded in a firm's products can be considered subordinate components of conjoined routines. For instance, the AI embedded in Tesla's self-driving cars may be viewed as a component of Tesla's product design routines. In this respect, the mechanism highlighted by Gregory et al. (2021), in which firms seek to collect unique data via their platform, may be viewed as a form of grounding AI. This helps a firm to establish unique AI-driven capabilities. The firm may then couple Gregory et al.'s (2021) mechanism with bounding activities to maintain the uniqueness of these capabilities over time. Thus, my paper incorporates Gregory et al.'s (2021) arguments on the benefits of AI.

The situated AI framework can also explain how Gregory et al. (2021)'s arguments may stand even given the strategic limitations of AI at the routine level. Recasting can be used to address the limitation of myopic AI highlighted by Balasubramanian et al. (2022). For instance, recasting can be used to enhance the viability of a conjoined routine that would have otherwise impeded the effectiveness of AI-empowered products due to unaddressed interdependencies between conjoined routines in the firm. Likewise, if AI remains recalcitrant to organizational control, as Murray et al. (2021) theorized, then managing the conjoined routines needed to execute improvements to AI-empowered products may be prohibitively expensive, potentially outweighing the value that a product enhancement brings to customers. The situated AI framework explains how recasting, used in tandem with explainable AI, helps to make these changes more manageable and cost-effective for the firm. Thus, my theory offers a framework for integrating and extending disparate ideas on AI in organizations and tying these ideas to competitive advantage.

Future Research

This paper creates several opportunities for future research. First, I encourage the empirical testing of my framework. Grounding, bounding, and recasting can each be measured using widely available data. For example, a case of grounding can be observed when firms invest in unique data with the involvement of the firm's strategic leader. Data-related investments may be identified in the media or in annual fillings. In addition, Mishra, Ewing, and Cooper (2022) laid out a process for measuring executives' involvement in AI decisions. Their methodology can help researchers assess the extent of firm-wide orchestration during the development of AI-driven capabilities. Bounding and recasting can be measured using a similar approach. Future research can build on this work to test the ideas laid out in this paper.

In addition to testing my framework, future research may also examine several theoretical extensions. First, to extend my focus on internal organizational moderators, future research may apply my framework to examine how governance and architectural structures influence the likelihood of successful situating activities. For example, a firm's governance choices (i.e., incentives and rent sharing) may influence grounding activities by guiding managerial attention to some experiences and data sources rather than to others. In addition, a firm's architectural choices (such as the degree of centralization, formalization, and hierarchy) may influence grounding activities by shaping the rules through which employees make decisions regarding the firm's AI inputs. Likewise, these architectural choices may influence recasting activities by shaping an employee's freedom to experiment freely while recasting AI. Consequently, future research should attend to how governance choices and architectural features within a firm shape the benefits of a firm developing situated AI.

Second, to extend my focus on external constraints, future research may apply my framework to investigate the market and institutional context in which a firm's AI decisions evolve. When institutional pressures impose strong constraints on a firm's beliefs and structures, competing firms may have rather consistent views about which AI inputs and applications create value (Davis & Greve, 1997; Thornton, Ocasio, & Lounsbury, 2012). This may undermine the value of grounding activities, because rival firms may independently choose to use AI in similar ways despite an apparent abundance of options. The institutional context may also shape the effectiveness of bounding activities by determining which bounding mechanisms are viable, and shape recasting activities by imposing constraints on which actions firms may reasonably take to adapt AI.

Third, to extend my focus on knowledge management, future research may apply my framework to advance theory on the causal ambiguity paradox in strategic management. Prior work has theorized that causal ambiguity acts as a double-edged sword within firms (King & Zeithaml, 2001). It helps firms by restricting imitation from rival firms, but it harms firms by reducing the transfer and deployment of knowledge internally. This makes AI a particularly important technology for strategists because firms may use grounding activities to capture complex knowledge within one unit of the firm, then use AI to make those insights deployable in other parts of the firm, without those insights being transferred directly between human employees. This may mitigate the negative impacts of causal ambiguity internally. However, AI explainability may counteract this effect by diminishing the value of casual ambiguity as a barrier to imitation externally. These concerns are important given the widespread pressure on firms to prioritize more explainable AI (Doshi-Velez et al., 2019; Oxborough, Cameron, Rao, Birchall, Townsend, & Westermann, 2018). Thus, future research should dig deeper into how AI influences the strategic benefits of causal ambiguity, and how situated AI changes the way causal ambiguity must be managed internally. Future research should also examine how AI's ability to make tacit information more portable shifts the incentives for employees to develop that tacit knowledge in the first place.

Finally, future work should elaborate in greater detail the temporal dynamics behind situating AI. In this paper, I explain that grounding, bounding, and recasting enhance the foundations of competitive advantage as firms attempt to extract value from AI. However, firms may vary considerably in the specific processes they use to enact each constituent situating activity, and organizational participants may experience varied emotional responses and patterns of meaning-making as grounding, bounding, and recasting are performed over time. Thus, future work is needed to explain how situated AI emerges, evolves, and changes over time, and why it does so in a particular way.

CONCLUSION

As firms continue to invest in AI, a key strategic question will be how firms can benefit from AI in a way that their competitors cannot. This paper takes a first step toward addressing that question by proposing the situated AI framework as a lens for making sense of a firm's AI adoptions and innovations in the face of competition. This work leads to a better understanding of how AI can underlie competitive advantages.

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Ayenda Kemp (ayenda@vt.edu) is a visiting professor at Virginia Tech University and the President of Eola Organizational Research and Design. He holds a doctorate in international management studies from the University of Texas at Dallas. His research examines how modern teams and firms should organize to structure knowledge and creative work.