**AUGMENTATION LOGICS AND THE FUNDAMENTAL ASSEMBLAGE: EXPLAINING ORGANIZATIONAL BOUNDARIES IN SITUATED AI THEORY**

**Abstract**

This paper advances the organizational literature on artificial intelligence by presenting an argument linking an organization’s internal treatments of artificial intelligence to its external boundary arrangements. To advance that argument, we introduce two constructs to the literature, augmentation logics and the fundamental assemblage. *Augmentation logics* are organization-specific design logics for combining human and artificial intelligence to create value at the task level. A fundamental assemblage is a minimal configuration of human and machine actors needed to execute a specific task. We explain how augmentation logics may differ in their treatment of machine agency and how this difference creates unique conditions under which splitting a fundamental assemblage across organizational boundaries is viable. From this analysis, one can deduce theoretical propositions relating a firm’s augmentation logic to a broad range of external strategic choices.

What determines the boundaries of the AI-augmented firm? We define artificial intelligence as any human-derived organizational knowledge tool that can influence organizational outcomes without direct human influence. Strategic management scholars are increasingly interested in understanding how artificial intelligence influences how firms organize (Adner, Puranam, and Zhu, 2019; Baum and Haveman,, 2020; Helfat et al., 2023). Recent research suggests that artificial intelligence is likely to become a core driver of firm value, with AI-driven capabilities replacing traditional human capabilities (Jacobides, Brusoni, and Candelon, 2021; Krakowski, Luger, and Raisch, 2023). Yet, while this research speaks to the potential of artificial intelligence for driving organizational change at the firm level, the boundary arrangements needed for an AI-augmented firm to create and capture in competitive markets are little understood.

Strategic and organizational theories almost universally suggest that creating value in modern markets requires that firms collaborate with external organizations to collectively develop and execute the core routines needed to serve customer needs (Baum, Calabrese, and Silverman, 2000; Gulati, Nohria, and Zaheer, 2000; Kellogg, Orlikowski, and Yates, 2006; Nickerson, Yen, and Mahoney, 2012; Puranam, Alexy, and Reitzig, 2014; Teece, 2007). Ideally, markets would easily facilitate this collaborative work, but they often fail when collaboration involves intense knowledge creation and exchange (Arrow, 1973; Nickerson and Zenger, 2004; Stiglitz, 1999). Since artificial intelligence is primarily an epistemic tool (Townsend et al., 2024), this raises questions regarding how firms can collaborate to create value with AI. Indeed, prior research on artificial intelligence in organizations points to the difficulties of contextualizing AI-augmented work in multitask multiagent ecosystems (Anthony, Bechky, and Fayard, 2023), and strategic management theory questions the extent to which artificial intelligence can be meaningfully leveraged across organizational interdependencies (Kemp 2024). Thus, while knowledge-driven firms need to collaborate with others to create value in markets, current theory calls into question the extent to which AI can be effectively coordinated across firm boundaries.

This paper offers a framework for addressing that puzzle from the perspective of situated AI theory (Kemp, 2024). We begin by displacing the firm as the basic unit of organizing in situated AI theory. To facilitate this conceptual shift, we introduce two constructs—the augmentation logic and the fundamental assemblage. We define a fundamental assemblage as a minimal combination of human agents, machine agents, and organizational artifacts needed to carry out a specific task. We define an augmentation logic as a system of design heuristics that provides organization-wide guidance for combining human and artificial intelligence to create value on specific tasks.

We categorize augmentation logics by the divergent heuristics they employ for partitioning and reintegrating subtasks among human and AI agents. Building on recent research on human-AI organizing, we highlight how distinct augmentation logics may differ in their approach to unlocking value from a human-AI assemblage the task level (Choudhary et al., 2023; Glaser 2017; Glaser, Sloan, and Gehman, 2024; Raisch and Fomina, 2024). We combine these ideas with the research on value creation in task ecosystems to hypothesize the types of tasks around which strategic augmentation is likely to emerge (Baldwin, MacCormack, and Rusnak 2014; Karim, Lee, and Hoehn‐Weiss, 2023). We highlight the role of task bottlenecks in augmented work and relate the strategic management of bottlenecks to the choice of augmentation logic used to govern the work in a fundamental assemblage.

Organizational boundaries can then be described as patterns of high-powered and low-powered governance ties connecting distinct human-AI assemblages. Conceptually, we describe a multitask ecosystem by building out from a bottleneck task and its associated fundamental assemblage and then adding tasks, algorithms, and humans that work in conjunction with the fundamental assemblage to create value. This framework offers a path toward addressing the larger question of how AI-augmented firms manage interorganizational life.

**THEORETICAL MOTIVATION**

What determines the boundaries of the AI-augmented firm?Boundary arrangements reflect instances in which an organizational unit must decide which tasks to complete internally and how to govern collaborations on tasks that need to be completed in tandem with others (Santos and Eisenhardt, 2005). Boundary decisions arise at the intersection of strategy and organizational design. From a strategic perspective, boundary arrangements are a question of value creation and value capture. The concern for value creation suggests that an organization's leaders internalize tasks within firm boundaries when the completion of those tasks produce unique value for the broader interorganizational ecosystem (Kogut and Zander, 1992). However, markets and technologies incentivize specialization, forcing organizational units to cooperate with others to create value (Conner and Prahalad, 1996). Concerns regarding competition and its adverse effects, such as opportunism, jeopardize value capture from these arrangements (Williamson, 1983). This requires that a firm leverages the technical, relational, and contractual tools at its disposal to prevent value created via the internalized tasks from being expropriated by other actors, thereby shaping the firm’s boundaries (Nickerson and Zenger, 2004).

When viewed from an organizational design perspective, boundary arrangements can be stated in terms of cooperation and coordination problems (Gulati and Singh, 1998; Kellogg et al., 2006). The basic problem of organizational design involves partitioning and re-integrating work (Puranam et al., 2012). In this view, organizations exist to address problems that are too large for one actor to solve. The job of organizational design then involves partitioning that work into subtasks, assigning subtasks to dispersed actors, and reassembling those component solutions into a cohesive whole (Dijksterhuis, Van Den Bosch, and Volberda, 1999; Puranam, Alexy, and Reitzig, 2014). The agents completing the subtasks are assumed to be boundedly rational, with potentially conflicting goals. This simple design problem of partitioning and integrating may be plagued with cooperation and coordination problems across actors. Cooperation problems involve instances in which parties with divergent goals must pursue aligned objectives (Puranam et al., 2012). Coordination problems involve difficulties in configuring interdependent resources to complete a task effectively, even when goals are perfectly aligned (Knudsen and Srikanth, 2014; Heath and Staudenmayer, 2000; Srikanth and Puranam, 2011).

Boundary decisions represent a specific type of design problem. Here, a task is partitioned, and the designer must decide whether to co-group subtasks into a single decision unit (e.g., the firm) or multiple decision units (e.g., the firm and a supplier). Thus, effective boundary decisions involve solving cooperation and coordination problems to produce and capture value in task systems where a single organization cannot complete all tasks alone.

Despite the importance of understanding boundary arrangements, there are very few explicit accounts in organizational theory or strategic management that explain how the boundaries of the AI-driven firm are constructed. Prior research has documented that AI-driven firms appear to be organized around unique principles relative to traditional firms and tend to display a variety of boundary configurations (Jacobides et al., 2021). Jacobides et al. (2021) highlight that large firms, particularly the big four tech firms in the US and their foreign counterparts (i.e., Alibaba and Tencent), are rather homogeneous in their boundary arrangements in the sense that they tend to be active in every area of AI development and deployment. This ranges from producing AI solutions for customers to running AI-driven capabilities to power their own operations. Beyond this small group of tech elites, however, firms seem to display far more heterogeneity in their boundary arrangements. Yet, while this research documents unique patterns of boundary configurations among AI-driven firms, there are no theoretical frameworks for articulating how a firm’s internal management of AI is implicated in how its external boundary configurations arise. We extend that research in this paper.

**CONCEPTUAL FOUNDATIONS**

This section discusses our model's assumptions and grounds those assumptions in existing theory. We model a market as an ecosystem of interdependent but distinct human-AI assemblages, each working at the task level (Glaser, 2017; Moser, Glaser, and Lindebaum 2024). A human-AI assemblage is an organizational unit comprising human agents, non-human agents, and artifacts (Glaser, Pollock, & D’Adderio, 2021; Glaser et al., 2024; Latour, 2007). The ecosystem as a whole acts to solve problems that can be packaged and sold to customers (Baldwin et al. 2014; Baldwin, Bogers, Kapoor, & West, 2024; Nickerson and Zenger, 2004). Each assemblage has an epicenter of intentionality—a sub-assemblage of strategic agents pursuing resources to protect the survival of a self it can identify. We will assume that it is this struggle for resources among assemblages that produces boundaries in a multi-task ecosystem.

Generally speaking, no single assemblage can complete all the tasks required for the full solution. Depending on how its boundaries are constructed, an assemblage may constitute a firm, a department within a firm, or a collection of networked organizations behaving like a cohesive whole to carry out the task at hand. From the perspective of situated AI theory, agents in the epicenter of intentionality for an assemblage act as organizational architects, who strategically rearrange the assemblage over time to create value (Kemp, 2024). Each assemblage that contributes to the overall ecosystem solution receives a portion of the total value retrieved from the customer (Baldwin et al., 2024).

Subtasks completed across assemblages are coordinated by market mechanisms unless (1) more advantageous coordination arrangements can be found or (2) no viable coordination arrangement can be found. In our framework, market coordination manifests as loosely coupled arrangements between assemblages (Callon, 1998). Whereas, hierarchical coordination manifests as tightly coupled governance arrangements between assemblages (i.e. Kellogg et al., 2006; Willimson, 1983). In cases where no market or organizational mechanism can be arranged, the collective solution fails or underperforms. This characterization of the market problem is consistent with research on ecosystems, meta-organizations, and platforms (Gulati, Puranam, and Tushman, 2012; Jacobides, Cennamo, and Gawer, 2018; Kapoor and Lee, 2013; Kretschmer et al., 2022). However, the treatment is broad enough to leave open the possibility that novel organizational forms might emerge within a market.

Within each assemblage, solutions to subtasks are decided through a combination of human intelligence and artificial intelligence. We will explain how the logic used to partition and integrate tasks between humans and AI within an assemblage influences how that assemblage can interact with others to create value in a multi-task multi-assemblage system.

Our argument necessarily draws on research from strategic management, organizational theory, and organizational design. When drawing on diverse constituting literature, conceptual development is enhanced by anchoring assumptions in a single integrative framework. We use situated AI theory as our overarching conceptual framework (Kemp, 2024). This framework is ideal for our case because it explicitly links value creation with artificial intelligence to the ability of an organization’s strategic leaders to manage humans and machine agents across systems of task interdependencies, which is essential for understanding how boundary arrangements unfold.

**Situated AI Theory**

Situated AI theory is a strategic management framework explaining how firms pursue competitive advantages with artificial intelligence (Kemp, 2024). The theory is anchored in the organizational capabilities tradition. It views a firm from the perspective of strategic organizers endowed with architectural knowledge, who constantly re-align the firm’s internal activities to create value and match them with opportunities in the environment.

Situated AI theory does not treat boundary arrangements as an outcome of interest. However, the theory does highlight *bounding* as a core activity needed to capture competitive advantages with artificial intelligence, where bounding is defined as the act of circumscribing machine agency in a firm’s nexus of contracts (Kemp, 2024). Higher bounding costs will be associated with greater difficulties in co-developing AI-driven capabilities across assemblages. Therefore, the theory is a useful launching point for understanding how an assemblage may organize the execution of augmented tasks while managing competition with other assemblages. Unpacking that idea in this paper requires relaxing situated AI theory’s focus on the firm as the unit of analysis, and importing into the theory research on design logics (Baldwin and Clark, 2000; Bingham and Eisenhardt, 2011; Kor and Mesko, 2013; Prahalad and Bettis, 1986), the work on ecosystem-wide value creation (Baldwin, 2024; Jacobides et al., 2018), and the emerging research on human-AI collaboration at the task level (Choudhary et al., 2023; Moser et al., 2024; Rasich and Fomina, 2024). We unite these research streams to introduce two new constructs into situated AI theory: the augmentation logic and the fundamental assemblage.

**Design Logics**

A design logic is a set of simple rules or heuristics that firms can apply to guide the adaptation of organizational structures over time (Baldwin and Clark, 2000; Bingham, Eisenhardt, and Furr, 2007; Ethiraj and Levinthal, 2004; Simon, 1991). Bignham and Eisenardt note that: “heuristics are at the heart of firm capabilities. That is, firm members must actively translate their process experience into shared heuristics for opportunity capture in order to develop a high-performing process”. They go on to note the role that an “explicit structure of heuristics” shapes efforts to create capabilities (Bingham and Eisenheardt, 2011: 29).

An augmentation logic is one form of design logic. When given a task and a goal, a complete design logic will contain two components: a heuristic for partitioning tasks (the partitioning heuristic) and a heuristic for re-integrating subtasks into full solutions (the integration heuristic). The partitioning and integration heuristics are intentionally chosen and implemented through deliberate organizational arrangements, albeit imperfectly. Augmentation logics are design logics focused specifically on the distribution of work between humans and AI for specific tasks. We identify two generic augmentation logics, the AI-as-informant logic and the AI-as-actant logic. We describe their integration and partitioning heuristics, and we link these augmentation logics to boundary arrangements in the multitask system.[[1]](#footnote-2)

In building our argument, we frequently leverage Simon’s (1991) principle of hierarchy in design. Tasks are hierarchical in that they may be decomposed into constellations of subtasks. Problems are hierarchical in that they may be decomposed into constellations of subproblems. Assemblages are hierarchical in that they may be decomposed into constellations of sub-assemblages. Accordingly, we model augmentation as the partitioning of a task into clusters of subtasks in a human-AI assemblage, with some subclusters assigned to machines and others assigned to humans*.*

Situated AI theory suggests that task-level augmentation may destroy organizational value when inconsistent with the firm’s overall strategy (Kemp, 2024). Augmentation logics help to connect the strategy-making layer of the organization to the strategy enacting layer. Generally speaking, strategic heuristics help coordinate organization-wide strategy execution and may act as a viable substitute for extensive planning and formalized procedures during strategy enactment (Bingham and Eisenheardt, 2011; Simon, 1993; Vuori et al. 2024). Thus, the heuristic foundations of the augmentation logic enable a firm’s strategy for situating AI to be meaningfully applied to specific clusters of tasks within the firm.

**Human-AI Assemblages, Conjoined Routines, and Task Bottlenecks**

In keeping with the capabilities tradition (Winter, 2003), situated AI theory anchors value creation in organizational routines, but focuses on conjoined routines, which allow augmented work to be developed and deployed repeatably and reliably at the discretion of strategic organizers (Kemp, 2024; Murray et al., 2021). Conjoined routines are organizational routines involving a mix of human and machine agencies (Kemp, 2024). Consistent with situated AI theory’s focus on the conjoined routine as the epicenter of value creation, we assume that the system of heuristics forming an augmentation logic will enhance value creation primarily through the development and enactment of routines in the firm (Amaya & Holweg, 2024).

Routines are patterns of coordinated action executed by multiple goal-directed actors (Feldman and Pentland, 2003). The notion of conjoined routines is useful for building ecosystem-based arguments for our framework. While routines may be wholly enacted in a single organization, they may also extend across organizations (Zollo, Reuer, and Singh, 2002; Delmestri, 1998). This helps us to frame boundary arrangements as arising from a strategic interconnecting of distinct assemblages, each struggling to create value in conjunction with others in ecosystem-wide routines.

The organizational atom in our ecosystem-extended situated AI argument is the fundamental assemblage. Recall that an assemblage is an organizational unit comprising human agents, non-human agents, and artifacts (Glaser, 2017). We define a fundamental assemblage as a *minimal combination* of human agents, machine agents, and organizational artifacts needed to carry out a specific task. The term minimal combination implies that removing any agent or artifact from the assemblage would result in an inability to complete the task at an acceptable level. It is possible to construct multiple fundamental assemblages to address the same task, potentially with different levels of efficacy. Moreover, adding unneeded members to an assemblage increases the cost of maintaining the assemblage in the face of competition. Thus, a fundamental assemblage is constructed at the limits of task decomposability, where those limits are contextually determined.

The fundamental assemblage construct is relational in the sense that the makeup of a fundamental assemblage can only be described with respect to specific actors, goals, and tasks (Emirbayer, 1997; Giddens, 1986). Starting from a fundamental assemblage, one can add humans, tasks, and algorithms to build out conjoined routines in a multitask multiagent system. Thus, a fundamental assemblage constitutes the foundational unit of organization in our extended situated AI framework and allows us to discuss the emergence of interorganizational arrangements as the outcome of competitive value creation among distinct assemblages.

In addition to allowing us to describe interconnected assemblages as either loosely or tightly coupled by governance and learning ties, the fundamental assemblage construct also helps us to highlight the role of bottleneck tasks in creating value within conjoined routines. Bottleneck tasks are those in a multitask system that impede overall system performance due to a dearth of acceptable solutions (Baldwin, 2019; Karim et al., 2023). Our basic argument is that the routine aspects of work within a task ecosystem allow actors in the task system to develop expectations about the “long-run” system strain imposed by specific tasks. When a bottleneck task is frequently invoked in ecosystem-wide conjoined routines, novel solutions will likely yield new strategic value and may become an epicenter of action, learning, and competition in the ecosystems (Baldwin, 2019). Once given a bottleneck task, one can identify a fundamental assemblage that can complete that task. Competition for a bottleneck task can be viewed from the perspective of that assemblage.

Given this setup, one can approach boundary decisions from the perspective of two questions. When is it okay to split a fundamental assemblage for bottleneck tasks across organizational boundaries? When does creating and capturing value from such tasks depend on keeping a fundamental assemblage intact? Figure 1 provides a high-level depiction of our conceptual arguments.

\*\*\* Figure 1 about here \*\*\*

**TASK BOTTLENECKS AS THE LOCUS OF STRATEGIC AUGMENTATION**

We show how the answers to these questions may reflect the choice of augmentation logic structuring the fundamental assemblage. Before relating augmentation logics to firms’ boundary arrangements, however, it is useful to first establish a baseline intuition for when augmentation creates value for firms. In situated AI theory, strategic value is created at the routine level (Kemp 2024; Moser et al., 2024). In practice, however, augmentation occurs at the task level ( Amaya & Holweg, 2024; Anthony, et al., 2023; Murray et al. 2021; Raisch and Krakowski, 2021). Thus, crafting situated AI arguments using augmentation as a central mechanism requires developing a conceptual apparatus for linking value creation at the task level with value creation at the routine level. We will anchor that conceptual apparatus on the idea of task bottlenecks.

Bottlenecks act as the strategic epicenter of task ecosystems. If a focal task acts as a bottleneck in an ecosystem, solutions appearing in the market make routines involving that focal task more efficient or more effective. Consequently, solving bottlenecks creates value for an entire ecosystem (Karim et al., 2023). In addition, because bottleneck tasks have few viable existing solutions, their bottleneck nature may hint at a lack of immediate competition if an improvement is to emerge. Thus, prior research suggests that these bottleneck tasks are likely to become the anchors around which strategies and organizations are designed (Baldwin, 2019).

Taking that intuition one step further, we argue that bottleneck tasks are likely to be the epicenter of augmentation in a task ecosystem. To see why, first consider tasks that are not currently bottlenecks. Regardless of how well or poorly such tasks are performed, improving solutions to those tasks does little to boost system performance. Yet, producing and protecting value with artificial intelligence requires a firm to incur capability development costs to ground, bound, and recast conjoined routines to make them appropriate for the market context (Kemp, 2024). Thus, taking steps to refine solutions to non-bottleneck problems may be futile regardless of how well a machine agent performs those tasks. This may make situating AI for non-bottleneck tasks unduly expensive, and suggest that both automating and augmenting non-bottleneck tasks can lead to competitive disadvantages.

Notice, that our argument is somewhat independent of the predictive power of the machine agent in question. It is quite possible that, for non-bottleneck tasks, an assemblage can be constructed in which machine agents display better predictive accuracy than humans. Our point is that such efforts may be futile because solving the problem behind the non-bottleneck tasks induces little strategic value in the ecosystem.

In contrast, crafting improved solutions to bottleneck tasks with augmentation may create value. Artificial intelligence solutions are contingent on the availability of existing data (Choudhary et al., 2023; Raisch and Krakowski, 2021). Without data, only human solutions are possible. However, if we consider that the focal task is currently a bottleneck, it becomes more likely that human and automated solutions are unsuitable because there is insufficient data for humans or AI to make good decisions. The dearth of quality existing solutions suggests that the data are presently inadequate. This makes the bottleneck task unfit for automation.

However, augmentation may still be viable for several reasons. First, augmentation may lower the data threshold needed to reach a satisfactory solution (Raisch and Fomina, 2024; Raisch and Krakowski, 2021). Prior theory suggests that, for every predictive task, there exists a data threshold at which human-AI teams leveraging divergent information may achieve satisfactory task performance even when neither AI nor humans could achieve that performance independently (Choudhary et al., 2023). So long as those solutions help to relieve a bottleneck in the task system, perfect performance on the augmented task is unnecessary.

Augmenting a bottleneck task may offer a second source of value when situated within the context of a conjoined routine. The routine nature of work suggests that even though the data are currently adequate for a perfect solution, there are opportunities for machine and human agents to repeat the problem over time. This creates the opportunity for new data creation and learning within the assemblage. Thus, augmenting a bottleneck induces a positive option value on the possibility of building an automated capability with that bottleneck in the future (Kogut and Kulatilaka, 2001). In this account, human and machine learning may play complementary roles. The repeated interaction between humans and machines within the assemblage may push both humans and artificial intelligence into regions of the solution landscape that they otherwise would not have explored (Raisch and Fomina, 2024). This promotes the continuous development of novel and diverse data within the assemblage. Since this knowledge is being applied to the bottleneck task, improving task performance improves system behavior as the routine is enacted over time. These arguments lead to the following proposition.

**Proposition 1 (augmentation bottlenecks):** The value created by using augmentation to carry out a focal task increases with the extent to which the focal task is an unresolved bottleneck in a system-wide conjoined routine.

To be sure, we do not suggest augmentation as a panacea for resolving bottleneck tasks. By identifying a task as an existing bottleneck, the organization is conceding that an augmented solution may be imperfect. However, our arguments do suggest that, relative to non-bottleneck tasks, the possibility of collecting rents by strategizing around the bottleneck within a conjoined routine raises the possibility that the costs of augmentation can be overcome.

**INTRA-ASSEMBLAGE DESIGN: CHOOSING AN AUGMENTATION LOGIC**

Once a bottleneck is identified, a fundamental assemblage can be constructed to execute the augmented task. Situated AI theory holds that the core consideration driving performance differences across organizational uses of artificial intelligence is heterogeneous affordances for conjoined agency in critical routines (Kemp, 2024), but does not fully articulate the nature of machine agency involved in strategic value creation (Moser et al., 2024). We extend that work by explaining how heterogeneous affordances for machine agency are reflected in the distinct augmentation logics used to structure a fundamental assemblage for a bottleneck task.

Each augmentation logic is a system of design heuristics aimed at helping organizations leverage the mixed consequences machine agency during augmented work. On the one hand, algorithms must be granted to some agency to become relevant in a firm’s value-creation processes (Raisch and Krakowski, 2021). The capacity of modern algorithms to process vast quantities of data, identify patterns, and forecast trends suggests the benefits of granting AI agency in key tasks (Krakowski et al., 2023). AI can drive task performance by considering a wider set of options and estimating the potential impact of various options with more precision than human actors (Anthony et al., 2023; Raisch & Fomina, 2024). On the other hand, research highlights problems that arise when AI is granted agency in organizations. For example, machine agency may exacerbate myopia in strategic search and may make key strategic routines built around AI difficult to change (Murray, et al. 2021). Likewise, poor data quality, algorithmic bias, and the black-box nature of agentic algorithms can introduce organizational risks that are difficult to manage due to competition and conflict (Anthony 2021; Cameron and Rahman, 2022; Leavitt, Barnes, and Shapiro 2024; Vanneste and Puranam 2024). As we will explain, both logics enable AI to enact some agency in both premise development and action selection. However, in both logics, value creation still depends critically on human action. This imposes ontological pressures to navigate the boundaries between forms of conjoined agency, as defined by Murray et al. (2021) through “metaphysical innovations” within the assemblage (Latour, 2007:51).

Kemp (2024) suggests that these challenges can be overcome in conjoined routines with deliberate organizational-wide coordination to create strategic value while conjoining human and algorithmic agencies. This coordinative function is enabled by the cognitive heuristics underlying the augmentation logic. Organizational heuristics may serve as more reliable strategy enactment devices than extensive plans or formalized procedures (Felin & Zenger, 2016; Simon, 1993; Vuori et al., 2024). Each augmentation logic comprises two constituent heuristics: a *partitioning* heuristic and an *integration* heuristic. The *partitioning* heuristic describes how the organizational architect intends to divide a problem into subtasks to be assigned among the human and machine agents available to the fundamental assemblage. When partitioning tasks, value is created in the organization through the division of labor (Knudsen and Srikanth, 2014; Puranam, Raveendran, and Knudsen, 2012). So, an augmentation logic’s partitioning heuristic reflects beliefs about the relative superiority of humans and algorithms in conducting the constituent subtasks contributing to a solution. We consider two expressions of the partitioning heuristic, one emphasizing pooled labor in which humans and algorithms focus on similar tasks and another emphasizing specialized labor where humans and algorithms focus on distinct tasks.

The *integration* heuristic describes how the architect intends to reassemble distributed work into a cohesive whole. When integrating tasks, the goal is to resolve or minimize incompatibilities across subtasks conducted by distributed actors (Srikanth and Puranam, 2011; Heath and Staudenmayer, 2000). In an augmentation logic, the integration heuristic helps to ensure that subtasks completed by humans and machines align.

In this paper, we consider two modes of integration: (1) rule-based integration and (2) improvisational integration. Rule-based integration is based on standards and standard operating procedures (Cyert and March, 1992; Kellogg et al., 2006). Improvisational integration is based on emergent coordination and encompasses the informal behavior needed to deal with unplanned contingencies (Bechky, 2006; Bechky and Okhuysen, 2011; Okhuysen and Bechky, 2009). We discuss partitioning and integration heuristics for the two generic augmentation logics below.

\*\*\* Table 1 about here \*\*\*

**The AI-as-Informant Logic**

The first generic augmentation logic is the AI-as-informant logic. The basic thrust of this augmentation logic is that algorithms act autonomously to gain and gather new knowledge, but are afforded little autonomy in task execution. This treatment aligns with the distinction between protocol development and action selection advanced by Murray et al. (2021). However, even though algorithms do not make the final decision in the task, AI still exerts agency in action selection. AI must take many actions to form the analysis it passes to humans. On a material level, these actions take the form of costly electric pulses on advanced processors (Vera and Simon, 1993). Symbolically, these actions involve AI manipulating ideas to make them accurate and fit for human consumption (Vera and Simon, 1993). These manipulations may be consequential in that they may shift the course of human action within an assemblage, in a way that does not allow one to identify the “true” causal agent (Glaser et al., 2024; Latour, 2007). In the AI-as-informant logic, therefore, machine agency on action selection is implemented indirectly through AI’s influences on decision “premises” (Simon, 1997).

This augmentation logic can be found in several emerging theories of human-AI work. For example, Choudhury, Starr, and Agarwal (2020) argue that while AI can augment human decision-making capabilities, the final decisions should be subject to human evaluation to mitigate any potential ethical concerns. Likewise, Raisch and Fomina (2024) suggest limiting AI’s agency during organizational search. In their model, AI helps to formulate organizational solutions but does not select them. Here AI’s value in the decision process is obtained by expanding the breadth of choice options, but their framework holds that humans mustgovern the actual decision. Lebovitz, Lifshitz-Assaf, and Levina (2022) demonstrate the use of the AI-as-informant augmentation logic in practice, where they studied applications of artificial intelligence in radiology departments. In their context, the hospital mandate insisted that machine learning tools may be used to create diagnostic assessments but that the final decision must be made by the human radiologist.

***Partitioning heuristic for the AI-as-informant logic.*** An augmentation logic’s partitioning heuristic reflects organizational beliefs about the relative superiority of humans and AI at conducting different types of tasks. The AI-as-informant perspective considers the main epistemic advantages of AI to be its predictive superiority and comprehensive search capabilities (Choudhary et al., 2023; Choudhury et al., 2020). However, for bottleneck tasks, there is likely insufficient data for achieving that predictive superiority. Thus, in this augmentation logic, AI may still drive comprehensive search so that the assemblage may discover and consider more solutions to the bottleneck task, but human knowledge is applied to the same task to enhance the aggregate prediction before arriving at a final decision (Raisch and Fomina, 2024).

This suggests pool-labor as the basis for partitioning work in the assemblage. Pooled labor refers to instances in which agents in a multi-task system work on tasks with similar input requirements and output specifications (Puranam et al., 2014). In the AI-as-informant logic, pooled labor is influenced by the need to combine human-derived premises with machine-derived premises before a task is executed. This requires that humans in the assemblage possess domain knowledge for the subtasks that the AI executes, raising the need for shared expertise between AI and humans (Allen and Choudhury 2022; Lebovitz, Lifshitz-Assaf, and Levina 2022). Thus, the partitioning heuristic for the AI-as-informant logic is pooled labor.

***Integration heuristic for the AI-as-informant logic.*** Integration in the AI-as-informant logic is rule-based. In this logic, AI is used to inform sensible decisions on a focal task, and human knowledge is applied to the same task to arrive at the final decision. Thus, it is taken for granted that humans can do a part of the task or that there is a socially legitimate mechanism for properly integrating human and machine knowledge *before* a final decision is made.

Remember that we are assuming that the integration heuristic is one prescribed for organization-wide action (that’s what makes it part of a design logic). By encouraging pooled work here, the organization is expecting that knowledge can be represented in forms that are verifiable by the average human in the context. This implies that there are expectations for minimally appropriate “human” behavior for this specific task (Faraj and Xiao, 2006; Kellogg et al., 2006). Otherwise, there would be no incentive to pool knowledge on the task or to prioritize human knowledge on the task. For example, in the case of medical diagnosis, legitimate paths for arriving at a diagnosis can be applied across radiologists to ensure consistent and appropriate diagnoses across space and time. In line with this intuition, Grant (1996: 114) notes that “pooled interdependence calls for coordination by rules”.

Rule-based integration may be observed across different organizational manifestations of the AI-as-informant logic. To see how, consider two distinct organizational implementations of the AI-as-informant logic: sequencing and ensembeling (Choudhary et al., 2023). Sequencing reflects an implementation of the AI-as-informant logic with interagent monitoring. In this case, AI is permitted to conduct analyses then those analyses are passed to a human who checks the output and makes a final decision. Ensembeling reflects an implementation of the AI-as-informant logic with no interagent monitoring (Choudhary et al., 2023). In this case, humans and AI work on similar tasks but in parallel. The parallel assessments made by humans and AI are combined mathematically to arrive at a final decision.

In the case of sequencing, rule-based integration is enforced by the requirement that humans be responsible and accountable for the final decision. The need to explain raises incentives for the human checker to leverage legitimated task-level accounts of value creation when integrating the solution. In the case of ensembeling, the humans conducting the task may not be solely accountable for the final decision. However, the use of a legitimated mathematical formula for integration implies that integration is rule-based.

**The AI-as-Actant Logic**

The AI-as-actant logic takes a different approach to partitioning and integrating clusters of subtasks from the bottleneck between humans and AI. The key feature of this design logic is the lack of shared knowledge in the integration stage. For example, Zhang et al. 2021 examine a firm’s conversion from an AI-as-informant logic to an AI-as-actant logic in the context of semiconductor production. The core task (chip design) was held fixed over time. However, in the second case, humans implemented very little checking of AI’s subtask executions—algorithmic inscrutability at the routine level would not permit it.[[2]](#footnote-3) Nevertheless, humans and AI were both required to execute the entire chip design task, regardless of which logic was used. This suggests that rather than displaying a contrast between automation and augmentation per se, the core difference across cases was the system of heuristics used to partition and reassemble subtasks between humans and AI. Following this intuition, we elaborate on the portioning and integration heuristics for the AI-as-actant logic below.

***Partitioning heuristic for the AI-as-actant logic.*** The partitioning heuristic for the AI-as-actant logic is the specialization of labor. Specialization of labor implies that AI and humans in the fundamental assemblage focus on different clusters of subtasks in the (partially) decomposed bottleneck. Specialization is enabled by removing the need for human review of AI work within the fundamental assemblage.

Because the task in question is a bottleneck, conjoined action is required to carry out the full task. However, improving the quality of AI’s subtask execution (judged relative to human execution) may not be needed to create value. Sometimes, a bottleneck task exists because the rate at which human knowledge can be applied to the task is inadequate for managing the system load (Karim, et al., 2023). When augmentation does not enhance the quality of task execution relative to a human solution, augmentation may still enhance value creation by improving the system throughput (Baldwin, 2019). Improved throughput provides a source of value creation for the assemblage, even if the AI’s subtask performance is inferior to existing human execution. Moreover, by increasing throughput, augmenting the bottleneck with the AI-as-actant logic helps to accelerate the speed at which the assemblage gathers the data needed to meet the automation threshold. So human review of AI work may impair value creation in these contexts.

Because human review of the AI’s task is either unnecessary or impossible, there is a lower need for task knowledge overlap between humans and AI. This frees organizational resources to be used elsewhere. If nothing is done with the resources, this reduces to pure automation (Choudhary et al., 2023). However, for bottleneck tasks, failing to reuse these resources in the assemblage may be value-depleting. Thus, some of the organizational resources that would otherwise have been dedicated to exception checking can be applied to deepening specialization on interdependent subtasks.

To use Murray et al.’s (2021) language, in the AI-as-actant logic, humans and AI are involved in protocol development *and* action selection for their clusters of subtasks within an assemblage (hinting at automation). Nevertheless, both humans and AI are needed to create value for the integrated task (hinting at augmentation). Thus, the bottleneck nature of the task imposes upon the assemblage an imperative to navigate the ontological boundaries between pure augmentation and pure automation within the design logic. The core difference between logics, therefore, is not the *degree* of AI agency, but instead the choice of integration heuristic needed to maintain system-wide value in the face of this agency.

***Integration heuristic for the AI-as-actant logic.*** While the AI-as-informant logic relies on rule-based coordination, the AI-as-actant logic relies on improvisational coordination as the integration mechanism. Some of the organizational resources that would otherwise have been dedicated to exception checking can also be applied to deepening the assemblages’ coordinative capacity for distributed work (Zhang et al. 2021). This heuristic is built on the notion that “transferring knowledge is not an efficient approach to integrating knowledge” (Grant, 1996: 144). Rather than having its actions subject to human review, AI is allowed to analyze and act on its assigned subtask. These actions are only *sometimes consequential* (Latour, 2007). Many of AI’s actions may fail to disrupt or enhance system behavior in a manner noticeable to other actors in the task system. When they are consequential, those consequences are reproduced as context for subsequent tasks (Kemp, 2024). To the extent that human actors on subsequent subtasks can properly account for context in their subtask performances, formalized rules to ensure integration may be counterproductive.

Indeed, research across the organizational sciences suggests that, when acting with recurrent context, humans are able to manage disruptions and surprises in their task inputs without disruptions to their task performances (Berente et al., 2016; Cohen and Bacdayan, 1994). For example, research on actor-network theory suggests that humans are capable of "metaphysical innovations”, allowing them to reorder their social worlds when idiosyncrasies of history dislodge a system’s behavior from its normal course (Latour 2007: 51). Likewise, research on human skill development suggests that even in emergent situations, experts are capable of performing domain-specific tasks as if steered by if-then rules that they have long forgotten (Dane, 2010; Dreyfus and Dreyfus, 2005). This suggests that human responses in novel contexts are triggered by associative linkages that afford the appearance of known patterns in the unfamiliar context. When this occurs, human actors who own the tasks disrupted by machine agency may find ways of spontaneously leveraging context in their task execution through improvisational actions, such as impromptu sensemaking, protocol breaking, and constraint tuning (Bechky, 2006; Bechky and Okhuysen, 2011; Okhuysen and Bechky, 2009; Faraj and Xiao, 2006; Zhang et al. 2021). Thus, assemblages leveraging the AI-as-informant and AI-as-actant logics may leverage the same underlying technologies but display differing integration and partitioning logics.

**INTER-ASSEMBLAGE ARRANGEMENTS: AUGMENTATION LOGICS AND BOUNDARY ARRANGEMENTS**

In this section, we use the arguments above to make sense of boundary arrangements in the task ecosystem. Boundary arrangements in a multi-agent ecosystem reflect the relative ease and difficulty of sharing work between social units that would otherwise be disconnected (Gulati and Singh 1998; Kellog et al. 2006; Nickerson and Zenger 2004). We begin by asking under which conditions it is possible to maintain a split a fundamental assemblage—a fundamental assemblage that is shared across two otherwise distinct assemblages. Formally speaking, a split assemblage occurs any time the fundamental assemblage assigned to a task is composed of agents and artifacts from two distinct parent assemblages. More formally, assume that we have two assemblages, . Each assemblage comprises constellations of tasks and agents. From these two assemblages, we are attempting to create a new fundamental assemblage, to address a bottleneck task Thus a *split assemblage* exists relationally with respect to a task and three constituting assemblages, the two parent assemblages } and the shared fundamental assemblage. When the costs of maintaining a split assemblage are lower, we would expect to see many cross-boundary collaborations in the ecosystem. As these costs increase, these relationships will be less likely to occur.

**Organizational Costs of Maintaining a Split Assemblage**

In this section, we develop a situated AI argument for explaining when it is feasible to split a fundamental assemblage across two distinct assemblages. Our argument centers on recognizing multilevel tensions in the competitive struggles that emerge between assemblages. Specifically, tensions jeopardizing the stability of are induced by the fact that capability-environment fit is pursued from the perspective of each of the distinct assemblages ( while competition for primacy at the bottleneck task is pursued from the perspective of the shared assemblage ().

***Capability-environment fit and bottleneck competitiveness***. In situated AI theory competitive advantages gained through capabilities that are unique, cheap to produce, and that display high capability-environment fit (Kemp, 2024). To understand why capability-environment fit is pursued from the perspective of the parent assemblages, rather than the shared assemblage, consider the requirements of constructing a capability from a collection of tasks.

Capabilities are constructed as bundles of routines, which themselves reflect repeated sequences of task executions (Winter, 2003). However, a parent assemblage may be accountable for more than one task. This means that, in addition to the bottleneck task covered by the shared fundamental assemblage, each parent assemblage may also manage other tasks that contribute ecosystem value. Because a parent assemblage also receives value from their additional tasks, the focus of each parent assemblage lies in maximizing the combined value of their task bundles, rather than maximizing the value of any single task (or task cluster) in isolation. This suggests that capability-environment fit is primarily attended to by the parent assemblages.

While capability-environment fit is pursued by the parent assemblage, competitiveness for the bottleneck task is pursued primarily from the perspective of the shared assemblage. The locus of competitiveness for a specific task reflects which assemblage will have the greatest awareness of competitive threats, the greatest motivation to respond to those threats, and the greatest ability to do so (Chen and Miller, 2015). Recall that in our argument, the shared assemblage is a fundamental assemblage, so it has only one core task—the bottleneck task. This suggests that, relative to agents in the parent assemblages, actors in the fundamental assemblage can be more attentive to the alternative bottleneck solutions that competitors may adopt. Use of these alternatives among other assemblages, would disrupt the primacy held by the fundamental assemblage in the task ecosystem for executing the bottleneck task.

In addition to their being more aware of competitive threats than members of the parent assemblages, actors in the fundamental assemblage also have greater motivation to respond to such developments. This is because a fundamental assemblage is more subject to survival fluctuations in response to emergent threats at the task level than a parenting assemblage, whose survival is more dependent on performance across a collection of tasks and, therefore, more buffered from competitive risks.

***Competitive hazards in a split assemblage.*** This rift between a fundamental assemblage and the parent assemblages regarding their relative focus on capability-environment fit and bottleneck competitiveness induces organizational hazards for the split assemblage. Staying competitive at the bottleneck task forces members of the shared assemblage to remain engaged in problem-solving to improve the quality of the solution over time (Nickerson and Zenger, 2004). Since the solution is AI-augmented, artificial intelligence in the fundamental assemblage raises the opportunity for autonomous learning in the bottleneck task. However, situated AI theory suggests that these efforts alone are unlikely to resolve competitive pressures around AI-augmented work (Kemp, 2024).

In situated AI theory, competitive hazards cannot be overcome solely through augmented learning because artificial intelligence exposes an organization to competitive hazards through its learning. AI can be described as generic, explicit, and myopic (Kemp, 2024). These challenges are created by AI-driven learning, making it difficult to overcome. For example, because AI is both generic and myopic, there may be a need for coordinated adjustments to a solution in the face of both misaligned AI and improved learning on AI-executed tasks. These coordinated adjustments require that members of a fundamental assemblage engage in robust interactions regarding the technical and organizational implications of different solutions for advancing the bottleneck task (Faraj and Xiao, 2006). This may involve discussing how to orchestrate the change of algorithms and routines surrounding the augmented task to improve learning over time (termed “recasting” in situated AI theory)(Kemp, 2024).

This is particularly relevant when members of the shared assemblage originate from separate parent assemblages. Explaining the merits or limitations of a proposed approach may require first divulging technical information related to secondary tasks (Awate, Makhija, and Xiao, 2024; Bechky, 2003). This may involve exchanging information about how the performance of a bottleneck task influences tasks that are unshared between the two parent assemblages (Carlile, 2002; Kellogg et al., 2006). This creates expropriation problems at the capability level since exchanging knowledge regarding the technical foundations of an unshared task may incentivize one parent assemblage () to begin competing for primacy on tasks owned by the second parent assemblage (). In short, the need to situate AI at the task-level through recasting within a fundamental assemblage creates an expropriation problem at the capability level for the parent assemblages. In situated AI theory, these expropriation problems can be resolved, but only by increasing the intensity of bounding activities within the collective, where bounding refers to actions taken to circumscribe AI in a nexus of contracts (Kemp, 2024). This raises the cost of splitting a fundamental assemblage for a bottleneck task between two otherwise distinct assemblages. Thus, we propose the following.

**Proposition 2a:** The stronger the tension between task competitiveness and capability-environment fit, the greater the bounding costs associated with splitting a fundamental assemblage for that task between otherwise distinct assemblages.

Even when expropriation problems are inconsequential, there may be task-level conflict over how activities in the split assemblage are recasted. Kemp (2024) argues that a critical form of recasting AI is restructuring linkages across the (sub)tasks connected to AI within the broader system of interdependencies. However, because the broader group of tasks in the different parent assemblages may be differentially dependent on the shared bottleneck task, the parent assemblages may have divergent preferences for how to revise subtasks and their interconnections within the fundamental assemblage. The need for increased mutual adjustment to resolve task-based conflicts raises the cost of remaining competitive in the shared assemblage. This raises the cost of splitting a fundamental assemblage for a bottleneck task between two otherwise distinct assemblages. Thus, we propose the following.

**Proposition 2b:** The stronger the tension between task competitiveness and capability-environment fit, the greater the recasting costs associated with splitting a fundamental assemblage for that task between otherwise distinct assemblages.

**Organizational Hazards in a Fundamental Assemblage across Augmentation Logics**

The section above highlights a general organizational tension that induces non-zero capability-development costs when maintaining a split assemblage across two parent assemblages. This section elaborates on that idea by explaining how the tension manifests across augmentation logics. Boundary arrangements follow from the need to situate AI for shared bottleneck tasks. Recasting AI in a split assemblage requires information exchange between actors with shared goals at the task level but potentially conflicting goals at the capability level. Moreover, failing to share the needed information within the fundamental assemblage may impair bottleneck competitiveness, but sharing information within a split assemblage creates the opportunity for knowledge expropriation between the parent assemblages. We argue here that the augmentation logic chosen to structure the fundamental assemblage for the bottleneck task may either exacerbate or attenuate this tension.

First, we argue that the combination of pooled labor and rule-based integration in the AI-as-informant logic reduces the tension between task competitiveness and capability-environment fit when situating AI for the bottleneck task. The joint use of pooled labor and rule-based integration in the AI-as-informant logic implies the need for continued knowledge redundancy between humans and machines. This becomes a key consideration if either the machine or the human is asked to improve their task performance over time. Mutual learning between humans and machines in the task space implies that humans and AI are both collecting data on the same tasks. This is important because prior research suggests that information sharing during coordinated search reduces the scope of exploration for a shared task (Knudsen and Srikanth, 2014). This implies that when the AI-as-information logic is used, humans and AI in the fundamental assemblage are likely to converge in their assessments over time (Eicke, Foege, and Nüesch, 2024). Critically, this convergence applies to members of both parent assemblages simultaneously, reducing cognitive conflict within the fundamental assemblage regarding appropriate solutions to the bottleneck. This cognitive alignment also reduces the need for inter-assemblage knowledge sharing while situating AI to enhance bottleneck competitiveness.

In contrast, the AI-as-actant logic may induce ambiguity in the fundamental assemblage due to specialized labor and improvisational integration. Improvisational integration recognizes that some of the truly noticeable disruptions caused by AI cannot be resolved by improving task-level performance. System performance may show diminishing returns to component-level improvement (Siggelkow & Levinthal, 2003). Systems get stuck (Rivkin & Siggelkow, 2002). This stickiness creates the need for architectural restructuring rather than component-level learning for system performance to improve (Crowston, 1997; Ethiraj & Levinthal, 2004). In such cases, value creation may depend on the potential for enhancing bottleneck competitiveness by restructuring the links between the subtasks that form the bottleneck.

When this is carried out in the AI-as-actant logic, these changes occur adaptively through collective improvisation. In line with this reasoning, Kemp (2024:625) suggests that rather than focusing only on guiding AI’s task execution, an organization may also focus efforts on *adaptively* restructuring links between tasks within a conjoined routine. Zhang et al. (2021) document this behavior empirically, showing that as their semiconductor firm moved from an AI-as-informant to an AI-as-actant logic to carry out chip design, human engineers focused increasingly on *adaptively* reordering constraints in the task system leveraging *situated intuition* rather than pre-established knowledge.

Executing these changes successfully increases the need for information sharing within the fundamental assemblage. For example, Faraj and Xiao (2006) argue that improvisational coordination relies on a “temporally unfolding and contextualized process of input regulation and interaction articulation” between interdepended participants. In line with this intuition, Kemp (2024) argues that recasting organization linkages to circumscribe AI’s agency requires *organizational-wide deliberation* to unearth interdependencies and create *shared* architectural knowledge. This suggests that, when employing an AI-as-actant logic, the need to situate AI to enhance task-level competitiveness within a fundamental assemblage raises the potential for costly knowledge spillovers and conflicting mutual adjustments between the parent assemblages. This increases the cost of situating AI across the split assemblage. These arguments lead to the following proposition.

**Proposition 3:** Use of the AI-as-actant logic (rather than AI-as-informant logic) to structure a fundamental assemblage for a bottleneck task increases the bounding and recasting costs associated with splitting that fundamental assemblage between otherwise distinct assemblages.

Increasing the costs of bounding and recasting in the AI-as-actant logic naturally implies the need for different boundary arrangements. As these costs increase, one would expect to see a move from loosely coupled assemblages reflecting market activity to tightly coupled assemblages reflecting more hierarchical arrangements (Gulati and Singh, 1998). As bounding costs become excessively high, one would expect to see organizational voids, in which developing AI-driven capabilities across organizations is technically feasible but organizationally impossible to maintain. Since our arguments are anchored primarily on the cost of situating AI in the fundamental assemblage, this account offers a novel set of mechanisms that shift the boundary arrangements between organizations that would not be observed absent the use of artificial intelligence in the assemblage, and that depend critically on the heuristics employed for organizing human-AI collaborations at the task level.

**Proposition 4:** The greater the use the AI-as-actant logic (rather than AI-as-informant logic), the *lower the occurrence* and *higher the formality* of collaboration ties between distinct assemblages in a multi-task ecosystem.

**DISCUSSION**

Although the use of artificial intelligence is widely recognized as a defining characteristic of modern firms, the role of AI as a driver of competitive advantages has only recently received systematic conceptual treatment in mainstream strategy research (Kemp 2024; Krakowski, Luger, and Raisch 2023). We extend this research to explain how distinct treatments of artificial intelligence may result in different arrangements of organizational boundaries in a multi-task ecosystem. We define an augmentation logic as an organizationally situated design logic for combining human and artificial intelligence to create value on specific tasks. We first explain how augmentation logics may differ in their approach to partitioning and integrating tasks among humans and AI in an assemblage. We then explain how the choice of augmentation logic may alter the cost of organizing work across otherwise disconnected human-AI assemblages.

**Contributions to the Research on Boundary Arrangements and Organizational Forms**

Our paper helps to shed light on the behavior of different firms in the AI-ecosystem. Jacobides et al. (2021) highlight that large firms, particularly the big four tech firms in the US and the tech giants abroad (i.e. Alibaba and Tencent), are rather homogeneous in their boundary arrangements in the sense that they tend to be active in every area of AI development and deployment. This ranges from producing AI solutions that are marketed to customers, to running AI-driven capabilities to power their own operations. Beyond this small group of tech elites, however, firms seem to display far more heterogeneity in their boundary arrangements. Jacobides et al. (2021) highlight that some firms act as AI creators, producing or customizing some of the AI sold to their clients but relying on big tech firms for other uses. Other firms act as AI-powered operators, who primarily leverage AI in a day-to-day operations, where this AI is sometimes developed internally, but sometimes externally sourced, depending on the task. AI traders purchase and sell off-the-shelf solutions to their clients but rarely leverage AI for their own operations. AI takers leverage heavily leverage AI in their own operations but rarely produce AI-driven solutions internally. Instead, they tend to source all of their AI from outside their firms.

Our framework offers a path toward making sense of this heterogeneity. In our framework, we view the intensity of the situating activities required to maintain a split assemblage as the primary determinant of boundary arrangements in a multitask ecosystem. We explain how bounding and recasting costs may come to reflect the choices made in an assemblage to structure human-AI collaboration work for bottleneck tasks. We argue that when an assemblage is structured using an information-as-actant logic, it will be less likely that the assemblage can be shared between two assemblages that are otherwise distinct, relative to when an AI-as-information logic is used. Since we are less likely to see multi-firm arrangements to collaborate on such tasks as these costs increase, our paper offers testable propositions relating augmentations logics to boundary arrangements in the multi-task ecosystem.

In addition to testing this proposition, further research may consider how the dispersion and institutionalization of an augmentation logic within and between firms may further shape how organizational boundaries manifest across an ecosystem. For example, one may surmise that firms that are more successfully institutionalizing an AI-as-actant logic may be more likely to display organizational forms reflecting AI-powered operators, as described by Jacobides et al. (2021). In contrast, firms successfully institutionalizing an AI-informant logic are more likely to display forms reflecting Jacobides et al.’s AI-takers. Moreover, in our framework, the two logics discussed are considered generic logics, but we leave open the possibility that firms may enact “metaphysical innovations” allowing them to craft augmentation logics not conceived here (Latour, 2007: 51). Thus, with some additional theoretical development, it may also be possible to explain how firms displaying mixed logics, or those inventing unique augmentation logics, may produce completely novel organizational forms. Future research should explore these dynamics in detail.

**Contributions to Situated AI Theory**

Our also framework offers several contributions to situated AI theory. Situated AI theory shows promise as a strategic management framework for explaining the competitive advantages of AI-driven firms. However, situated AI theory focuses solely on the firm as the level of analysis. Thus situated AI theory fails to explain how AI creates value across a multi-organization ecosystem and fails to account for the diverse organizational forms that AI-driven firms display (Jacobides et al., 2021). Accordingly, Haftor, Costa-Climent, and Ribeiro-Navarrete (2024) argue that situated AI theory “focuses on intra-firm capability build-up, thereby disregarding the fact that value is often created and appropriated by firm-boundary spanning networks of actors that execute an activity system.”

Our framework extends situated AI theory beyond its core focus on firm-level competitive advantage and offers an explanation linking the theory's core constructs (grounding, bounding, and recasting) to the cost of maintaining interorganizational relationships. Reframing the theory around the assemblage as the primary unit of organizing (Glaser et al., 2024), we define a novel construct to drive our arguments—the fundamental assemblage. The construct is important because it emphasizes locating a minimal combination of humans, algorithms, and other artifacts needed to complete a task. This allows the analyst to consider the relative efficiency of alternative assemblages, aligning with situated AI theory’s focus on the potential for AI-driven competition between organizations (Kemp, 2024). We then use the concept to explain how tensions between task-level competitiveness and capability-environment fit may manifest due to a need to situate AI within a fundamental assemblage. This alters the intensity of the bounding and recasting activities needed to capture value from an assemblage that’s shared across to otherwise distinct organizations, thereby influencing boundary arrangements in a multi-task multi-assemblage ecosystem.

Second, situated AI theory has been criticized for undertheorizing its main construct—the conjoined routine. Although the conjoined routine is proposed as the epicenter of value creation in situated AI theory, the theory has been accused of over-emphasizing the role of human agency, while failing to articulate how machine agency is implicated in value creation (Moser et al., 2023). The conceptual advances in this paper allow us to do so. Our conversation about augmentation logics suggests that (1) machine agency is independent from autonomy, and (2) that machine agencies can be “hidden” in an augmentation logic even when humans have the final say. A comparison of the AI-as-informant vs. the AI-as-actant logic shows that machine agency may be present regardless of which logic is being used. Even when humans maintain the autonomy to check and revise an AI’s outputs, machines in an assemblage may gather information that allows for task improvement beyond current human understanding. This implies that AI may create and act on the decision premises in ways that depart from human understanding. Moreover, these actions may go unnoticed by humans but may remain consequential for organizational performance (Glaser et al. 2024).

This allows us to better highlight why organizing around artificial intelligence is a unique phenomenon for strategic management researchers to consider. Scholars have long argued that the need to adjust technologies can create tensions in interorganizational relationships. However, in prior theories, shared technologies stabilize with refinement, allowing interorganizational hazards to disappear over time. However, because artificial intelligence has the capacity for agency, its behavior in an assemblage is always subject to change. This implies that the need to situate AI within an assemblage may not dissipate with time (even if the core algorithms used are relatively unchanging from a technological standpoint). This means that organizational hazards may remain long after technological uncertainty (as traditionally conceived) is resolved. Thus, our extended situated-AI argument brings the theory into closer alignment with actor-network theory and the emerging research on algorithmic assemblages. It also allows us to offer novel arguments relating an organization's internal treatments of artificial intelligence to the emergence of different interorganizational arrangements. Future research should elaborate on this tension.

In addition to underemphasizing machine agency, situated theory may be overly concerned with appropriation issues surrounding conjoined routines while failing to explain how they take shape or, more importantly, how they create value. This paper develops a solution to that problem by offering a conceptual framework that explains how conjoined routines generate value in a task ecosystem. We highlight the role of bottleneck tasks, and we explain how the routine nature of work in the ecosystem allows firms to establish augmented solutions to such tasks, thereby creating value through conjoined work. However, the routinization of conjoined work also creates expropriation problems for a shared assemblage, by creating the need for extensive information sharing and conflict resolution to continuously situated AI within a shared assemblage over time.

**Contributions to Broader Organizational Research on Artificial Intelligence**

This conceptual advance helps us to connect situated AI theory to the broader research on algorithm-induced conflict in organizations. This research generally shows that implementing algorithms within organizations creates many novel forms of conflict, with opaque algorithms the epicenter of conflict for knowledge and control rights (Anthony et al. 2023; Cameron and Rahman 2022). Prior work has shown how this conflict may impair the benefits algorithms are purported to produce in the organization for tasks and for workers (Allen and Choudhury 2022; Cameron 2022). Our framework extends those arguments by implicating algorithm induced conflict in strategic questions related to value creation and value capture within and across organizations. Thus, we construct a novel micro-macro link within the research on algorithms in organizations, opening a path toward a multilevel understanding of when and how firms can feasibly create and capture value with artificial intelligence.

Our paper may also contribute to the work on artificial intelligence in entrepreneurial ecosystems. Townsend et al. (2024) frame the conversation concerning artificial intelligence in entrepreneurship around the notion of Knightian uncertainty, arguably the foundational construct in contemporary entrepreneurship research. They argue that the effect of artificial intelligence in entrepreneurial contexts is difficult to disentangle conceptually primarily because, even if AI is better than humans at coping with uncertainty, those effects may be inconsequential for entrepreneurial action. This is because humans ultimately need to understand and implement the ideas and recommendations supplied by AI. This paradoxically requires that humans match the knowledge capacity of AI, which will be infeasible in a context where AI is worth using in the first place. In short, they argue that human intelligence acts as the boundary condition on AI’s effectiveness, and that this fact is increasingly constraining as uncertainty increases.

Our paper raises the possibility that this limitation can be overcome, but only if humans are willing to transfer agency to AI. In our paper we consider two augmentation logics. Once we distinguish between the AI-as-informant and the AI-as-actant logics it seems that Townsend et al.’s argument applies perfectly to the AI-as-informant logic, but perhaps not to the AI-as-actant logic. In the AI-as-informant logic, human checking of AI’s recommendations requires the humans to understand why AI is arriving at its choices. In such cases, recommendations that are uninterpretable (perhaps due to Knightian uncertainty) may be erroneously rejected even if they would lead to entrepreneurial success. In contrast, the AI-as-actant logic does not impose human review prior to AI’s actions. Consequently, if AI can manage higher degrees of uncertainty than humans, then those benefits *may* be realized by the assemblage. However, in the AI-as-actant logic, unchecked agentic AI is organizationally possible only because humans may wield agency on interdependent task. This implies that, when AI can manage higher degrees of Knightian uncertainty than humans, the rise of AI increases the need for effectual thinking in entrepreneurial contexts. Thus AI-augmented entrepreneurship raises the need for agentic human action and agentic machine action alike. Future research should examine this tension.

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**Figure 1**

**Conceptual Framework**

Capability Development Costs

Boundary Arrangements

Strategic Augmentation

Explicit Proposition

Latent Argument

***Organizational Constraints****: Socio-technical arrangements governing the fundamental assemblage*

Augmentation Logic

Task Bottleneck

***External Constraints****: Ecosystem affordances for value creation*

Split Assemblage

P1

P2

P3

P4

|  |  |  |
| --- | --- | --- |
| **Table 1. Generic Augmentation Logics in Situated AI Theory** | | |
|  | **AI-as-informant Logic** | **AI-as-actant Logic** |
| **Partitioning Heuristic** | Pooled Labor | Specialization of Labor |
| **Integration Heuristic** | Rule-Based Integration | Improvisational Integration |

1. We follow actor-network theory by affording organizations the latitude for “metaphysical innovations” to create firm-specific argumentation logics (Latour, 2007: 51). However, we present generic augmentation logics in our theory to demonstrate their influence on organizational arrangements. [↑](#footnote-ref-2)
2. To highlight that algorithmic inscrutability was induced routine-level, rather than task-level, Zhang et al (2021) introduce the concept of procrastinated binding, in which the computational resources needed for AI to work had to be assembled at runtime (rather than when the algorithm was designed). Various sub-routines were executed to pull resources (eg. data and computational power) from *different* sources every time the AI was called to conduct a new instantiation of work. This induced process-level randomness beyond the task-level randomness embedded in the AI’s solution logic. [↑](#footnote-ref-3)