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AI and Near Decomposability: A Procedural Representation View

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Much strategy research focuses on AI's impact on how individual strategists (or, at least, firms as unitary actors) solve mostly given problems. This paper develops theory on AI's impact on how complex organizations are decomposed to represent novel strategic problems. To do so, we introduce a view of information processing that we call procedural representation, which links Simon's (Simon 1962) seminal work on the near decomposability of organizations to Sussman's (1977) theory of AI problem solving. We propose that AI-augmented procedural representation should yield finer-grained organizational units, increase interactions between these units, create demand for more differentiated knowledge specialization, and establish problem representation as a dynamic, continual process. Our effort highlights that whether AI can do strategy depends in part on its capacity to decompose problems, and takes an important step toward understanding strategy and organization design in an AI world.

1. Introduction

Information processing perspectives study the gathering, interpretation, and synthesis of information in organizational decision making (March and Simon 1958, Tushman and Nadler 1978, Burton et al. 2006, Joseph and Gaba 2019, Raveendran et al. 2020). They derive from Simon's information theory, in which individuals solve complex problems as a basis for making decisions, but have limited processing capacity, time, and cognitive (i.e., attentional) capacity to do so (Simon 1956, Newell and Simon 1972). To economize on information processing demands required for solving complex problems, nearly decomposable organizational structures accommodate managers' cognitive limitations by representing problems as simpler, mostly independent sub-problems (Simon 1962, Augier and Sarasvathy 2004, Egidi and Marengo 2004). Near-decomposability aids strategic decision making and adaptation in that it allows units to be responsive to demands in their environment (Ethiraj and Levinthal 2004, Marengo 2015, Lee et al. 2016), keeps the perturbations in one unit from negatively affecting other units (Fang and Kim 2018), and facilitates more effective utilization of resources (Galunic and Eisenhardt 2001, Helfat and Eisenhardt 2004, Karim 2006).

Strategy and organizational research has also long held that information technology (IT) increases the extent to which an organization can be nearly-decomposed (Galbraith 1977, Bloom et al. 2014, Burton et al. 2015). In this research, IT increases each unit's capacity to search and evaluate alternatives (e.g., make predictions) about problems on their own, substituting for costly communication and coordination. It is often implied that organizations' adoption of artificial intelligence (AI) augments such capacity for prediction, and hence would accelerate this prediction effect of IT on near decomposability. In fact, AI has been thought to lower organizations' cost of search or prediction (Agrawal et al. 2018) to such an extent that units may simply specialize in the technical work of making AI predictions (e.g., agile data science teams), displacing domain experts (Iansiti and Lakhani 2020, Alaimo and Kallinikos 2024, Reineke et al. 2025). By programming AI systems to automate this technical work, some conjecture that soon there may be a "unicorn" firm that achieves a billion-dollar valuation without hiring a single employee (Confino 2024).

Such conjectures, however, rests on a quite restrictive assumption that firms use AI primarily to increase its technical capacity to search or make predictions about given, isolated problems (Davenport 2018). What extant strategy research on AI is only beginning to account for is how emerging intelligent systems — including but not limited to those based on generative AI (GenAI) technologies — may be used by domain experts or anyone in an organization not just for technical search or prediction about given problems, but also to generate and interact with semantically-rich representations (text, code, images, etc.) of new problems (Krakowski 2025, Zamfirescu-Pereira et al. 2025).

By AI-generated representations, we refer to managers' open-ended and interactive (e.g., prompt-based) generation of text, diagrams or other symbols to inform their search for solutions to given problems (e.g., generating more distant solutions or synthetic data), as well as defining, formulating, or otherwise representing new problems (Baer et al. 2013, Posen et al. 2018, p. 235, Raisch and Fomina 2024, p. 5–7). Such interactions manifest in the organization in the construction of diverse artifacts such as product designs, customer profiles, and digital twins (Berglund et al. 2020). Emerging intelligent systems may, in turn, augment the capacity of the organization to generate representations of strategic problems facing the firm (Csaszar, Heshmati, et al. 2024, p. 28, Retkowsky et al. 2024).

The potential to use AI to augment the organization's capacity to interactively generate representations of strategic problems calls for revisiting the relationship between IT and organizational structure and, in particular, the traditional information processing assumptions underlying the structural properties of organizations. These include the elements subject to decomposition as well as the process by which integration of those elements is achieved to construct a problem representation. Despite its emphasis in Simon (1947), information processing perspectives have long neglected the problem representation phase of problem solving and focused almost exclusively on how organizations may be nearly decomposed to search within a given set of solutions to given problems (Posen et al. 2018, p. 235–6, Joseph and Gaba 2019, p. 291–2, Keil et al. 2023).[1] What is the impact of AI-augmented representation

[1] Baer et al. (2013) and colleagues have examined problem formulation in the context of comprehensiveness in strategy.

of problems on the near-decomposability of organizations? How might intelligent systems have an impact on strategic decisions regarding the structuring and interactions of subunits, and the value of specialization of these units?

To address these questions, we adapt and expand to the organizational context, Sussman's (1977) theory of *procedural representation*. Whereas decomposition in search is based on the modularization of a set of choice variables for a given problem (Simon 1962), Sussman's theory is based on the tentative construction and decomposition of a *network of constraints*. The nodes of this network are *observational variables* (i.e., columns of data) within a broader problem domain. The links of the network are the constraints, which can be any restrictions on the values of subsets of these variables, and which reflect goals and subgoals grounded in domain-specific principles (logical, causal, or functional relationships or conventions that must be satisfied for the overall system to be coherent). Constraint violations direct organizational attention to a subset of variables. An intelligent system then has access to procedures for (1) querying a shared repository of data on these variables to evaluate the constraint violation, (2) propagating (sending) the resulting information to neighboring constraints; and using this information to (3) "debug" the overall network to piece together a coherent understanding and representation of the underlying problem.

We apply Sussman's conception of procedural representation to the utilization of AI at the organizational-level, using Simon's famous watchmaker parable as a comparative example, and deriving implications for problem solving. We then use our resulting "Simon-Sussman" view to derive propositions about the impact of AI on organizational structure.

Our procedural representation view of AI differs from that of prior work in strategy (Raj and Seamans 2019, e.g., Haenlein and Kaplan 2019), which has largely been premised on a view of AI as a prediction technology (i.e., for search and evaluation), and which specifically has presumed a reduction in the need for specialists (with the possible exception of data analysts). Instead, we proffer that in an organization where AI is fully integrated, AI-augmented procedural representation should increase the value of specialization and, further, that decomposition will reflect units specialized in areas of a problem domain rather than tasks. We further argue that contrary to perspectives of near decomposability emphasized for hierarchical search which emphasize the need for coarse-grained decomposition of the organization (Rivkin and Siggelkow 2003), we propose that such problem domain-specific decomposition with AI will be more fine-grained to surface complex and overlapping interdependencies and, as a result, enhance the cognitive integration of the organization. Finally, by enabling the organization to construct problems based (partly) on stable domain-specific principles, AI improves the robustness of an organization's capacity to represent problems in response to changes in its environment and supports problem representation as an ongoing, dynamic process.

Our paper extends information processing perspectives on the relationship of IT and organizational structure (Joseph and Gaba 2019) by contributing a procedural representation view that goes beyond the focus on search and instead towards recognizing that an important source of structural variation begins with the absence of a clearly defined problem (Baer et al. 2013, Zellweger and Zenger 2021), and the utilization of AI-enabled information processing to formulate one (Krakowski 2025). In so doing, our theory departs yet complements problem-solving perspectives (Nickerson and Zenger 2004) and theories of problem representation (Baer et al. 2013, Park and Baer 2022) in strategy in that the former's emphasis is on boundary concerns rather than, strictly speaking, information processing, and the latter is largely focused on individual-level (or, at least, treating the firm as a unitary actor) problem framing and formulation. Moreover, the potential effects of AI, and IT in general, on problem representation have been neglected or downplayed (Simon 1973, Felin and Holweg 2024). By integrating theory from the AI field (Sussman 1977) with the Carnegie perspective (Simon, 1962) and those of organization design, our resulting Simon-Sussman model of information processing identifies novel mechanisms by which AI may augment problem representation at the organizational level.

Finally, though the organization literature has recently explored the possibilities and limits for emerging technologies such as Gen AI regarding problem representation (Csaszar, Ketkar, et al. 2024, Felin and Holweg 2024, Raisch and Fomina 2024), they have not explored effects on organizational structure. Our effort takes an important step toward developing a deeper understanding of organization design in an AI world, including novel predictions as to when and how AI will decrease near-decomposability. Our theory thus offers important insights into a central concern of strategic decision making with AI: how to design the organization.

2. Near Decomposability

2.1 Near Decomposability and Search: Simon's Watchmaker

The role of organizational structure is, in part, to improve the information position of the organization as much as possible so as to ensure better decision making with respect to the environment (Miller and Frick 1949, Shannon and Weaver 1949, Garner 1962, Downey et al. 1975, Galbraith 1977, Tushman and Nadler 1978). Strategy and organization design scholars have long concerned themselves specifically with the relationship between key design choices and the structure of information processing, especially the near decomposability of the organization and problem-solving (Baumann et al. 2019, p. 303). The reason for this focus is twofold. First, organizational structure aids decision makers in finding a representation of a decision problem. As Simon remarked, "an organization's structure is itself a representation of the [problems] that the organization was designed to deal with" (Simon 1947, p. 124). Second, near decomposability bears directly on strategic decision making: Structural decomposition of a firm's activities can facilitate identification and adaptation of new solutions (e.g., strategies) (Siggelkow and Levinthal 2005).

Near decomposability refers to the ability to represent a complex system as a set of mostly independent subsystems. "Mostly independent" means that interactions within a subsystem are more frequent and intense than those across subsystems, such as the groups or units of an organization (Augier and Sarasvathy 2004, Egidi and Marengo 2004). The main effect of decomposition into mostly independent subsystems is to enhance the adaptability of the organization's problem-solving activities. Empirical research in the organization literature has found such an effect of near decomposability in phenomena ranging from strategy formulation (Gavetti et al. 2005), attention (Joseph and Ocasio 2012), innovation (Fang et al. 2010), authority (Levinthal and Workiewicz 2018), firm performance (Burton et al. 2006), and learning and routines (Marengo et al. 2000).

Much of the emphasis on near decomposability concerns its facilitating role in the organization's search for solutions to *given problems*. Search problems are given in the sense that the overall performance goal and choice alternatives are provided in advance and hence manifest as much more than mere symptoms. In complex organizations, the adaptation challenge that near decomposability addresses in this context of search problems is one of "combinatorial complexity", or how interdependence in the contributions of choices to overall performance means that the "possible solutions to [problems] grows exponentially with the number of [choices]" (Baumann and Siggelkow 2013).[2]

The search literature highlights how individuals' limited processing capacity makes search amid combinatorial complexity prone to errors that complicate effective adaptation. Learning pathologies arise both from how decomposition by the designer and search by managers are vulnerable to path dependence, and hence to converging to suboptimal solutions (i.e., to "local peaks" or "sticking points" in a performance landscape) (Rivkin and Siggelkow 2003). It follows that an organization lacks the capacity to represent and decompose the "true" complexity of interdependencies among choices (Ethiraj and Levinthal 2004, Podolny 2018). Near decomposability is a means for ignoring (or at least reducing) these complex interdependencies to confine errors within subsystems (Agre 2003, p. 418), and thereby attenuate the exposure to such pathologies.

Research suggests that as a design solution to the problem of complexity, decomposition should be *coarse-grained*, meaning that the choices underlying a search problem are decomposed only at a highly aggregate level (Rivkin and Siggelkow 2003). For example, rather than decompose R&D, marketing, and finance into fine-grained subsets of choices that the designer may not fully understand, the designer may simply decompose these functions into three departments. Coarseness is essential in the

[2] This core challenge of adapting beliefs about given sets of choices equally applies to the challenge of adaptively coordinating given sets of *tasks* in classic information processing perspectives (Galbraith 1977, Postrel 2002, Raveendran et al. 2020).

search context since, given combinatorial complexity, aggregate effects of errors on performance become compounded the finer-grained the decomposition is. Coarseness contains the fallout of such error aggregation both for decomposition errors (designers who assign units the wrong choices) and search errors (managers who select suboptimal values for these choices). Coarse-grained decomposition includes assigning units spatially to high-level functions or modular components of a technology or product or based on sequential attention to progressively larger subsets of choices (Baumann and Siggelkow 2013, Keil et al. 2023).

Research also suggests benefits of imposing *hierarchy* on how information is processed in a nearly-decomposable structure (Ethiraj and Levinthal 2004). Hierarchy refers to a sequential precedence ordering on information flows or constraints asymmetrically from top to bottom (Levinthal and Workiewicz 2018). Hierarchy's provision of decision premises, for example, allows complex organizations to engage in orderly search and stabilize around a common set of fixed choices, without creating mutual confusion (Gavetti et al. 2005). Accordingly, hierarchy may also prevent, in the search for alternatives, one part of the organization from conflicting with that of another part or inability to settle on solutions (Rivkin and Siggelkow, 2003). In contrast, trying for a more "realistic" nonhierarchical decomposition results in much greater variance in the effects of decomposition errors. This notion of hierarchy extends to efforts to embed in IT technologies the means for enabling members to observe information about other units, thereby allowing for establishing a set of decision premises and increasing the likelihood of predicting the choices of others (Srikanth and Puranam 2011).

2.2 Assumptions of Near-Decomposability for Search

Both of the key features of near decomposability for efficient information processing— coarse-grained units and hierarchically structured information — are contingent on the assumptions in search of mostly given performance goals, choices, and choice alternatives. Relaxing these assumptions — in accordance with its potential impact on problem representation (Zellweger and Zenger 2021), and with AI's potential effects on this phase — implies a need to revisit these dimensions.

First, if the relevant set of choices is unclear, errors in the selection of even a small subset of choices or their grouping into units may create "ripple effects" to distant parts of the organization that are far more severe than learning pathologies (Clement 2023). Beyond ending up on a local peak or sticking point on a given landscape, such "ripple effects" make the organization vulnerable simply to identifying irrelevant goals or choices, and hence the wrong problem (i.e., the wrong performance landscape) (Podolny 2018).

Second, hierarchy structures feedback for the (given) set of choices to search, but not regarding the goals themselves. In reality, strategic problems often appear initially as mere "symptoms", which require constructing or changing the firm's goals. For example, a steel producer where profits are down, Simon (1947, p. 119) noted, might change its very goals from problems of steel production to problems of investing in steel-related projects, entailing "fundamental change in organizational knowledge and skills… [such that] a new problem representation and a role system are created". In such cases, decomposition or search errors concern not just erroneous beliefs about given choices or alternatives, but errors of kind (content) and the need to construct new problem representations. If goals (problems) are incorrect, either from initial misspecification or from a change in the environment, then the power of hierarchy —in the sense of sequentially ordering information flows across units — disappears.

In the context of problem representation, it follows, that the effects of near decomposition on adaptability cannot depend on "containing fallout" by ignoring interdependencies across units. The designer cannot simply decompose units by assigning them subsets of choices. Adaptability concerns flexibly surfacing complex interdependencies to understand the decomposition process. The designer does not so much assign units given subsets of choices, as find ways to enroll them in the decomposition process itself, such that the units need to be grouped based on elements that are stabler in their relevance to the underlying problem than sets of choices pertaining to a solution.

Example: Simon's watchmaker. Consider the above discussion in the context of Simon's (1962) watchmaker parable, a canonical illustration of near decomposability. Simon's parable describes two watchmakers[3] who have the goal of assembling a mechanical watch composed of 1,000 parts. If the assembly task is interrupted, the task starts over, but not for any components that are already assembled. One of the watchmakers, by coarsely decomposing the watch into ten components of 100 parts each, achieves vast gains in the efficiency of adaptation (e.g., in assembling the watch even amid regular interruptions) over the other watchmaker, who assembles it part by part.

Simon explains the efficiency gains as arising from how just a small number of components serve as "stable intermediate forms" that contain the fallout of an interruption, analogous to the idea in search of coarsely decomposing the choice set to contain the fallout of "interruptions" in the form of decomposition or search errors. Yet if the design of the watch itself is changed, or if there is a malfunction in the existing watch design, then such mechanisms are inadequate (Agre 2003). What arises is not just a change in the assembly task, but a different task of more systemically understanding the nature of the watch functions and their interdependencies. In the parlance of this paper, prior to decomposing the organization according to watch component-specific subsets of choice variables for search, the hypothetical watchmaking organization needs to observe a stabler set of elements — i.e., the fundamental constraints — regarding the new or malfunctioning watch.

2.3 Near Decomposability and Procedural Representation: Revisiting Simon's Watchmaker

To apply Simon's concepts of near decomposability to the representation of new problems, and hence set up an analysis of the effects of AI on these constructs, we turn to the AI scholar Gerald Sussman's (1977) theory of *procedural representation*. Sussman's theory proposes distinct elements and structures of decomposition that he intended to address the limits of search — that is, of *surfacing complex interdependencies* to develop systemic understandings and for modifying goals and choice sets. Sussman drew on his experience as a hobbyist mechanical watchmaker to frame his theory in terms of an alternative version of Simon's watchmaker parable. His version enables us to frame the relationship

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[3] Though the parable assumes a single watchmaker, it can just as well be viewed as an organization in which the ten watch components are mapped to ten organizational units.

between the procedural representation of problems and near decomposability, and to develop key mechanisms to explain the relationship — and, subsequently, the effects of AI.

Sussman's version of the parable (from Sussman and Steele 1980, p. 15–17) describes and a watch of five components and 17 parts. The watchmakers have the goal not of assembling a watch, but of *representing how the components and parts function together to display the time*. The understanding does not so much involve choice sets but primarily *observing* the various components and parts of the watch to try and piece together the process through which they work. Unlike Simon's assembly task, there are no interruptions and both watchmakers nearly decompose the watch into mostly independent subsystems. The first one, however, depicted in Figure 1a, decomposes the watch only into its parts and components, akin to the "efficient" watchmaker in Simon's parable. Sussman notes that this first watchmaker only understands how the parts and components are assembled (the "anatomy" of the watch), rather than how they actually function together to display time (its "physiology"). To develop a deeper understanding (i.e., accurate interpretation), the second watchmaker makes two further decompositions.

First, depicted in Figure 1b, the watch is decomposed into a sequence of five functions derived from the fundamental principles and conventions of mechanical watches, starting with the generation of mechanical forces ("Energy Source") and ending with the conventional display of the time in hours and minutes ("Display"). Second, depicted in Figure 1c, the watchmaker defines how the five components and 17 parts function together *as a set of constraints* (target ranges or thresholds) *to be satisfied* with respect to the five functions. The minute and hour hands map to the "Display" function, so an example of a constraint might be a target accuracy for time displayed. The full set of constraints constitutes this second watchmaker's decomposition of the watch. At the organizational level, the constraints in Sussman's watchmaker can be analogized to detailed sets of key performance indicators (KPIs), accounting ratios, finance or management principles, business requirements, or even scientific or engineering laws.

Since parts or components of the watch may share functions, the decomposition forms what Sussman calls an overlapping *constraint network*. Sussman explains that, to understand the watch, the constraints in this network can be independently observed as satisfied or not, even if the underlying components and parts are interdependent with respect to an assembly task. For example, if the time displayed is inaccurate, this observation can be made without considering the component-level interdependencies in Figure 1a. Hence, even though the constraint network visually appears as an overlapping mess, it meets the essential criteria for near-decomposition of mostly independent subsystems.

---INSERT FIGURES 1A AND 1B---

Translating Sussman's description of Figure 1c and the second watchmaker to the organizational context, we frame problem representation as processes by which its members construct and decompose a constraint network – a process referred to as *procedural representation*. The elements of procedural representation include: (1) a broad goal of understanding how some system works (e.g., how the watch functions, rather than a specific assembly task); (2) a set of observational variables (e.g., any variables about the watch components or parts, or processes that can or should be observed), (3) an overlapping network of constraints on these variables (target ranges or thresholds, corresponding to subgoals), derived from principles and conventions of the domain (e.g., the domain of mechanical watchmaking); and (4) knowledge of procedures for how to *propagate* information (about values of variables or about whether a constraint is satisfied or violated) across the constraint network. The process of representing a problem using such procedures then eventually leads to a "debugged" network of constraints that, in turn, informs the selection of a subset of choice variables.

The problem may refer to inadequacies or errors in the organization's existing representation of the constraint network (e.g., of formulating a novel theory of what a watch should look like), as well as where it understands the constraint network, but there is an error in the underlying phenomena (problems of *troubleshooting* or *diagnosis*, such as defects in a watch manufacturing facility. In either case (theory formation or diagnosis), a problem representation process transitions the constraint network from some initial state, to an intermediate state, to a goal state. This is the same basic structure as the search process (Newell and Simon 1972), but here the goal state is tentative and can be changes and the initial state corresponds to mere symptoms rather than an initial set of beliefs about a choice set.

By "symptoms", we refer to where the relevant set of choices is inadequately known, as has been discussed in much recent organizations and strategy literature (Baer et al. 2013, Posen et al. 2018). Specific to near decomposability for problem representation, we characterize symptoms as manifesting as an apparent *violation* of one or more constraints in a (possibly unknown or incomplete) constraint network. The symptoms hence trigger the organization to process information to represent the problem underlying the constraint network. Differences between decomposing the organization for search and problem representation are detailed in Table 1.

---INSERT TABLE 1 ABOUT HERE---

2.4 Decomposing the Organization for Problem Representation

Having conceptually distinguished near decomposability for problem representation from that of search, we next turn to operationalizing the differences in terms of dimensions to precisely theorize the impact of AI (see Table 2). Since constraints may share variables (Ulrich and Seering 1989), they form an overlapping network that represents the interdependencies of a problem, or the "web of symptoms" (Ananth et al. 2024). In information processing terms, this piecing-together of a representation of the constraint network is called *constraint propagation*, referring to how evaluating one constraint enables sending ("propagating") information to any related constraints in the network. Since propagating information equates to surfacing interdependencies (constraints on subsets of variables) that are grounded in domain-specific principles, piecing together the constraint network leads to an understanding how a problem should be represented.

Sussman explains the efficiency of adaptation as arising from how near decomposition into an overlapping network of constraints serves several adaptive roles. First, whereas the consequences of errors (i.e., interruptions) in Simon's assembly task are aggravated the less coarse-grained the decomposition is (with Simon's first watchmaker who does not decompose into watch into coarse-grained components as the worst-case scenario), the "errors" in Sussman's understanding task are merely ones of misunderstanding some observation. Sussman frames such errors not as having path-dependent effects on performance, but instead as *learning opportunities* that are reconciled simply by making *finer-grained* observations, and where such learning opportunities are hence enriched by a finer decomposition (i.e., by decomposition into a more detailed and overlapping set of constraints that enables richer observations). To explain this learning mechanism, Sussman (1977) referred to errors in problem decomposition as "bugs". For Sussman, bugs are intimately linked to the process of near-decomposition in that the "manifestation of a bug is only a surface indication of some deeper failure" that cannot be resolved through search alone, requiring a distinct "debugging" process. For example, if the watchmaker observes that the accuracy of the time displayed by the minute and hour hands is out of range, the watchmaker may naturally check constraints on the minute and hour wheels to accumulate evidence for learning where the root of the problem is. Decomposing each of these functions further — such as into multiple variables that relate to the functioning of the minute and hour wheels — only enriches the opportunities to learn from any possible misunderstandings.

Second, since procedures for propagating information are open to any learning opportunities and are not susceptible to learning pathologies, any "units" of a hypothetical watchmaking organization could simply observe any part of the network of constraints on the watch to accumulate evidence. It follows that the approach in search of containing the fallout of errors by hierarchically structuring information flows across units does not provide any clear adaptive benefits. In fact, any structuring of information flows, hierarchical or not, would only reduce these hypothetical units' opportunities to learn about complex interdependencies among constraints. Hence, unlike search, designs for problem representation should support concurrent flows of information across units.

Third, decomposing into a network of constraints (e.g., functions of Sussman's watch) that can be defined in terms of target ranges or thresholds specific to a domain is much stabler across problems, and hence less prone to decomposition errors. For example, any mechanical watch will have to obey basic mechanical principles for creating and transferring energy, whereas any particular watch may have dramatically different components. Consider that, in Simon's parable, there is no explicit problem domain. The watch is simply a collection of unnamed components, and the parable could be about an assembly task for anything. This reflects how adaptation in search is with respect to a problem that is already given (i.e., driven by trial-and-error updating of beliefs about given choices) and requires no additional explicit use of domain-specific concepts. In contrast, in Sussman's watch, the particular names given to watch components define how they are bound by constraints specific to the domain of mechanical watchmaking, and these constraints are central to the ability to process information (i.e., to engage in "constraint propagation") to understand the overall functioning of the watch. Observing variables about watch components, functions, and their constraints can hence be used to inform the evaluation of any related variables (to any overlapping components in the watch). As an example, in Figure 1c, if the "Minute hand" part is not functioning satisfactorily, that information can be propagated to the "Minute wheel" to help the watchmaker understand that there may be an issue with this part.

Finally, hierarchical control over the management layers of a hypothetical organization in such understandings task cannot be limited to given constraints and choices. What is really needed are mechanisms to construct an understanding - out of the observations at various levels of abstraction – procedural knowledge of how to solve whatever functionality problem arises by changing the relevant set of constraints and learning through debugging problem representations.

---INSERT TABLE 2 ABOUT HERE---

3. Intelligent Systems and Problem-Solving

We have presented our Simon-Sussman view of information processing as procedural representation to frame the process of problem representation at the organization-level (Park and Baer 2022). A capacity for procedural representation enables the effective decomposition of an organization by facilitating (1) the processing (i.e., propagating) of information across a network of constraints and their underlying observational variables and (2) learning from this information at a fine-grained level to "debug" the inevitable errors in initial problem representations.

What makes identification of a problem representation different when using intelligent systems (AI) is the potential of these systems to augment the organization's capacity to: 1) identify a more *comprehensive* set of constraints (Lyles and Mitroff 1980); (i.e., the constraint network); 2) facilitate the debugging process; 3) improve the procedures for subsequent problem representation (i.e., second order process change). Intelligent systems — such as Gen AI — are able to carry out such processes more efficiently. Intelligent systems not only execute actions, but also represent, evaluate, and repair their own reasoning processes. When a failure occurs, intelligent systems use constraint propagation to track where in the network a violation has occurred (e.g., an unsatisfied precondition or a failed outcome), and then initiate a debugging process to revise that part of the procedure. This debugging is done locally: intelligent systems do not restart from scratch but target and repair only the failing subcomponent, preserving the rest of the system. In contrast to static pieces of information or rules, procedural representations are dynamic—they actively unfold in time and respond to particular contexts. In contrast to conventional AI prediction techniques, the representations need not be tied to a given problem (i.e., where what is to be predicted is given in advance, in the sense that the data and their distribution (Felin and Holweg 2024)).

As a result, departing from prior prediction views of IT and AI that posit a positive relationship between such technologies and near decomposability, we propose that the AI-mediated procedural representation of problems should *reduce* near decomposability of the organization. This is because, firstly, enhanced capacity for propagation to surface interdependencies will enable the perceivable constraint network to become more comprehensive, such that problem representations will be *finer-grained and interactions between modules are likely to increase.* Second, the provision of finer-grained problems may demand *more differentiated knowledge specialization* among units beyond just data analysts at the corporate office, thereby increasing the value of domain expertise. This effect arises since, as AI enhances the capacity for understanding problems, there will be a greater need for understanding the problem domain and corresponding constraints. Finally, knowledge in intelligent systems is embedded as procedures rather than rules or facts, which enhances the organization’s capacity to learn. As a result, *problem representation becomes a dynamic, continual process* that is more iterative. Moreover, collaboration (e.g., between domain experts, data scientists, software engineers, and managers) to properly train and maintain interdependent modules of an AI system will be needed on an ongoing basis to allow for continual problem representation.

We next discuss organizations' use of AI to develop and interact with representations (i.e., engage in problem representation through the use of AI-augmented procedures). We then develop propositions which link this process to implications for organization design.

3.1 Implications for Division of Labor: Fine-Grained Decomposition of Units

In search, organizations are conventionally structured to *ignore* (or at least reduce) interdependencies in problems by using the decomposition of the organization as a means for confining errors within subsystems (i.e., units), thereby attenuating their effects (Agre, 2003: 418; Simon 1962). The basic approach is to impose hierarchy, by sequentially ordering how information is processed across units or essentially providing broad guidance (decision premises) for making decisions across layers of the organization (Ethiraj and Levinthal 2004). As we have discussed, decomposition is commonly restricted to coarse-grained units (Rivkin & Siggelkow 2003; (Baumann and Siggelkow 2013, Keil et al. 2023) because a more "realistic" nonhierarchical decomposition results in much greater variance in the effects of decomposition errors.

In our procedural representation view, AI augments decision makers capacity to *surface* interdependencies as basis for bottom-up decomposition (Simon 1947). In this view, members use the superior processing capacity of AI (specifically, its superior capacity to propagate information across a network of constraints on a problem) to query information (e.g., ask questions) about more complex interdependencies in problems than they could answer otherwise. Using intelligent systems (either to aid decision making or to make final decisions) increases each member's capacity to propagate information about the subsets of constraints to which they pay attention and generate outputs in response to questions about any constraint on a potentially vast dataset (i.e., a digital twin). By enhancing the capacity for constraint propagation, augmentation of problem representation processes by AI vastly increases the number of "symptoms" that the organization pays attention to, and the sensitivity of causal paths that can be anticipated. In doing so, AI enables the organization's members to carefully reason about the continuous evolution of data and the potential for mismatches between the real world and evaluation sets (e.g., continuous monitoring of quality states), making it less reliant on heuristically-driven or myopic decomposition processes (Simon 1983).

Much prior literature suggests that such an impact of AI is not just additive. Organization scholars, for example, find that making sense of complex problems only emerges after adequately "complexifying" the representations shared by members. Formally, AI theories find that qualitative changes in both the complexity and robustness of behavior of a system arise when the constraint network is above a certain size threshold (Hodgson and Knudsen 2010). For example, the VLSI revolution in chip design in the 1990s was in part made possible using software to simulate more complex chips (Baldwin 2024 Ch. 13).

AI theories (Sussman 1977) emphasize more broadly how, to the extent that AI technologies increase the capacity to identify and propagate information about constraints, they empower any domain expert to represent and decompose problems more like engineers do. By enabling interdependencies to be surfaced and attended to, using AI to enhance the propagation of information across diverse constraints leads not only to nuanced understandings of problems (through debugging), but also of surfacing the "correct" decomposition of the organization, which accordingly should be more fine-grained. Hence, AI should mitigate the consequences of initial (coarse-grained) decomposition errors.

As problems become more fine-grained in their representation, the traditional rationale and need for large, multifunctional organizational units declines. Under a Simonian logic, the rationale for grouping tasks into larger units or divisions was to contain interdependencies. But when intelligent systems embedded with procedures for flexibly representing problems (i.e., for propagating information about constraints and debugging violations in these constraints), the need for embedding interdependent tasks within a single division diminishes. Instead, smaller, more specialized units—organized around narrower problem domains— interact frequently through shared procedural infrastructures (rather than hierarchical oversight). The granularity of task decomposition makes task-specific modularity more scalable, even in complex environments.

Thus, AI does not simply augment or automate tasks within existing divisions of labor—it re-shapes how and where boundaries are drawn on problems and subproblems, enabling smaller units in place of larger, molar units. In sum, we therefore expect that AI will, on average, lead to decompositions of organizations into finer-grained units.

Proposition 1. AI-mediated problem representation, on average, increases the decomposition of the organization into finer-grained units.

In an AI world, data generated by the organization are vastly greater in volume, variety and velocity than in the contexts in which classic information processing perspectives were developed. Amid this complexity, it has been tempting for managers and scholars to simply count on increased capacity for AI prediction, such as the popular vision of a fully automated "smart" factory operated by predictive AI models coupled with data from vast numbers of sensors. Yet as Amershi et al. (2019a) note, problem representations in an AI world are characterized by a heterogeneous and evolving "entanglement" of functions (in our parlance, an overlapping network of constraints) that is far more complex than traditional operations or product design contexts or even complex software development. Since AI prediction technologies are largely black-boxed, attempts in organizations to rely on AI predictions without creating shared problem representations can result in both blind adherence or willful ignorance of managers (Kim et al. 2024), or simply to failed implementation across the organization.

Conversely, even building shared understanding about just a small number of constraints on a problem (e.g., about two distinct functions in a product design) can involve "a time-consuming process of [one specialist] explaining its proposal to the other specialist" (Postrel 2002, p. 309). Our paper suggests that AI-augmented problem representation, contra AI prediction, will increase the value of domain experts relative to abstract AI prediction techniques by enriching experts' capacity to query and build a shared understanding of problems cross-functionally. In other words, domain experts are better positioned to solicit (i.e., query information about) and understand the semantically rich representations generated by emerging intelligent systems. Given that such systems will enhance an organization's capacity to propagate information across a constraint network (i.e., their capacity for more comprehensive problem representation), and given that this network is grounded in the principles of a specific domain, then it follows that AI will likewise enhance domain experts' capacity to perceive this constraint network. Hence, AI-augmented problem representation should reduce the cost of developing and using domain expertise.

Further, since flexibly generating semantically or categorically rich outputs using these technologies enhances specialists' capacity to build shared cross-functional understanding, there is less incentive for the organization to substitute abstract predictions about tasks for context-rich domain expertise. That is, the organization is decomposed into units with specialized domain expertise (Raveendran et al. 2016) who design and reconfigure novel task structures (Zysman and Nitzberg 2024), beyond solving given prediction tasks. Hence, we proffer that in an organization where AI is fully integrated, procedural representation should increase the value of specialization and, in particular, that decomposition will reflect more fine-grained units specialized in both process and task-related areas of a problem domain.

Proposition 2. AI-mediated problem representation increases the value of decomposing the organization into units specialized in domain expertise rather than into task units.

3.2 Implications for Integration across Units: Organizational Plasticity

As organizations increasingly embed AI systems with procedural knowledge required to propagate and debug information about networks of constraints on problems, the need for formal structural integration is relaxed. In foundational work, integration in nearly-decomposable structures (Simon, 1962) was achieved through hierarchy, policy directives, or other broad parameters under which subunits must operate. However, when human-AI systems equipped with greater capacity for constraint propagation and debugging are layered into organizational infrastructure, the burden of integration may be redistributed to the procedural layer. That is, rather than relying on predefined unit interfaces and sequentially ordering information (decision premises), AI (with or without humans) can monitor and dynamically manage overlapping constraints, activating appropriate procedures based on real-time information and constraint satisfaction. This allows for a more adaptive cognitive form of integration, less tied to static formal structural design.

At the same time, the use of AI to propagate information about constraints makes costly communication more efficient. AI also lowers the costs of changing problem representations (Csaszar et al. 2024) and, therefore, of initial decomposition errors (whether decomposition is from the top-down or bottom-up). As a result, the relative benefits of imposing hierarchical orderings of information flows (Ethiraj & Levinthal 2004) for containing the fallout of decomposition errors should diminish.

As we have argued, and as Sussman's work demonstrates, constraint-based AI systems can adjust how problems are decomposed. When these systems are deployed at the organizational level, grouping of activities into a single unit is not required. Instead, grouping is guided by the procedural logic encoded in intelligent systems and becomes context-dependent and situation-specific. As constraints evolve—in response to performance feedback—the system can alter how tasks are decomposed and distributed across organizational members. We take the prevalence, for example, of self-selecting agile teams when organizing the use of AI as strong evidence of this effect on bottom-up decomposition.

In this view, the organization is not a set of semi-permanent modules but a more flexible architecture, whose integration logic is enacted through AI-managed procedures that flexibly stitch together knowledge, goals, and resources. This kind of integration gives rise to *organizational plasticity*—the capacity of the organization to reconfigure patterns of interactions without requiring formal restructuring (Levinthal and Marino 2015). Unit boundaries become more fluid, as units can be temporarily "assembled" to address specific interdependencies—and then dissolve when the integration need passes (e.g., when the problem is solved). Hence, AI-mediated problem representation opens up possibilities to recast near decomposition as an ongoing, bottom-up and dynamic process that members of the organization engage in more frequently as symptoms of problems (i.e., violations of constraints) emerge.

Part of this shift is a result of how managing intelligent systems requires more bottom-up integration, since improvements in one part of the system easily decrease overall system quality if the rest of the system is not tuned to these latest improvements. Intelligent systems are characterized by stages of development that are blended, where components are entangled and boundaries are eroded (i.e., constraints overlap), and which are permeated by heterogenous and evolving data, leading to the risk of non-monotonic error propagation, and hidden feedback loops (Amershi et al. 2019b). Close collaboration to properly train or maintain the full system is needed on an ongoing basis to allow for continual problem representation and, in turn, modifying the decomposition of units.

As it uses AI to augment members' capacity to surface interdependencies in problems and decompose units from the bottom-up, the organization also learns complex attention patterns (March and Simon 1958) that enable the non-hierarchical ordering of information flows (i.e., of constraint propagation) across units. Such patterns go beyond standard precedence orderings across fixed units and instead correspond to the temporal decomposition of the organization's actions into intricate, cross-functional workflows with complex feedback loops. The semantically-rich outputs of emerging AI facilitate the development of intricate workflows through the automation of mundane support tasks for cross-functional collaboration, such as generating dashboards, documentation, or reports. At the same time, cognitive integration through shared problem representations (i.e., augmenting managers' capacity to propagate information about constraints) enables members to self-select into modules or units, adapting to how symptoms of problems emerge at varying levels of abstraction that may affect a single unit or the entire organization's strategy (Clement 2023, p. 2016).

Second, AI may itself be enrolled in the design (and continuous redesign) of more temporally fine-grained workflows, based on extracting sequential attention patterns from natural language articulations by managers or domain experts about how they interact with other units. Hence, whereas the design (and potential automation) of temporally-complex workflows has long been a key application of AI or analytics technologies regarding rote tasks for given problems (i.e., robotic process automation;

RPA), we expect that AI will enable workflow design to be used by organizations to order the principled propagation of information for complex processes of problem representation.

Importantly, this does not mean formal structure becomes irrelevant. Rather, it implies that structure is supplemented by a layer of procedural infrastructure that governs cross-unit interaction. The strategic challenge shifts from designing optimal organizational charts to designing systems of intelligent procedures for augmenting the capacity of shifting assemblages of organizational members to process information. Organizations that develop AI capabilities for encoding and revising procedural knowledge—not just storing data—will be better positioned to orchestrate flexible integration across functions and units, allowing them to adapt structure to environmental demands and feedback. This integration-through-procedure model marks a significant evolution in how coordination is achieved in complex firms.

In sum, we propose that AI-augmented problem representation should tend to decrease the extent to which near decomposition of the organization into mostly independent units also involves imposing hierarchical orderings on information flows among these units. Further, it should tend to increase the extent to which smaller, fine-grained units are integrated.

> *Proposition 3a. AI-augmented problem representation increases, on average, the ordering of information into complex, non-hierarchical workflows.*

> *Proposition 3b. AI- augmented problem representation increases the integration between smaller fine-grained units.*

3.3 Limits to Current AI's Capacity for Procedural Representation

Whereas our main propositions relate AI effects specifically to the propagation of information across a network of constraints, these effects are only indirectly supported by the current state-of-the-art focused on Gen AI. Recent research has also highlighted limits to the information processing capacity (Csaszar, Ketkar, et al. 2024, Felin and Holweg 2024) of the current state-of-the-art. Hence, AI effects on near decomposability will also be shaped by the future progress of AI technologies.

The constraints on problems in an organization are grounded in the concepts and principles of a specific domain. In contrast, Gen AI technologies are programmed with procedures for generating representations mostly at the extremely low-level of statistical patterns, called "embeddings", and in a general rather than domain-specific fashion (Hinton et al. 1984). As a result, while outputs generated by these technologies may often be effectively correlated with constraints on a problem, they do not directly emulate the propagation of information across conceptual or causal structures by a domain expert and may not be reliable or robust, leading to several challenges for AI-mediated problem representation.

"Hallucination" — the tendency of Gen AI technologies to generate outputs that are plausible and semantically-rich, yet factually incorrect — may lead to incorrect problem representations, or at the least may create inefficiencies from the need for extensive checking of the outputs by humans for correctness. Inefficiencies also arise from inability to precisely predict the outputs of prompts, which leads to a frequent need for users to continually re-specify the prompt until the output is relevant to the constraints in a problem that are of interest (Sarkar 2022). More fundamentally, since Gen AI technologies do not explicitly propagate information about constraints at the conceptual or causal level, they also arguably do not develop an actual understanding of the outputs that they generate and, hence, are likewise limited in their capacity to make relevant modifications to these outputs at the right level of abstraction as novel symptoms of a problem emerge (Clement 2023). This limitation, known as the "frame problem" (McCarthy and Hayes 1969) — the challenge of adapting to "situational frames" that emerge in the course of problem-solving — has been recognized as a fundamental bottleneck to AI for decades and, more recently, in the strategy literature as a bottleneck to problem representation (Felin et al. 2014). While it is clear that current progress in AI technologies opens up vast possibilities for AI-mediated problem representation, persistent limitations in the state-of-the-art would mitigate these possibilities. The effect on the granularity of decomposition and hierarchical orderings of information flows in organizations, however, is unclear since lack of progress in AI technologies for problem representation may simply result in a more pervasive use of AI for prediction and search. A clear effect, however, is that lack of progress would bound any increases in the value of domain expertise realized from the current state-of-the art.

> *Proposition 4. Limits on AI's capacity for constraint propagation will have unclear effects on the granularity of decomposition (Proposition 1) and hierarchical ordering of information flows (Propositions 3a and 3b), but bound any increases in the value of domain expertise (Proposition 2).*

4. Discussion

Our paper develops a theory of AI-augmented procedural representation to explain the impact of intelligent technologies on the near decomposability of organizations. To do so, we draw on seminal work by both Herbert Simon (1947, 1962) on near decomposability and Gerald Sussman (1977) on AI problem-solving to develop a procedural representation view of information processing. The procedural representation view that we have developed suggests that decomposition of an organization for the purpose of representing a strategic problem involves processing (i.e., propagating) information about a network of constraints and their underlying observational variables and learning through "debugging" problem representations in fine-grained detail. As depicted in Table 3 below, AI enhances the organization's capacity for such procedural representation, which implies that (1) it can be decomposed into smaller units organized around narrower problem domains; (2) these units will be more specialized in both process and task-related areas of this domain and (3) the organization's structure will resemble a flexible architecture whose integration logic is enacted through AI-managed procedures that stitch together knowledge, goals, and resources. We expect organizations to ultimately to benefit from these AI impacts by enabling representations of strategic problems that are both more comprehensive and robust.

Next, we summarize the core contributions of our procedural representation view, and the propositions that we have derived from it, for the broader strategy literature on AI and organization design more generally.

---INSERT TABLE 3 ABOUT HERE---

4.1 Connecting AI to Problem Representation

First, we introduce the AI idea of a constraint network (Sussman 1977), which allows us to describe complex representations generated or mediated by AI not as black boxes, but as understandable by an organization as sets of variables and constraints that are grounded in the principles of its problem domain (Russell and Norvig 2020: Ch. 6). Prior research has focused instead on how AI enables organizations to use more complex yet opaque representations to enhance their prediction ability (Csaszar, Ketkar, et al. 2024, Raisch and Fomina 2024). Consistent with views of problem representation as an organizational accomplishment for building shared cross-functional understanding (Bechky 2003, Joseph and Gaba 2019), the idea of a constraint network also introduces a novel type of information processing— procedural representation (Sussman 1977) — that allows us to precisely identify how these activities may potentially be mediated by emerging AI technologies. In particular, we extend theories of the effects of AI from lowering the organization's cost of prediction for given problems (Agrawal et al. 2018), to enhancing its capacity to generate representations of problems. In doing so, we highlight that AI enhances the comprehensiveness of the organization's representations of problems (i.e., the size of the constraint network) about which it can process (i.e., propagate) information, enabling its members to surface more complex interdependencies and leading to richer understanding of problems rather than necessarily more accurate predictions.

4.2 Recasting AI as a Driver of Cognitive Integration

Second, we connect these AI-augmented activities to the organizational-level by identifying mechanisms by which they promote cognitive integration across units and, hence, to the creation of shared problem representations. Whereas prior literature has identified mechanisms for creating shared representations based on enhanced observability (e.g., through tacit coordination, Srikanth and Puranam 2011) or flexible interpretation (e.g., boundary objects: Bechky 2003) of particular IT artifacts or objects, we emphasize the possibilities in emerging intelligent systems for generating semantically-rich outputs interactively and from a vast variety of data. The overall effect is to increase the complexity of problem representations (i.e., to expand the size of the constraint network) that are shared across units. This effect suggests an alternative information processing mechanism (i.e., constraint propagation) to fulfill Weick's (1979) call for organizations to "complexify" their representations of problems that is ultimately bound by limits to human-to-human communication about these representations (i.e., sensemaking). Likewise, it suggests that AI may enable more systematic exploration of problems and hence reduce the need for organizations to fall back on simple rules or adaptive strategies to avoid myopia or path dependence when coordinating across functions.

4.3 Near Decomposability in an Emerging AI World

These first two contributions allow us to make our third and main contribution, which are propositions about the relationship between AI-augmented problem representation and the near decomposability of the organization. The ideal of an organization decomposed into clean modules of task-level units goes back to classic information processing perspectives on IT (Galbraith 1977) and has continued with the contemporary digital platform and its coordination around APIs (Iansiti and Lakhani 2020). Further, as noted by Agrawal et al. (2024), whereas studies of AI have focused "adoption at the individual task level… AI adoption is shaped by the fact that organizations are composed of many interacting tasks". This gap is often mirrored in practice, with organizations focusing on adopting AI for discrete use cases.

In line with the AI theories of constraint propagation that we have drawn on (Sussman 1977), and broadly consistent with constructive perspectives on organizing (Rindova and Martins 2021), we recast near decomposition in an AI world as an ongoing and bottom-up accomplishment of the organization. Specifically, our model suggests that an organization's use of emerging AI technologies enables more fine-grained decomposition into units and decreases the need for imposing hierarchical orderings on information flows across units, both of which should induce nuanced, cross-functional understandings of problems. Whereas the organization design literature has long recognized the importance of mechanisms for coordinating across units — cross-functional teams, task forces, committees, etc. — these have typically been thought of as only contingently appropriate under specific environmental conditions. The distinct effects of AI in our model offers a view of near decomposition as not just a strategy for *ignoring* complex interdependencies to contain the fallout of search and decomposition errors (Rivkin and Siggelkow 2003; Ethiraj and Levinthal 2004), but also as a strategy for *surfacing* these interdependencies to create shared representations of problems.

Our model also points to several subtleties in how AI's effects on organizations may play out, and which also have important normative implications. In particular, we point to contingent effects of AI-augmented representation on the value of domain expertise. As recent research implies (Alaimo and Kallinikos 2024), if an organization views problem-solving as driven primarily by prediction and search, then near decomposition will be into units specialized in abstract predictive techniques with domain experts at best serving as auxiliary informants. In one sense, our propositions suggest that AI-augmented procedural representation simply amplifies this arrangement by enhancing the capacity of technical data science teams to collaboratively build a network of constraints that represents how data flow through an AI prediction model. In contrast, if a designer uses AI to augment procedural representation throughout the organization, units should be organized around domain experts whose understanding of the constraints and principles of the problem domain better positions them to ask questions and evaluate the semantically-rich outputs of emerging AI technologies.

4.4 Boundary Conditions

Our propositions have several boundary conditions that limit their implications for strategy, but at the same time point towards possibilities for further theory development. First, our information processing approach to problem representation assumed that problems are unknown to the organization, but are given by symptoms that are "out there" in the environment. This assumption does align with many real-world problem representation contexts, ranging from troubleshooting during routine operations (De Kleer and Williams 1987) to the pursuit of breakthrough innovations (Kneeland et al. 2020). As an example of the latter, it is known that developing an AI semiconductor that is significantly more efficient than currently dominant GPU technology is a valuable problem, but it is currently unclear which approach will work or how to implement it. Yet in other organizational contexts, such as new product design or entrepreneurship (Rindova and Martins 2021, Ehrig and Schmidt 2022), problem representations are generated from human agents' creative and imaginative cognition in ways that lead to sources of value with no obvious antecedent from the environment. Though recent work has considered how intelligent systems may augment creative and imaginative design processes (Seidel et al. 2018), this work has been mainly at the individual or group-level. Future research should explore the effects of the AI-augmented creation or imagination of problem representations – especially in the presence of ambiguity - on organizational structure, and in particular near decomposability.

Second, we have assumed that members of organizations have learned to become domain experts, such that decomposition into specialized functional units is affected only by exogenous factors such as the economic feasibility of using AI for procedural representation. In practice, there are well-known learning pathologies when accumulating domain expertise in an organization, which include over- and under-specialization (Ethiraj and Levinthal 2004) and learning rigid tasks rather than more flexible domain knowledge (Postrel 2002). In principle, many of the same desirable effects on coordination enabled by AI-augmented procedural representation (i.e., inducing nuanced understandings of a constraint network) should also apply to learning. Future work could explore how our organization-level conceptualization of procedural representation activities connects to prior theories of organizational learning (Argote 2012), and consider implications for our propositions regarding near decomposability.

Third, we have focused on problem representation alone, whereas many activities in organizations can be modularized into isolated tasks and, as highlighted in much recent literature, organizations' use of AI also increases the opportunities for task modularization. As a result, our propositions regarding near decomposability are only partial. In reality, an organization will need to be nearly decomposed in a variety of ways to achieve true cognitive integration, reflecting the diversity of problem-solving situations that it faces (Agre and Horswill 1997). The designer of the emerging AI organization, it appears, will face increasingly intricate situations not just of the extent of decomposition, but also *how* to combine different approaches to decomposition — i.e., task modularization, coarse-grained decomposition for search or, as explored here, finer-grained decomposition for problem representation. The design challenges for organizations in general may reflect those currently encountered in particular by large tech firms, where coordinating activities depends on architecting diverse layers (i.e., the "software stack") of an intelligent system for augmenting problem-solving activities of various types and at levels of abstraction. Future work should likewise combine the version of near decomposability that we have presented here to theorize higher-level "cognitive architectures" for the emerging AI organization (Prietula et al. 1998).

Fourth, we have also abstracted away from issues of time pressures such as industry- or ecosystem-driven competitive pressures or technological evolution that often shape changes in the strategy and structure of an organization, including its near decomposability. Such pressures may affect the organization designer's choices regarding the comprehensiveness of representations. For example, whether a chemical manufacturer develops a digital twin for its current factory may depend in part on how rapidly the manufacturing process is expected to change. Scholars have found that rapid change encourages reliance on "simple rules" (Bingham and Eisenhardt 2011), which, in the AI context, may correspond to turning to focusing AI use on well-defined prediction problems where data are readily available and need only be minimally structured.

Fifth, we have glossed over issues of organizational scale (Knudsen and Levinthal 2007), such as whether our propositions apply equally at the cross-functional team-level as they would across an entire organization or platform. Formally, our central information processing mechanism of constraint propagation is scale-friendly (consistent with micro-structural views of organization design, (Puranam 2018)) — a linear increase in the size and density of the constraint network should lead to combinatorial growth in the opportunities to propagate and, hence, to surface and understand complex interdependencies in problems. In practice, however, the elaboration of any information system is prone to complications — or what in contemporary AI and software technologies is referred to as "technical debt" (Sculley et al.

2015). Future research could examine this concept of technical debt in the context of organizations' development of information artifacts and objects for using AI.

5. Conclusion

Shannon pioneered a measure of information as units of prediction about systems whose behavior has a given statistical distribution (Shannon and Weaver 1949). Information processing perspectives on organizational structure have, consistent with Shannon, viewed the effects of IT as lowering the organization's cost of prediction for mostly given problems. This view has naturally carried over into recent work on organizations' use of AI predictions. Emerging intelligent systems, however, generate semantically-rich representations that are used by the organization in part to understand new problems, and not necessarily according to a known distribution corresponding to a mostly given problem. Hence, such systems make it timely for us to revisit the relationship between organizational structure and IT. To explore implications of this emerging technological context, our study draws on Simon's (1947) fundamental insight that structure is not only modified post-hoc by the organization but also emerges from its activities for representing problems and, correspondingly, goals. As Sussman said in the introduction of his thesis (1973): "The Maharal of Prague (Judah Loew ben Bezalel, c. 1512-1609) noticed that "And God Created Man" is recursive". Likewise, intelligent AI technologies have the potential to qualitatively shift both how organizations represent problems and, in turn, how they are nearly-decomposed. Greater near decomposability will in turn affect how they represent problems and thus make strategic decisions to search for, evaluation and implement solutions. Our theory also raises a distinct set of questions about the possibilities and limits of AI technologies on the intelligence of organizations and, hence, points to novel directions for research in organization design and problem-solving perspectives more generally.

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Figure 1a. Constraints on watch components

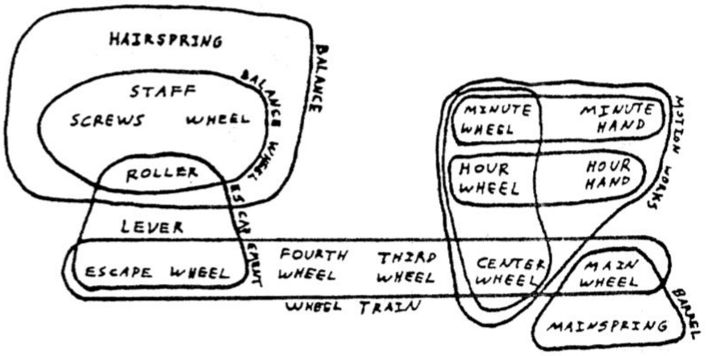

Figure 1b. Constraints on watch functions

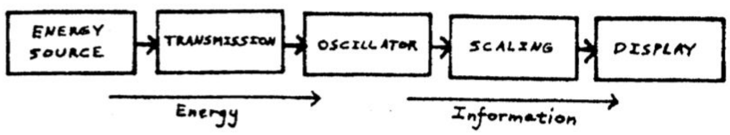

Figure 1c. Constraint network depicting interdependencies of watch components and functions

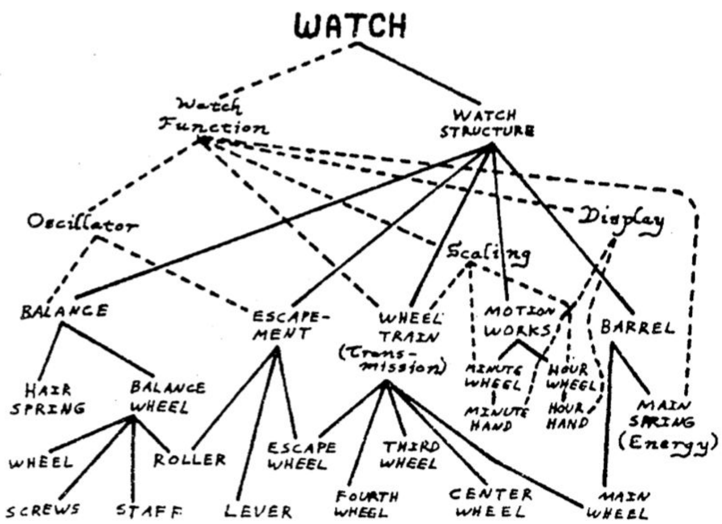

Table 1. Dimensions of near-decomposability for search vs. problem representation

Dimensions of near-decomposability	**Decomposing for search**	**Decomposing for problem representation**
Goal	Well defined (i.e., problem given)	Tentative (intermediate goals, open to change)
Elements of information processing	Choice variables	Observational variables (includes choices, but also any other data variables)
Key information processing activity	Decomposing tasks to limit fallout from learning pathologies	Understanding functions to expand learning opportunities
Grouping of organizational units	Units assigned coarse-grained subsets of choices	Units assigned fine-grained subsets of observations/constraints
Structuring of information flows	Sequential ordering of information flows (hierarchical); trial and error learning to select values for giving choices	Concurrent information flows (non-hierarchical); constraint propagation and debugging to allow for reasoning about relationships
Extent of interactions	A small set of variables with few interactions (choice set)	Large set of variables with (potentially) many interactions (constraint network)
Risk of decomposing errors	High	Low

Table 2. Concepts associated with our procedural representation view

Term	**Definition**
Procedural Representation	A form of representation in which knowledge is encoded as procedures for achieving goals (by evaluating constraints), rather than static facts or rules.
Constraint Network	A directed graph that captures the logical or procedural dependencies among goals, subgoals, and actions. The nodes of the network are observational variables and the links of the network are restrictions on the values of subsets of these variables. It is used to reason about cascading effects among variables, where relationships among them are governed by constraints that must be satisfied.
Constraint Propagation	The process of updating and enforcing relationships across a constraint network to ensure local consistency and identify feasible solutions or next actions.
Debugging	A process in which the system identifies, traces, and corrects errors in its reasoning or execution by analyzing where constraints have been violated then decomposing the representation in finer-grained detail. Only the faulty component (the “bug”) of a procedural representation is revised, rather than redesigning the entire procedure from scratch.

Table 3. AI impact on decomposability for problem representation

AI impact on procedural representation	Impact on organizational structure	Impact on the representation of strategic problems
Units assigned fine-grained subsets of constraints	Smaller units organized around narrower problem domains	More comprehensive representations of strategic problems
	More specialized units in both process and task-related areas of a problem domain	
Constraint propagation and debugging	Flexible architecture, whose integration logic is enacted through AI-managed procedures that flexibly stitch together knowledge, goals, and resources	More dynamic and continual representations of strategic problems