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Timo Seppälä | Tomasz Mucha | Juri Mattila (eds.)

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ARTICLE 3

What Have We Learned About Machine Learning?

A Meta Analysis

Tomasz Mucha[a]
Timo Seppälä[a, b]
Robin Gustafsson[a]

Affiliations:

[a] Aalto University, Finland
[b] ETLA Economic Research, Finland

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Abstract

Recent advances in machine learning (ML) have triggered many firms to try putting the technology into commercial use. However, the creation of ML-based organizational capabilities remains a major challenge. With the aim of extending our understanding of organizational capabilities, this paper takes a socio-technical system perspective on the microfoundations of capabilities, develops an integrative conceptual framework, and discusses the resulting insights relevant to organizational ML initiatives. In contrast to past IS research, our framework is more general and versatile, since it is not restricted to dynamic capabilities only, as well as incorporates a temporal dimension facilitating the inspection of processes leading to the formation and change of organizational capabilities. This is illustrated with multiple propositions, which we develop by applying the framework to the context of organizational ML initiatives. Conceptual insights are backed with rich anecdotal evidence.

Keywords

Artificial intelligence, Machine learning meta analysis, Socio-technical systems, Organization

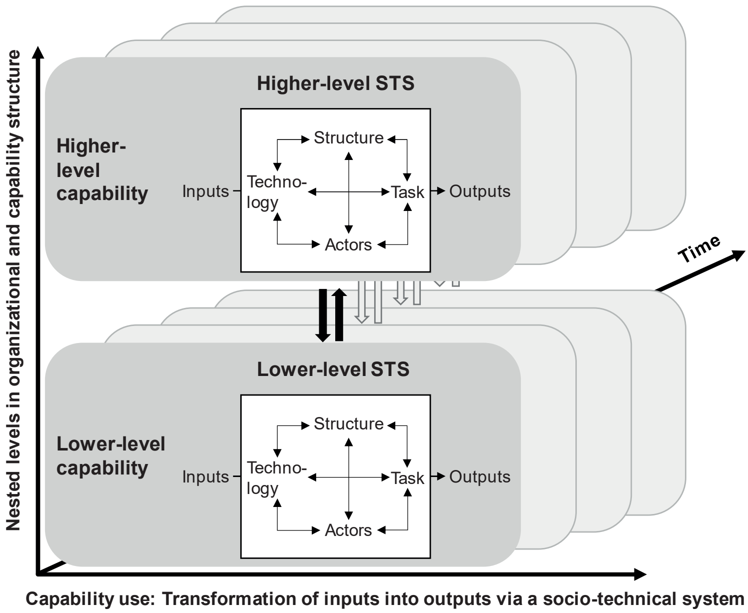
1 Introduction and conceptual framework

ML, which is at the core of the ongoing commercialization wave of artificial intelligence (AI), is currently viewed by large organizations as the most important and disruptive new technology [1]. Unlike traditional approach to programming, ML is a category of statistical and computational techniques to learning patterns and constructing inductive inferences from data or experience [1], [2]. ML coupled with modern computing resources and abundant data have enabled computers to significantly improve state-of-the-art performance on many tasks, including machine translation, speech recognition, image recognition, and generation of text, audio, and images [3]. These advances have triggered an increasing number of companies to try putting ML into commercial use [4], [5]. Despite this heightened interest, organizations face major challenges in enhancing existing or developing new capabilities with ML. While piloting ML is relatively easy, scaling and deployment have proven challenging [1], [5]. Ransbotham and colleagues [4] find that only one in ten companies gets meaningful value out of their ML initiatives. Clearly, creation of ML-based capabilities is a major challenge.

Organizational capabilities do not come into being solely based on capacities of a technology [6]–[9]. Instead, they require a process of practice and routinization, which aligns not only the tasks with technological tools, but also with skills and roles of people, as well as with the organizational structure and communication flows [6], [10]–[12]. Similarly, introducing new technology to modify or develop an existing capability might require a period of practice and routinization before the new level of capability performance is reached [12], [13]. Hence, to understand better the relationship between new technologies, such as ML, and organizational capabilities we need to study the process of capability formation and change, while explicitly recognizing the links between technology, tasks, people, and structure within which they operate. Thus, we need to shift the focus of our analysis to the level of microfoundations [14], [15]. Despite the calls for investigating microfoundations of organizational capabilities [14], [15], there is only a limited number of studies discussing this topic. Notable examples from IS domain [8], [16]–[18] recognize that socio-technical system (STS) perspective [19], [20] is a useful conceptual framing to understand the interplay between digital technologies and organizational capabilities.

We define the microfoundational elements of organizational capabilities and recognized that they correspond to the building blocks of an STS. Furthermore, our analysis of organizational capabilities and STS theory literature highlighted the prominence of the following characteristics shared by these perspectives: (1) routinization; (2) deep structure; and (3) nesting. Based on these, we propose an STS framework for organizational capabilities, as presented in Figure 1, and apply it in the context of organizational ML initiatives.

Figure 1 STS framework for organizational capabilities



Our generalized version of the framework includes two organizational capabilities, each at a different level. These capabilities are practiced and routinized transformations of inputs into outputs via the underlying socio-technical systems. The vertical axis represents levels in the capability structure, while horizontal axis spatially distributes inputs, STS, and outputs. For the sake of simplicity, we assume discrete time, thus the transformation of inputs into outputs is assumed to take place within a single time increment. The depth axis represents progression of these capabilities through time, which might involve changes in one or multiple elements, as well as bidirectional impacts between the capabilities (or their underlying STSs) on different levels. The proposed framework presents a simplified structure, which, can be extended to cover more than two levels in the capability structure, as well as more than one capability on each level. In the remainder of this section we apply this framework in the context of organizational ML initiatives and develop propositions based on that. In our discussion, we follow the path of an increasing organizational engagement with ML. We start with one-off uses of ML, then proceed to the development and use of ML capability; creation of ML-based capabilities; learning in and improvement of ML-based capabilities; and conclude with full automation of a capability.

In this paper, we assume an STS perspective on organizational capabilities and develop a conceptual framework integrating these two levels of analysis. Based on the extant literature, we identify strong links between STS-level microfoundations and organizational capabilities. The resulting framework not only captures the temporal aspect of capability change, but also interrelationships between multiple capabilities within a single organization. We then use the framework to develop insights in the context of organizational ML initiatives. In our discussion, we follow the path of an increasing organizational engagement with ML, starting from one-off uses of ML and ending with full automation of a capability. Based on these, we develop multiple propositions. The propositions are backed by and clarified with anecdotal evidence collected from published case studies focusing on organizational use of ML, as well as from an ongoing 2-year-long research involving interviews and participatory observation of a national government funded accelerator promoting and facilitating AI use in organizations (Accelerator name blinded for review. The accelerator primarily caters to established organizations, covers the full range of ML technologies, and organizational ML maturity levels.)

2 Use cases and value propositions of machine learning for organizations

2.1 One-off uses of ML within an organization

ML can be used in two types of situations – one-off analysis and repeated use [31]. While the dominant focus in IS and business literature is on the second type, which corresponds to ML-based capability, one-off analysis continues to represent a meaningful share of projects, in which in-house data science teams and consultants engage in. Therefore, our discussion covers both types of ML uses.

One-off analysis utilizing ML, in isolation, does not lend itself to routinization within the context of the STS performing the analysis. Hence, on the level of that STS, there are no new instant capabilities being created. Nor ML becomes a permanent component of the technology underlying STS of the focal capability. The change that is brought by ML typically manifests itself at a lower-level capability and relates to the rearrangement of actors, technology, and structure configuration, or modification of inputs going into that system. More specifically, it is the new insight or knowledge that results from the use of ML and which points to the needed changes in inputs to the STS or STS itself. Such uses of ML potentially bring value to organizations in two ways. First, they can allow organizations to deal with one-off challenges by leveraging new insight or knowledge and existing capabilities. For example, when hurricane Frances was approaching Florida's coastline, Walmart's CIO decided to "start predicting what's going to happen, instead of waiting for it to happen" and mobilized her team to identify which products would be in high demand in the region [32]. Subsequently, Walmart's existing capabilities were used to top up the store shelves with soon-in-demand strawberry Pop-Tarts and beer [32]. This example illustrates that in some cases with new insights generated through one-off ML analysis organizations can leverage existing and unaltered capabilities to resolve a unique problem at hand or benefit from a unique opportunity. Second way, in which organizations can benefit from ML powered one-off analysis is less dramatic but might be even more valuable. New insight or knowledge resulting from the application of ML might be more permanent in nature. For example, one real estate management company relied on an outdated methodology to estimate soil humidity and reimbursed subcontractors for part of their work based on that. (This example was provided on May 24, 2021, by an expert when we were validating the practical relevance of our framework.) When the company received a new ML-based humidity estimation method from consultants, it has turned out that many site types had a dramatically lower humidity than previously expected. This resulted in multimillion-dollar savings on future projects. In this case, ML did not enter into an on-going use by the company, but the insights from one-off analysis improved the overall performance of existing capability and created long-term positive impact on value creation.

P1. One-off use of ML within an organization does not lead to the creation of a new capability.

Returning to the two examples of ML use we discussed above allows us to draw more propositions. While these uses of ML fall into the category of one-off analysis, there is a stark difference between how Walmart generated the new insights compared with the other case. The retail giant relied on an in-house ML capability, while the real estate management company leveraged external ML capabilities. Thus, in both cases ML played a role at a higher-level than operational capabilities. It was used as a tool within the technology element of a higher-level STS. However, Walmart retained that STS within its own organization, while the other company ran one-off projects using external resources. Furthermore, Walmart had all the pieces of the STS needed to carry out the analysis in place, thus demonstrated a routinized process. Hence, we conclude that Walmart had an ML capability. This contrasts with the other company, which not only didn't have the required resources in-house, but also had to carry out non-routine data collection activities to bring the project to fruition. The possession of ML capability within an organization is an important differentiator. Organizations with such capability can not only more rapidly carry out ML initiatives, but also are likely to identify opportunities and deliver on these with higher success rate. Furthermore, multiple executions of one-off ML initiatives might develop or strengthen organizational ML capability, by increasing experience and the level of routinization within that system.

P2. One-off use of ML within an organization may lead to the enhancement of an existing ML capability.

P3. Multiple one-off uses of ML within an organization may lead to the routinization and establishment of ML capability.

2.2 Use of ML capability

While Walmart's use of ML in the example we used related to one-off use, the existing organizational ML capability could also be used when pioneering new or enriching existing operational capabilities [23]. For example, Walmart is developing ML-based capabilities to monitor shelves for product restocking and replenishment needs, as well as to spot problems, such as spills [33]. These operational capabilities are being developed within their Intelligent Retail Lab, which in that context is the higher-level system possessing ML capability. Thus, ML capability can contribute to both one-off uses of ML as well as development of ML-based capabilities. In both cases, the availability of an established and routinized STS underlying ML capability provides an advantage, when compared against organizations without such capability. The case of early collaboration between an external team of researchers and the Atlanta Fire Rescue Department on Firebird serves as a good counterfactual illustration of how the lack of in-house ML capability can undermine ML-based capability establishment. Firebird is a "framework to help municipal fire departments identify and prioritize commercial property fire inspections, using machine learning, geocoding, and information visualization" [34, p. 185]. At the time of writing, Madaio and colleagues concluded that due to poor data sharing practices of the relevant municipal departments, part of the ML development process would need to be redone regularly. Without that the system could not capture changes in the activities and locations of business operating in the commercial properties. Consequently, at the initial phase and due to lack of previously established ML capability, Firebird turned out to be a one-off ML use, which was beneficial, although at that stage did not become an initially envisioned ML-based capability.

P4. Use of an existing ML capability by an organization positively influences the probability of successful outcomes from ML initiatives, including one-off uses of ML and ML-based capability development, in that organization.

However, one-off use of ML by an organization is possible even without having established in-house ML capability. Also, repeated use of ML, thus, an ML-based capability, can be developed without the possession of an ML capability. The most common examples falling within that category are those where ML technology is incorporated into the third-party tools being used within the STS underlying the operational capabilities of an organization. This includes, for instance, prediction of sales leads conversion into opportunities by sales managers using Salesforce Einstein. While this example of tool-like use of ML within the scope of existing operational capabilities has been packaged as a service by cloud vendors, more complex uses of ML, which require, for instance, physical changes in equipment, can also be developed without an in-house ML capability. For example, a German mass producer of electronic sensors and actuators has been developing an ML-based automated visual inspection capability for use by their quality control team by leveraging a collaboration with a university [35].

P5. Possession by an organization of an ML-based capability does not require or imply the possession of an ML capability by that organization.

2.3 Creation of ML-based capabilities

The possession of required, yet disjoint elements of an STS is not sufficient for the establishment of ML-based organizational capability. What is needed beyond these elements is the routinization of their joint activity, to the extent that performance has reached sufficient level of reliability. Such level of routinization is marked by the achievement of stability or balance in the deep structure of the underlying STS. For example, in case of Firebird, due to the one-off nature of data cleaning and joining [34], there was no routinization of the tasks. Thus, the organizational capability to identify and prioritize property fire inspections was not turned into being ML-based. A counter example is that of a global ship brokering company based in Norway, which developed a new ML-based capability to produce oil trade tables – "spreadsheet documents which contain information about activities of certain ships, including timestamps of departures and arrival, destinations, and in which ports they loaded or discharged cargo" [36, p. 6]. The creation of that capability required not only development and integration with existing systems, but also developmental iterations with the maritime activity researchers and redefinition of their role in the process. The establishment and routinization of that ML-based capability took approximately two years.

P6. Creation of a new ML-based organizational capability requires not only the presence of suitable actors, social structures, tasks, and technologies, but also establishment of a balanced deep structure linking these elements into a socio-technical system.

Creation of ML-based organizational capabilities is often rooted in previously existing organizational capabilities. Therefore, ML-based capability creation can often be seen as development or renewal of existing capabilities [12]. Since, by definition, existing capabilities exhibit certain level of balance in their STS's deep structure, introduction of new technological element poses potential threat to that balance. In this section we explore, in the context of first-time ML technology introduction, the relationship between capability performance and stability of its STS.

Returning to the example of ML-based capability of the Norwegian ship brokering company, allows us to elaborate the case of STS being pushed off balance. Since from the initial phase of the project the intention was "to have the algorithm clean, prepare and classify 'raw' AIS data, similarly to what the researcher manually did to generate the tradetables" [36, p. 7], change in the role of maritime researcher was expected, as trade tables' generation was the main responsibility for that job. Yet, at the outset it was not guaranteed that the ML-capability would have superior performance. Thus, unbalancing the STS of an existing capability is not a sufficient condition for performance improvement. This point is also illustrated by the case of a large European company – a member of a global fast-moving consumer goods group with annual revenue of over $50 billion – which aimed at removing "subjectivity and bias from workforce decisions, by drawing on data science, neuroscience, and machine learning" [37, p. 2]. Despite ambitious hopes, the introduction of ML into the trainee recruitment process in Europe resulted in pushing the STS of the underlying capability off balance, while producing disappointing results in terms of improvement of fairness in the selection and recruitment process. Not only did some of the candidates contest the fairness of the process, but also the hiring line managers, the in-house AI team, and the HR managers, who originally spearheaded the project. This imbalance resulted in conflicts between hiring managers, who couldn't hire their preferred candidates, and HR managers defending the ML-based decision rationale.

P7. Unbalancing of an existing capability's STS by introducing to it ML technology element is not a sufficient condition leading to performance improvement of that capability.

While unbalancing of an STS by the introduction of ML is not sufficient by itself to generate capability performance improvement, we posit that it is nonetheless a necessary condition for a performance improvement that is significant. This is because a significant change in the relationship between inputs and outputs of a capability means that the focal STS needs to undergo (or has undergone) a reconfiguration allowing it to exhibit a new range of responses and emergent properties [13]. Such reconfiguration implies not only a substitution of some existing technology with ML, but rather a more encompassing change within the scope of the focal STS. The introduction of ML, in that case, leads to change in one or multiple other elements of the focal STS. Thus, changes in the other elements of the technology, role of actors, social and organizational structure, or underlying tasks are always associated with significant capability performance improvements stemming from the introduction of ML. For example, the case of a Norwegian ship brokering company enriching its tradetable generation capability by introducing ML vividly demonstrates the change in the role of actors and the nature of tasks [36]. After the successful transition to ML-based generation of tradetables the maritime activity researchers became the “teachers and supervisors” of ML algorithm generating the tables used by the rest of the organization. In another study investigating the introduction of ML to Chinese e-commerce giant’s fulfillment center – Alibaba’s smart warehouse [5] – the traditional areas for manual handling of goods using forklifts and manual labor were replaced by an automatized tridimensional storehouse, where for safety and efficiency reasons people are normally not allowed to enter, position of individual pallets with goods is calculated using an ML-based prediction of the demand for these goods, and robots transport pallets to their destinations. Once orders for goods are received, employees do not need to move around the warehouse to collect goods from a single order, but rather robots do that based on an ML algorithm’s probability estimates of various items from multiple real-time ordered being bought together.

P8. Unbalancing of an existing capability’s STS by introducing to it ML technology element is a necessary condition for a significant performance improvement of that capability.

2.4 Learning in and improvement of ML-based capability

Having covered the creation of ML-based capability, we shift the focus to subsequent improvements and learning that might take place in such capability. An established ML-based capability must have reached certain level of reliability, has been practiced and routinized, and thus exhibits balance in the underlying STS. Further improvements in the performance of that capability are not guaranteed, despite ML having learning in its name. This notion is evident from even a cursory investigation of ML lifecycle [38], where an ML model deployed into production may go into a new round of learning (re-training), but does not have to. It is thus in the hands of those who develop the ML-based capability to determine whether, how often, and in what form such re-training might take place. In other words, ML model training and inference are two distinct phases in the model lifecycle, and at least one round of training (learning) must take place for an ML to be able to carry out inference in production. For example, a drone capable of object detection and tracking [39] has gone through a training phase and is able to carry out inference using on-board software and hardware. If an organization incorporated such drone into its surveillance or visual inspection capabilities, it could potentially improve performance of these capabilities. However, continuous use of that drone would not by itself result in any changes in the ML algorithm embedded into the drone.

P9. Ongoing use of an ML-based capability by an organization does not require or imply presence of a learning loop, which would improve performance of the ML technology within the STS of that capability.

Thus, organizations developing ML-based capabilities often recognize the need and require keeping ML models up-to-date and, potentially, continuously learning. This is especially the case in the context of high environmental dynamism. Thus, learning feedback loops are often integrated into the overall technology element of the underlying STS. They can take the form of (1) offline maintenance activity or (2) online updating [38]. For example, a European bank periodically retrains their customer service chatbot, which has been developed by an in-house team. (This example was provided by an expert during a workshop, which took place on November 20, 2019.) Such offline maintenance exercise takes place approximately every three months and requires involvement of not only the technical team, but also customer service agents. The retraining targets improvement of ML technology performance related to correctly recognizing customers' intents, as well as updates chatbot's responses, which must correspond to the ever-changing offering and terms of the service. An illustration of an ML-based capability, which has an integrated online learning feedback loop, is the case of Chinese petrochemical plant using digital twin system to control processes of a catalytic cracking unit [40]. Within that system, real-time operational data is not only used by ML to find optimal production settings, but also continuously serves as an input to automatic retraining of the ML model.

While these examples indicate that a feedback learning loop integrated into an established ML-based capability can lead to performance improvement, they do not elucidate the magnitude of changes that are expected or feasible. To complement our discussion with respect to this, we turn to two currently prominent areas of ML development – large transformer-based language models and autonomous driving. OpenAI, an artificial intelligence research and deployment company released in 2020 its third-generation of a large language model called Generative Pre-trained Transformer (GPT-3) [41]. GPT-3 has captured the imagination of media and many practitioners by demonstrating previously unseen performance on multiple tasks. However, plots demonstrating improvements of GPT-3 accuracy for various tasks as a function of number of input parameters consistently show diminishing marginal improvements [41]. Hence, getting ML to perform better gets increasingly harder, as the performance improves. This observation is consistent with the pattern of performance improvements in autonomous driving, where the initial successes were followed by mounting challenges to deal with corner and edge cases [42].

P10. Presence of an integrated learning feedback loop within an established ML-based capability provides, at best, diminishing marginal improvements in the performance of that capability.

Flattening out of capability performance is an expected outcome for all types of capabilities, yet significant performance improvements may be possible even after reaching such plateau [12]. Hence, improvements that would exceed the rate enabled by the integrated learning feedback loop of an ML-based capability might take place in some cases. This, however, requires a new round of development that is substantial and, thus, creates the need to unbalance the established deep structure of the capability's STS. For example, when Airbnb replaced its manual scoring function for property search rankings with a gradient boosted decision tree model, which is a type of ML algorithm, it experienced "one of the largest step improvements in homes bookings in Airbnb's history, with many successful iterations to follow" [43, p. 1927]. However, the algorithm's performance plateaued eventually. This triggered the team responsible for search ranking development to "trying sweeping changes to the system" [43, p. 1927] and introduce a new approach based on deep neural networks. Initially, the team aimed at "keeping everything else invariant and replacing the current model with a neural network" [43, p. 1934], which would retain the existing balance within the underlying STS. This, however, proved to only lower the performance of their search ranking capability. Only by "rethinking the entire system surrounding the model" [43, p. 1934] were they able to gain significant performance improvement.

P11. One-off improvements in the performance of an ML-based capability, which are beyond the improvement rate enabled by the integrated learning feedback loop of that capability, may be possible, in which case, to be realized, they require unbalancing of the STS within that capability.

2.5 Capability automation with ML

In an extreme case, ML, typically in combination with other technologies, can fully automate an existing capability. Such full automation requires a complete encapsulation by technology of four classes of functions, which are (1) information acquisition; (2) information analysis; (3) decision and action selection; and (4) action implementation [44]. Full encapsulation of a capability by technology is possible not only for narrow capabilities, but also in case of socially very complex and core organizational capabilities. Yet even full automation of a capability does not divorce the technology from socio-technical systems constituting an organization. Since STSs are nested structures, encapsulation of a lower-level STS into technology leaves it as an element of technical subsystem of a higher-level STS. Furthermore, the social structure and communication flows within the STS of that higher-level capability may be impacted. Thus, the event of capability encapsulation into ML-based technology may unbalance the STS of the capability being directly above the encapsulated capability. A good illustration of this is provided by the case of a German banking group substituting its in-house capability for small private loan approval and lending term setting with an ML-based technology [45]. Initially, this capability was enriched by incorporating a tool providing "recommendations that loan consultants could change, adapt, or ignore" [45, p. 308]. Later, an enhanced version of the tool, which was ML-based, was implemented as a fully automated solution, which "makes loan approval or denial decisions, determines the terms and conditions of loans, and autonomously alters lending criteria based on customer behavior and current market changes" [45, p. 308]. Thus, the capability for small private loan approval and lending term setting was encapsulated into an ML-based solution, which became an element of technology within the STS of the overarching loan granting capability. This change also brought an upheaval into the social structure within the loan granting capability. The loan consultants, who previously enjoyed relatively high status within the bank because of their experience, required training, certification, and independence in their work, regarded the tool as a threat to their professional role identity and esteem. At the same time, the ML-based tool enabled a new group of employees, such as those working previously at service front desks, receptions, as well as newly hired employees, to promptly assume the role of loan consultants. This equated to a significant professional identity boost for those employees. Furthermore, the use of ML-based loan approval tool erased the need for part of the internal communication flow, which previously served as a document verification step. Thus, the encapsulation of a capability resulted in this case in unbalancing of the STS underlying the loan granting capability of the bank.

> *P12. Automation of a capability through its encapsulation into an ML-based technology transforms it into an element of the technical subsystem belonging to the STS of a higher-level capability.*
> *P13. Automation of a capability through its encapsulation into an ML-based technology may transform it into an element of the structure within the social subsystem belonging to the STS of a higher-level capability.*
> *P14. Automation of a capability through its encapsulation into an ML-based technology may unbalance the STS of a higher-level capability.*

3 Discussion and implications

This paper extends the current debate on organizational capabilities. The topic continues to attract attention of IS and strategic management scholars. Despite this interest, understanding of microfoundations underlying organizational capabilities is still limited. This is especially the case in the context of organizational initiatives, which aim at integrating disruptive digital technologies, such as ML, into their capability portfolio. Evidence from empirical surveys on ML use by organizations show that only one in ten ML initiatives meaningfully contribute to value creation [4]. Thus, practitioners are also facing challenges in this context. With the aim of extending our conceptual understanding of organizational capabilities, this paper takes an STS perspective on the microfoundations of capabilities and discusses the resulting insights relevant to organizational ML initiatives. By conceptualizing organizational capabilities as practiced and routinized transformations of inputs into outputs via underlying socio-technical systems, which are nested in layers and evolve over time, our framework enables a granular insight into the process of digital technology integration into the capability portfolio of an organization. Our contributions arise from the integration of insights from organizational capabilities and STS theory literatures, as well from the derivation of propositions centering on the context of organizational ML initiatives.

With respect to practical implications, our framework and propositions provide several insights, which might be counterintuitive to professionals with limited experience in ML initiatives. For example, use of ML in an organization does not imply that the organization has ML capability or has created any new capability (P1 and P5); there is no free lunch with ML – significant performance improvement of a capability thanks to ML requires significant changes in the STS underlying that capability (P8); ML does not learn by default, once it is put into production (P9); feeding more data into ML leads to, at best, gradually decreasing performance gains (P10); and, full automation of a capability does not completely eliminate the need for people (P12).

3.1 Future research

Future empirical research can build on our work in several ways. First, in the context of ML, future research can test hypotheses drawn from our propositions and identify boundary conditions. Second, our conceptual framework is not limited to ML context, thus, can be used in future studies investigating more broadly the impact of digital technologies on organizational capabilities. Third, by explicitly linking microfoundations to organizational capabilities, the framework allows investigation of technology impact on employees and jobs. Overall, such empirical research will not only advance our understanding of organizational capabilities, but also in the context of ML, will help guide managers and their decisions relating to this transformational technology.

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