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POINT OF VIEW

Navigating more or less: AI and resource allocation on the intensive and extensive margins

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Organizational adaptation suggests the possibility of a firm changing its strategy over time, and in particular the possibility of changing strategy in a manner that keeps the firm aligned with a possibly changing environment. Andrews (1971) characterized strategy as a pattern of decision making and resource allocation, and thus why in turn the allocation of resources has long been viewed as central to the consideration of firm strategy (Bower 1970). The technology of resource allocation, particularly that of capital, has evolved over time with estimating discounted cash flows (Brealy et al. 2019) and in more recent years the development of real options (Trigeorgis 1996). Recent advances in artificial intelligence offer another important technological advance. These advances speak to different challenges of adaptation and resource allocation. While the organization's literature has emphasized the tradeoff between exploration and exploitation (March 1991), the analogue in the economics literature is between tradeoffs on the intensive margin, changing resource allocation among an existing set of initiatives, versus tradeoffs on the extensive margin, engaging in new initiatives or withdrawing from existing ones.

In assessing the possibility and potential limits of AI's use in resource allocation, it is useful to distinguish between its use in making tradeoffs along the intensive versus extensive margin. These two distinct economic calculations suggest different forms of AI. The intensive margin speaks to the marginal value of doing more, or less, of the same set of activities. As Levinthal and Wu (2025) argue that sort of allocation decision often has a rich set of data and metrics on which to draw. Predictive AI tools would seem most amenable to the intensive margin. Problems of the intensive margins can incorporate a rich set of operating metrics on which the evaluation of the best use of incremental resources can be made. A strength of AI as the resource allocator is its capacity to make tradeoffs among seemingly incommensurate measures and why it may serve as a superior basis for decisions on the intensive margin across the full array of a firm's activities. Dawes' (1979) pioneering work on the superiority of unbiased linear decision rules over expert judgment points to the weakness of human experts in making tradeoffs over alternatives that vary along a number of attributes. For traditional human-based judgement processes, common metrics are important to facilitate resource allocation within an enterprise to the best, or new-best use (Levinthal and Wu 2025). As a result, the effectiveness of a non-AI-based resource allocation is often restricted to allocation within domains with shared metrics. In contrast, a predictive AI algorithm is not bound by the "pipes" [organizational structures] and "prisms" [metrics on which evaluation of merit is based] of a traditional resource allocation system (Levinthal and Wu 2025).

In contrast, the extensive margin speaks to the possibility of engaging in a novel set of actions. The extensive margin not only requires an opportunity cost logic to be employed (Levinthal and Wu 2025), but the extensive margin also poses the question of what constitutes the set of possible actions and their possible value. Generative AI is a powerful tool with which to explore the extensive margin. By way of illustration, in the life sciences generative AI has allowed researchers to expand the set of molecules that might be considered as drug candidates with extraordinary speed (Grangwal et al. 2024). Generative AI offers an expanded technology of offline search (Gavetti and Levinthal 2000). In the life sciences that offline search driven by generative AI is then supplemented with a mixture of predictive AI as a basis of evaluation, exprimental on-line testing, with laboratory of non-human animal models and ultimately human trails.

Generative AI is masterful at exploring the design space of the possible. However, what constitutes the pragmatic adjacent feasible and profitable needs to incorporate a firm's distinct set of capabilities and constraints. As noted in the

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literature on organizational search, it is important to distinguish between actions that are novel from the firm's perspective or novel with respect to the broader world (Rosenkopf and Nerker 2001), with important implications with respect to the possibility of relevant data in the distinct settings. However, even if novel just from the firm's perspective, the firm's economic logic is likely to be idiosyncratic—how a given action generates value given the firm's existing set of resources and capabilities—and not simply forecasting a baseline probability of some technological development (Wu et al 2014).

Applying machine learning to the firm's resource allocation problem entails two distinct challenges. One is the pairing of the general to the firm-specific, while the other is the challenge of the degree to which past knowledge and associations are predictive of future circumstances. The former problem can be readily addressed by pairing a foundation model that incorporates insights from a common pool of information with firm-specific data. There is the further question as to whether there is knowledge available to the human actor that is not available in the form of data to the machine learning algorithm. However, a different distinction, that between codified and tacit knowledge (Polanyi 1962; Winter 1987), does a disservice to the nature of the knowledge developed via machine learning. The classic contrast between tacit and codified knowledge treated the latter as a form of declarative knowledge (Cohen and Bacdayan 1994). However, the knowledge reflected in machine learning consists of associations among data elements in, potentially, a very unstructured manner, not unlike the brain's neural net and the bases for tacit knowledge. Indeed, it is this tacit like quality that underlies that explainability challenge of AI algorithms (Caruana et al. 2015).

The problem as to whether the past is prologue is a concern from the perspective of both applications of machine learning to challenges of the intensive margin, as well as for those of the extensive margin. Even among extent initiatives, there is the possibility of change in their value and need for capital. However, among existing initiatives there is likely a fair degree of continuity in terms of the various metrics that effectively guided capital allocation in the past to their appropriateness to the present. In that regard, it is useful to distinguish between choices that change because of specific circumstances—say changes in population, economic activity, market share—and changes in the underlying structure of the basis of competitive advantage. Essentially, the former sorts of changes change the inputs to an algorithm of resource allocation, while the algorithm itself remains valid. In contrast, the latter sort of changed circumstances suggest that the model itself needs to be adapted.

While business strategists speak of disruptive technological change, how emerging technologies may shift the bases of competitive advantage, from a machine learning point of view the challenge is one of cognitive discontinuity. Is the theory of success embedded in machine learning on prior history a useful guide to new initiatives (the extensive margin) in the new circumstances? Generalization is a challenge for both machine learning (Sutton and Barto 1998; Hinton et al. 2015) and human decision makers (Nosofsky 1988). While the power of AI trained systems hinges on the degree to which the training set is indicative of the "test" conditions, human decision makers struggle as well in extrapolating from past experience to distinct future possibilities. Rather than focus on some intrinsic quality of individual human judgment, I highlight three different classes of considerations. First, the importance of diversity in effective judgment and search processes. Second, the role of persuasion and actors' commitment to a course of action, what might be viewed as the "implementation problem". And third, the bases of statis that may inhibit the adaptation of judgment processes to new circumstances.

Firms of non-trivial scale tend to have non-trivial scope—they are involved in distinct markets and possibly leveraging distinct technologies and may even employ somewhat different business models and have a set of managers with possibly diverse experience. This diversity not only generates an array of distinct options for resource allocation, a rich menu of intensive margin choices, but the adjacent possible from these distinct starting points (Kauffman 2000; Levinthal 2021) poses a possibly rich array of extensive margin choices. Furthermore, these extensive margin options will be advocated for by actors using distinct logics and arguments—arguments premised on distinct data and distinct implicit and explicit theories regarding the firm's potential.

A long-standing line of arguments points to the power of diversity in perspectives and information in group decision making processes (Page 2008). Of course, the ultimate power of diverse inputs of ideas and perspectives hinges on how this diversity is aggregated (Csaszar and Eggers 2013). A particular challenge in this regard for organizations of considerable scale and scope with some degree of hierarchical structure is whether the diversity across various facets of the organization is suppressed or reflected and possibly even amplified by organizational processes (Levinthal 2021). While machine learning has tended to be understood with respect to a single algorithm, increasingly we are seeing architectures of machine learning incorporating division of labor and specialization (Jacobs et al. 1991). Furthermore, in enlisting generative AI in the creation of business plans and the like, these algorithms can be given distinct prompts, such as to assume distinct roles or perspectives, such as that of a marketing manager or a technologist. Thus, the challenge of and possibilities of diversity are present in both the context of machine learning and in populations of human agents.

While the discussion to this point has addressed the challenge of predicting the future, a different sort of projection is potentially shaping a new future (Pontikes and Rindova 2020). For instance, persuading potential ecosystem partners of the merit of a new business model is not simply a forecasting problem. An important aspect of the persuasive case is the economic logic being set forth—such as the assumptions about technological milestones and market penetration (Adner 2021; Adner and Levinthal 2024). The explicit theory of the case is the basis of persuasion, not a point estimate of a most likely outcome or even a forecast of the distribution of more or less likely outcomes.

The future is not exogenous. The ultimate merit of an initiative is not independent of the energy, passion and beliefs of those tasked with enacting it (Adner and Levinthal 2008, 2024). Thus, when it comes to the extensive margin, not only is there the issue of bold forecasts of the unknown, but there are the corresponding bold acts of creation and commitment—actions that are likely to find inspiration less in the point of view of an AI algorithm than in a compelling leader. That is not to suggest that leaders are, on average, infused with great wisdom or insight (March 2006). However, it is important to recognize that resource allocation of capital and other firm-level resources only have indirect effects on the hearts and minds of those responsible for the execution of a given initiative. Thus, not only is there endogeneity at a more macro level of potential external ecosystem partners and such, but also within the organization among those responsible for a given initiative.

Finally, while individuals are subject to cognitive lock-in and inertia, machine learning algorithms can also suffer a lock-in of sorts and be “prisoners” of their training set. Thus, both human actors and machines are subject to possible statis. Another basis of statis is organizational power structures (Ocasio 1994; Levinthal and Pham 2024). Entities within a firm may garner resources not as a function of merit but also as a function of power and even simply the role of inertia. Furthermore, with respect to inertia, there is the important point that deviating from an existing arrangement of resource allocation may invite contestation and politicking as the prior allocation may have represented what Nelson and Winter (1982) term an organizational truce. However, there are arguments that political conflict can facilitate adaptation of a complex system (Cohen 1984; Ganz 2024; Levinthal and Pham 2024). Conflict can engender search and discovery relative to more consensus or collective interest-based processes (Levinthal and Pham 2024). While individual decision makers are prone to inertia and even escalation of commitment (Staw 1976), political processes that shift the power relationship among actors within an organization can lead to changes in the dominant coalition that can facilitate a change in the organization’s strategy and resource allocation (Levinthal and Pham 2024).

In contrast to this drama of the contestation among individuals, the recommendations of a machine language algorithm can provide a message regarding the merit of reallocation of resources across existing initiatives and to new initiatives unfiltered by the biases and self-interest of parties and structures prone to motivated reasoning (Kunda 1990). In contrast to the contestation of a political process, the AI algorithm will revise its suggested actions based on being presented with new data about the firm and its initiatives. However, given the periodic nature of recalibrating an AI algorithm with a new or revised training set, its underlying logic will be frozen in interludes between the birth of version x and version x + 1. However, it is important to distinguish between a potentially static algorithm and the potentially dynamic data on which it acts. Thus, the firm and its decision problem as a state variable will change over time and can lead to new answers, even if the underlying “logic”—set of associations developed in the training data—remain static.

The knowledge embedded in machine learning offers a powerful guide to organizational resource allocation. It is a guide informed by data, but potentially subject to its own biases or (non)representativeness of its training data. Part of the value of technologies of choice is that they become a common ground for discourse among human actors (Bechky 2003). Older technologies of choice such as spreadsheets and discounted cash flow analyses, in their own way, offered structured basis for organizational debate and discussion as well as specific answers. The non-explicit or less transparent casual arguments of machine learning presents a different sort of debate partner and offers a different sort of contribution to organizational decision-making processes. Whether through delegation to machine learning or as an insightful and provocative “research assistant” and debate partner to human actors, machine learning offers a powerful basis by which to navigate the intensive and extensive margins of capital allocation.

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Declarations

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