Organizational Learning in the Rise of Machine Learning

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Abstract

Organizational learning (OL) is associated with experience and knowledge in an organization. Information Technology (IT) enables the creation, dissemination, and use of knowledge, and as such, plays an important role in an organization's learning process. This role has inspired a large body of literature studying the link between OL and IT and the relation between IT and knowledge exploration and exploitation. The recent rise of Machine Learning (ML) with its Deep Learning (DL) capabilities has nevertheless brought about new ways of creating, retaining, and transferring knowledge. I argue that the learning occurring within the machine plays a role in the learning occurring within the organization, calling for revisiting OL in light of this disruptive IT. In this paper, I focus on three different ways in which the machine achieves its learning, namely supervised, unsupervised, and reinforcement learning, and advance propositions on how each impacts OL differently.

Keywords: Organizational learning, machine learning, deep learning, artificial intelligence, knowledge, experience, exploration, exploitation, ambidexterity

Introduction

"An entity learns if, through its processing of information, the range of its potential behaviors is changed" (Huber 1991, p. 89). This puts IT with its information processing capabilities at the core of learning. It comes as no surprise then that Information Systems (IS) and organizational scholars alike have investigated extensively the relation between IT and OL. A legitimate question is therefore why revisit this relation with ML? A short answer, further elaborated in the remainder of this article, is that ML is fundamentally different from the IT considered in extant literature in that learning occurs not only around or through the system but also within it (Li 2017), therefore suggesting a more complex interplay between the learning of the machine and the learning of the organization. This relevance of revisiting OL is further heightened by its timeliness. Indeed, few people would deny that recent times have witnessed an increase in environmental turbulence and an acceleration in change both outside and within organizations. This is largely brought about by a digital transformation that is disruptive enough to grant it the name of a fourth industrial revolution or Industry 4.0 (Lu 2017). AI is at the heart of this revolution; and at the heart of AI resurgence is ML, especially with the last decade's DL developments. Nevertheless, the diffusion of this technology in organizations is still in its early phases, and therefore a better understanding of its relation to OL presents imminent benefits to practice and thought-provoking avenues for future empirical research.

Drawing from an understanding of OL as "a change in the organization's knowledge that occurs as a function of experience" (Argote 2011, p.1124), I examine OL in light of these technological advances, emphasizing the critical role of IT as an enabler of the creation, dissemination, and use of knowledge

(Davenport et al. 2008). Traditional IT has already been found to alter its users' experience and behavior (Bhattacherjee and Premkumar 2004) and with altered experience, learning happens. As organizations are composed of individuals, their learning depends on, although it is not a simple aggregation of, individuals' learning. (Kim 1993). However, an intelligent and learning form of technology impacts OL in ways that neither traditional IT nor earlier rule-based forms of AI could.

The aim of this article is to outline ways in which the distinctive approaches to learning in ML impact OL differently and to formulate propositions with a potential for empirical testing. I start with a review of the OL literature and its relation to experience and knowledge, and what has been said about the impact of IT. I follow with a justification of ML's differentiation from other IT and an explanation of its approaches to learning. Next, I argue how these learning approaches influence OL and present propositions accordingly. Finally, I conclude with a discussion of the research and practice contributions and the limitations of the study, as well as avenues for future research.

OL and IT in the Literature

The 1990s saw a surge of research in OL, especially following March's (1991) seminal paper which presents it as a balance between mechanisms of exploration of new knowledge and exploitation of existing one. In parallel although to a lesser extent, an IS stream of research started investigating the influence of IT on OL. A simple search on Web of Science for IT AND "Organizational Learning" yields over a thousand results. Researchers have often associated it with improved performance (e.g., Baker and Sinkula 1999; Bapuji and Crossan 2004), contributing to a sustained interest in it.

Extant literature has typically adhered to two perspectives on OL theory (Langer 2017). The first one follows an adaptive approach pioneered by Cyert and March (1963) for whom organizations are goal oriented and where the heterogeneity of goals shapes decision-making and repeated experiences shape learning through a continuous process of adjustment. This perspective has inspired abundant research on OL (e.g., Argote 2012; Argyris and Schon 1978; Cangelosi and Dill 1965; Huber 1991; Levitt and March 1988; Miner and Mezias 1996; Shrivastava 1983). The second perspective focuses on vicarious learning from other organizations rather than experience within the organization (Denrell 2003; Tushman and Anderson 1986). This paper adopts the first perspective as it is a better conceptual fit for the introduction of innovative technology which diffusion is not yet significant enough to learn from others.

An adaptive approach to OL brings experience to the fore as a basis for learning. Experience has often been associated in research with discussions of learning curves which stipulate that repetition leads to improved productivity for the individual (Huber 1991). For these individual experiences to contribute to OL, they would have to be embedded at a higher level (Argote 2011). As more research developed over time, what started with repetition-based improvements in productivity for manufacturing organizations was later generalized to OL at large through experiential-based knowledge (Levinthal and March 1993). Experiential learning is therefore an organizational process whereby organizations act based on past successes and failures, trying to repeat successful behaviours and refrain from unsuccessful ones (March 1981). This model of learning relies on maintaining focus through self-reinforcing behavior that improves competencies in the organization's areas of strength and increases its specialization (Levinthal and March 1993; March 1981). Levitt and March (1988) refer to this idea of experience driving the learning as learning by doing.

It is the distillation of that experience into knowledge that translates into learning (Attewell 1992). Knowledge is therefore at the core of OL, and more precisely it is the change in this knowledge as incurred by experience that leads to learning (Argote 2011), which earlier scholars described as "the process of improving actions through better knowledge and understanding" (Fiol and Lyles 1985, p. 803). The strong relationship between knowledge and experience can also be found in Gherardi's (2008) knowing through doing, where knowledge is the result of collective action and is therefore enacted by and situated in practice. It is through interactions that knowledge is negotiated and through joint implementation of situated practices that it is created. Other scholars share this understanding of knowledge. Nicolini (2012, p. 58) states that "knowledge is first and foremost acquired in practice and rendered explicit in response to practical necessities." Such a practice approach to studying knowledge allows for the benefits of a fine-grained approach to characterizing knowledge and experience (Argote and Miron-Spektor 2011) and acknowledges the dynamic nature of knowledge. We can therefore say that knowing emerges from situated practices (Orlikowski 1996; 2000). A closer look at how it emerges can be found in Nonaka's (1994) theory of organizational knowledge creation. He bases his organizational knowledge creation theory on Polanyi's (1966) classification of human knowledge as tacit or explicit. Explicit knowledge "is transmittable in formal, systematic language" while tacit knowledge "is deeply rooted in action, commitment, and involvement in a specific context," (Nonaka 1994, p. 16) making the latter hard to communicate. The organizational knowledge theory postulates that tacit and explicit knowledge are two extremes of a continuum and that it is through continuous dialogue and conversion between the two that knowledge is created. Since tacit knowledge is *deeply rooted in action*, this knowledge creation is enacted in practice. While the new knowledge is created at the individual level, organizations then articulate it, amplify it, and crystallize it as they link it to their knowledge system (Nonaka and Von Krogh 2009).

OL can therefore be seen as change in knowledge enacted in practice. IS has often been associated with a transformative effect on work practices (Vaast and Walsham 2005), and organizational routines (Edmondson et al. 2001), therefore changing experience, knowledge, and learning. This resonates with what Zuboff (1988) stated three decades ago about the transformative effect of IT as a result of its powers to automate and informate. The latter is rooted in the data and its ability to lead to improved OL. Further, the contribution of technology to the creation and enhancement of knowledge capabilities in organizations has been acknowledged by many scholars (e.g., Alavi and Leidner 2001; Tanriverdi 2005). Robey et al. (2000) for instance discussed IT's contribution to OL though its information and knowledge abilities. IT's role as enabler of learning was also supported by Tippins and Sohi (2003) who emphasized aspects of information acquisition and sharing speed, consensus facilitation, and information storage, leading to IT being considered an OL mechanism (Iyengar et al. 2015). Kane and Alavi (2007) further looked into IT enabled knowledge transfer, differentiating between explicit and tacit knowledge transfer, and its impact on exploration and exploitation forms of OL. Some IS researchers have also referred to a proactive IT stance, one where organizations continuously use their IT resources to reach business opportunities, as an enabler of sustained learning (Joshi et al. 2010; Lu and Ramamurthy 2011). One stream of IS research studied this search for ways to enhance the use of IT and knowledge through processes of exploration and exploitation, with findings supporting the influence of IT on both (Attewell 1992, Gray 2001, Pentland 1995).

Earlier intelligent systems, Expert Systems (ES), have also been investigated in relation to knowledge and learning since the OL 90s surge. ES have the primary purpose of capturing and representing the expertise of experts for other organizational members to use it (Bhatt and Zaveri 2002). In order to capture that expertise, they apply knowledge acquisition techniques such as interviews and protocol analysis in an effort to elicit the experts' tacit knowledge (Liebowitz 2001). ES therefore serve as a knowledge base or a form of organizational memory where expertise is retained (Venugopal & Baets 1995). In doing that, they make organizations less vulnerable to employee turnover and reduce the cost of acquiring expertise (Hong et al. 2000). These systems support some aspects of OL processes and hence have a positive impact on OL in general (Venugopal and Baets 1995) and decision support in particular (Bhatt and Zaveri 2002). They also provide opportunities for higher order learning which involves adoption of new paradigms, assumptions, or principles by the organization (Stein and Vandenbosch 2015). However, typical ES employ deductive reasoning and are therefore not capable of generating new rules of inference (Bhatt & Zaveri 2002). It is the inductive nature of ML that allows it to bring unique learning capabilities to the organization in ways neither traditional IT nor earlier AI rule-based ES can achieve. It is therefore important to revisit OL in light of recent ML advances, especially since Industry 4.0 technologies of which ML are changing the way knowledge is acquired, shared, and used (Ediz 2018). Few researchers have recently looked into ML's contribution to OL. Bohanec, Robnik-Sikonja, and Kljajic Borstnar (2017a) found that OL was enhanced by ML through improving sales forecast and changing beliefs, and Lenart-Gansiniec (2019) found that ML as part of Industry 4.0 positively impacts OL given its knowledge capabilities. An increase in the sustainability of OL has also been observed as a result of explaining the decisions reached by ML (Bohanec, Robnik-Sikonja, and Borstnar 2017b). However, no research to the author's knowledge has unpacked ML and looked into the different approaches to learning it presents and each one's impact on OL. Analyzing how the learning is achieved in ML and the different possible impacts on OL advances knowledge of the relationship between this emerging technology and learning in the organization and provides a framework for subsequent research.

Theoretical Framework for Analyzing OL

In presenting this study's propositions later in the manuscript, I base the discussion on Argote and Miron-Spektor's (2011) theoretical framework for analyzing OL (figure 1). In line with the aforementioned Argote's (2011) conceptualization of OL, which key elements are experience and knowledge, this framework provides an analytical representation of the learning processes as a cycle where experience generates knowledge through interactions with the context. While the environmental context is outside the boundaries of the organization (e.g. customers, regulators), the latent one is internal and, being unable to perform action, impacts learning through its influence on the active context. Examples of latent context elements could be the organizational culture and trust among employees. As to the active context, as the name indicates, it directly performs action. Its main constituencies are organizational members and tools of which technological ones. The framework's starting point is experience. Knowledge is acquired through either new experience (knowledge creation) or the sharing of experience within the organization (knowledge transfer). Retention of this knowledge is represented by the arrow going from knowledge to the active context. Members and tools are therefore repositories of knowledge. In turn, they generate new experiences through task performance in the arrow from active context to task performance experience.

This framework helps us analyze how the introduction of a new type of tools, one that has learning embedded in it, can influence this learning cycle. In other words, it helps us analyze how with ML the learning of the machine influences the learning of the organization.

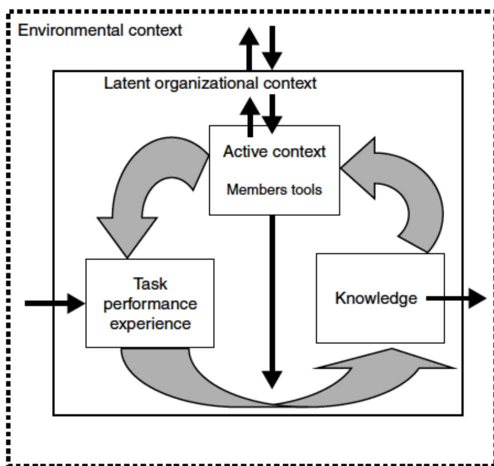

Figure 1. A Theoretical Framework for Analyzing OL (Argote and Miron-Spektor 2011, p. 1125)

What Makes ML Different from Traditional IT? An Overview of Learning Approaches

From Shallow to Deep Learning

Early computer systems, while successful at solving complex mathematical problems were powerless in front of easy daily human tasks such as recognizing the image of a person or object. The reason is that those easy tasks are hard to formalize and describe in explicit rules that can be coded in digital form. In other words, hard-coding of knowledge in systems made it impossible to account for informal tasks. From there emerged the need for machines that can learn by extracting knowledge not from code but from data (Goodfellow et al. 2016). This has helped develop systems that are not as "brittle" in facing real world situations where rules are not the norm. Thanks to its learning capabilities which rely on statistical approximation that improve with experience rather than on rigid rules, ML is therefore more flexible than other IT (Choy et al. 2018).

ML however has accompanied AI from its start; why now all this interest in it? To answer this question, it is important first to understand ML's relation to AI, and the difference between DL, ML, and AI as these terms are often used interchangeably but are not at the same level. They are best described as "as a set of Russian dolls nested within each other, beginning with the smallest and working out" (Nicholson 2017). AI is the general concept for computer systems able to perform tasks that usually need natural human intelligence, whether rule-based or not, while ML is that subset of AI that is capable of "learning from data and making predictions and/or decisions" (Li 2017, p. 7) without human dictated rules. The smallest doll, DL, is a cutting-edge machine learning scheme with enhanced learning capabilities. What differentiates DL from the more general ML is its artificial neural network architecture. Conventional ML can produce optimizations with as little as one- or two-layer neural networks. This simple architecture is often referred to as shallow ML, as opposed to the more complex architecture of deep ML or DL. The latter has many more layers often in the order of hundreds capable of processing high dimensional data such as images. One is not better than the other in absolute terms. Shallow ML is actually more accurate than DL in instances where only a small amount of low dimensional data is available. It is with large amounts of data, often referred to as big data, that DL outperforms and by far shallow ML, allowing the modeling of more complex functions. Recent increase in data availability coupled with advances in computational power have played a major role in the resurrection of neural networks, DL, ML in general, and consequently AI (Aggarwal 2019).

ML is therefore a subset of AI, and a renewed interest in ML is closely associated with the awakening of AI. A quick look at the history of AI shows that it can be traced back to Alan Turing (1950, p. 436) who stated decades ago that "digital computers [...] are intended to carry out any operations which could be done by a human computer". After decades of hibernation, AI resurfaced and ignited the interest of researchers and practitioners alike. AI's awakening can be attributed to the convergence of big data and computing power advances over the last few years. These developments have driven recent AI breakthroughs and have granted AI a reputation of having a transformational power over the economy and society. An annual growth of AI research publications of 12.9% over the past five years is a good indication of this renewed interest in AI and its impact (Elsevier 2018). In closer relation to IS research, Von Krogh (2018, p. 404) has recently highlighted the importance of AI as a "fundamental, pervasive economic and organizational phenomenon that holds many theoretical challenges and opportunities in store for management scholars."

While the reputation of AI hit high levels and a hype developed around it, it is mostly ML, and more specifically its cutting-edge DL, that can be credited with most prowess of the mother technology. Conventional ML can produce optimizations with as little as one- or two-layer neural networks. This simple architecture is often referred to as shallow ML, as opposed to the more complex architecture of deep ML or Deep Learning (DL). Shallow ML is more accurate than DL in instances where only a small amount of data is available. It is with large amounts of data, often referred to as big data, that DL outperforms and by far shallow ML, allowing the modeling of more complex functions. Recent increases in data availability coupled with advances in computational power have played a major role in the resurrection of neural networks and DL, and as a result of AI in general (Aggarwal 2019).

Learning at the Heart of ML: The Three Approaches

Understanding how the learning happens in the machine is essential to understanding its relation to learning in organizations and to identifying the opportunities and limitations it presents (Von Krogh 2018). ML approaches are of three types: supervised, unsupervised, and reinforcement (Li 2017). These approaches apply to all ML, whether shallow or deep; however, they have gained much stronger capabilities with DL, and have consequently a much stronger impact on OL with it. Furthermore, systems are most useful when it is possible to generalize the learning acquired from experience to unknown situations, which is mostly possible with DL. Without DL, reinforcement learning for example cannot be used beyond simple game settings (Aggarwal 2019). In the remainder of this article, I refer to ML to denote both shallow and deep.

Supervised Learning*:* Supervised learning relies on past data. In this approach, humans label the data and input it to the system to train it (Choy et al. 2018). The system, through its intelligent algorithm, identifies patterns and infers its own rules from the labeled data rather than being programmed to follow rules embedded in a code as is the case with more traditional technologies (Lu et al. 2015). As the system learns, it starts predicting output and the number of correct predictions measure its performance. The aim is to reach a certain level of predictive accuracy (Van Otterlo and Wiering 2012).

An example of supervised learning is that of recruitment. An AI algorithm can be fed a large number of CVs that are labeled as having been either recruited or not recruited at an organization in the past. The outcome you expect from the system in this case is the decision to recruit or not. The algorithm can then identify CV features that are associated with positive or negative outcomes. Given a large enough set of labeled cases, the system will graduate from training and reach a level of prediction accuracy enabling it to make recruitment decisions when presented with a new CV. Amazon has adopted such a system to assist in its recruitment process using ten years of CVs. A company of that size receives large numbers of job applications and therefore has enough data over this period to accurately train the AI algorithm with a supervised approach. Their AI system is then able to extract the implicit recruitment rules in the past human recruiters' behaviour and give new CVs a rating of one to five stars accordingly (Dastin 2018).

Applications involving supervised learning are widely used in a variety of industries and are based on multiple types of data. However, a major challenge associated with this approach to learning is the significant human effort needed to label the training data (Bakis et al. 2017).

Unsupervised Learning*:* A major challenge associated with this approach to learning is the significant human effort needed to label the training data . In unsupervised learning, no labels are assigned. The large training data sample is input into the system without indications as to the expected output. The system then analyzes the training data's statistical properties and structure (Goodfellow et al. 2016). The ultimate purpose of unsupervised learning is to mimic human logic, which is largely unsupervised by nature, hence opening the door for a richer set of applications (LeCun et al. 2015). The AI system in this case finds the global probability model of all the features in the data and can discover new relations that were not detected by the humans operating it.

One common method of unsupervised learning is that of clustering or grouping of data based on hidden structures identified in it by the algorithm. (Choy et al. 2018). Customer segmentation is a good illustration of this learning approach. Unsupervised types of AI systems can process a wealth of data about individuals that is either available inside the organization or obtained online and group them automatically in segments that do not depend on any human perception of criteria. AI provides in this case a solution to the problem of complexity associated with substantially large databases and enables targeted marketing to the various segments (Boone and Roehm 2002). Clusters are based on pattern recognition to identify similarity of data points, enabling the unsupervised system to group seemingly unrelated individuals. The result is a segmentation that is claimed to be more effective and free of the human bias associated with the choice of segment criteria such as demographics or income. Once the clusters are defined, their interpretation is performed by humans as not all clusters will be meaningful (Migdal 2018).

Both supervised and unsupervised learning go through two phases: a first training phase where the learning happens and rules are inferred from the data, and a second operational phase where that model is stabilized and used with new data where it generates its own decisions and predictions as output.

Reinforcement Learning*:* Human beings learn through a continuous experience-driven process guided by environmental reward and punishment in what is best described as trial and error. This understanding is the inspiration behind reinforcement learning in ML and is best adapted for tasks that are *simple to evaluate but hard to specify*. (Aggarwal 2019). It is therefore fundamentally different from the first two in that it does not learn from past data. It learns from experience through interactions with external entities, whether human or machine (Li 2017). Unlike the first two approaches, a reinforcement system is pursuing something, it wants something, much like a *hedonistic* system with goal-directed learning (Sutton and Barto 2018). The core idea is that the system has an *objective* set by a human agent and a *reward* based on how well it is meeting that objective, which involves finding the best *strategy* or possible combination of actions and steps referred to as *policy*. It keeps exploring the environment and exploiting its own experience to find better strategies until it reaches the optimal value (Li 2017). A challenge associated with reinforcement's iterative algorithm continuously searching for better strategies is the need for a large number of iterations until an acceptable strategy is reached. The more complex the application, the higher is the number of needed iterations to train it (Aggarwal 2019). An example is the AlphaGo Zero Atari Dota2 five, which training was equivalent to 45,000 years of playing for a human

(Shek 2019). Despite the challenges, reinforcement learning has an advantage in that it is a dynamic system where the learning never stops and is perpetuated through interactions rather than data observation (Van Otterlo and Wiering 2012). It is worth noting here though that both supervised and unsupervised, while initially more static in their reliance on separate training and operation phases, can also achieve a quasi-continuous learning. This dynamism can be reached if the system is scheduled to retrain in high frequencies or even live in online settings (Baier et al. 2019).

Recommender systems used by many websites such as YouTube or Amazon are examples of the reinforcement approach. "Reinforcement learning is applied to continuously evaluate the users' acceptance of presented recommendations and to adapt the recommendations to reflect the users' interests" (Golovin and Rahm 2004, p. 1). There are many ways a recommender algorithm can be designed to balance between exploring and exploiting, and one example can be in the form of a strategy where recommendations are issued based on the highest estimated reward as per past interactions, with a random recommendation pulled occasionally to account for continuous changes to the website content (Bouneffouf et al. 2012) and to user behaviour (Golovin and Rahm 2004).

How do these learning approaches translate in an organizational context? The next section looks into the influence of these ML approaches on OL. The above illustrations of the three learning approaches (recruitment, customer segmentation, recommendations) will be used as running examples in the following discussion.

OL in Light of ML

Extant literature reviewed earlier in this paper has shown a positive impact of IT on OL. This section attends to the call by multiple researchers to re-examine this relationship emphasizing the high importance of AI in transforming organizing and management (e.g. Argote 2011; Brynjolfsson and McAffee 2017; Schildt 2017; Von Krogh 2018). I argue that ML with its different learning approaches is an area of AI that has known significant recent advances and can improve OL on one hand, but also increase the risks associated with it on the other. The introduction of ML therefore alters the learning process in the organization as explained in the remainder of this section. Figure 2 proposes a summary representation of how ML modifies the traditional cycle described by the Argote and Miron-Spektor (2011) model. As learning is inherent to ML, a parallel cycle of learning is integrated with the traditional one and complements it. Figure 2 (a) zooms in on this new case of a contextual element that is conceptualized as a *tool* not only used for learning, but also having learning capabilities itself. ML, an addition to the active context, engages a cycle where supervised and unsupervised types learn from past experience in the form of labeled or unlabeled training data, adding to the organization's knowledge. Reinforcement learning systems learn from a different type of experience, one that is continuously generated in the present, also adding to the knowledge, albeit differently as will be explained in the propositions. In all cases, and as knowledge is acquired and transferred, multiple biases risk to interfere with the quality of learning. In figure 2 (b), the final integrated modified OL framework is proposed where human members, traditional tools, and ML all engage in experience and knowledge acquisition and all retain the resulting knowledge. While the initial components of the active context – members and traditional tools – acquire this experience through traditional task performance, the ML acquires it through the means explained in figure 2 (a). The propositions hereafter provide further details on experience and knowledge change, bias risk, and adjustment to environmental changes in light of ML.

According to Argote and Miron-Spektor's (2011, p. 1125) framework, experience alters knowledge leading to OL. The authors define experience as "what transpires in the organization as it performs a task". Therefore, a challenge when it comes to experience is that it manifests through practice and results in tacit knowledge that is difficult to articulate and communicate (Lam 2000). It is created and retained by the individuals performing the task and can be vulnerable to employee turnover. While the problem originates at the individual level, the repercussions are also felt at the organizational level as the depreciation of the organization's stock of knowledge negatively impacts OL (Argote et al. 1990). Attewell (1992, p. 6) expressed the link between the individual and the organization in learning by explaining that the organization "learns only insofar as individual insights and skills become embodied in organizational routines, practices, and beliefs". I propose here that an additional way of embodying them is within ML.

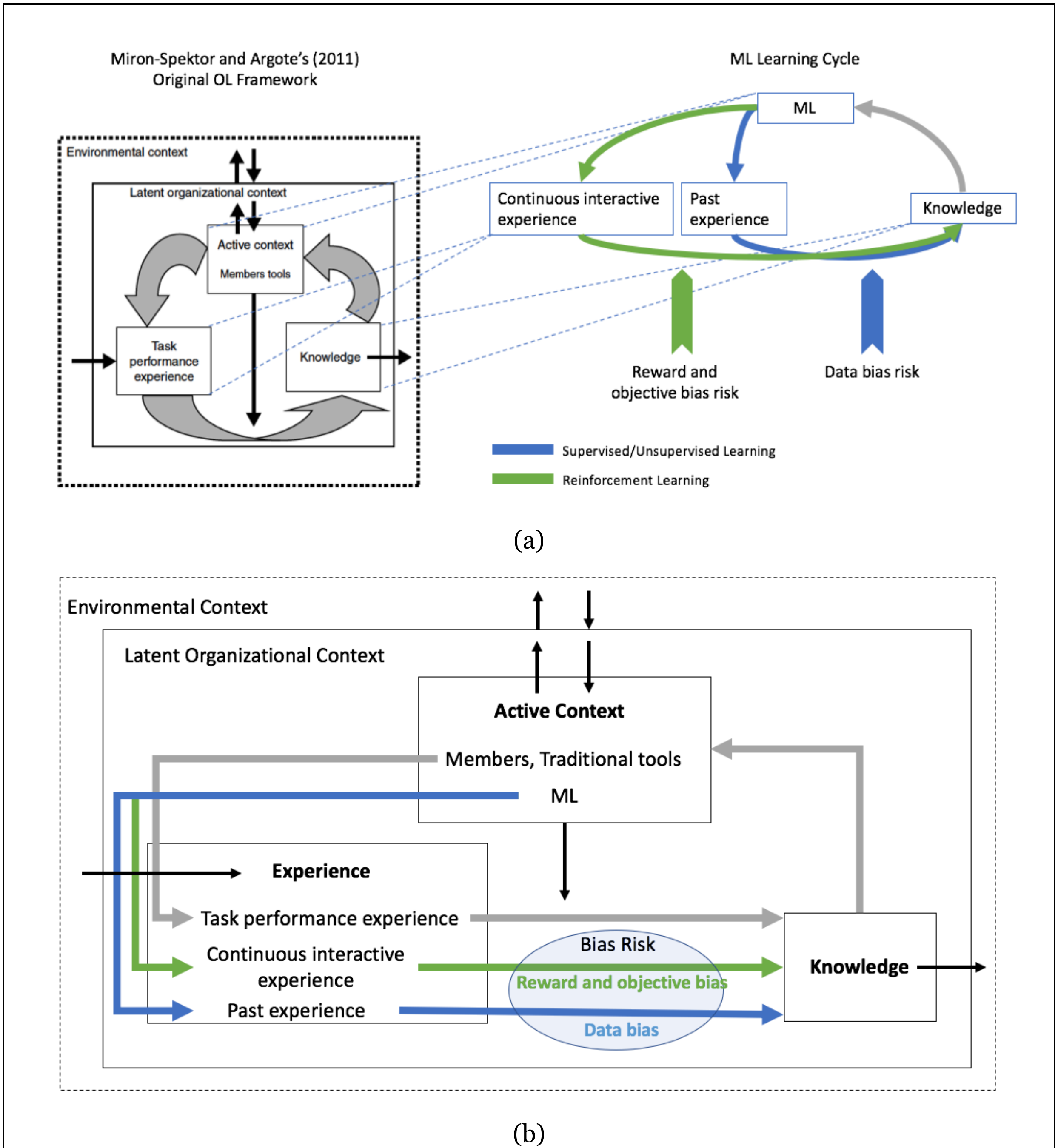

Figure 2. A modified OL framework with ML

ML offers a way to reduce experience volatility and subsequently knowledge depletion in organizations. How? Experience can be acquired by either performing new tasks or building on past tasks (March 1991, Rosenkopf and McGrath 2011). The former applies to reinforcement learning and the latter to supervised and unsupervised. Taking the AI recruiter example of supervised system, the training data used to teach it is a large set of CVs labeled with a mix of favorable and unfavorable outcomes decided in the past by recruitment agents. Their decisions are the result of an experience that allowed them to judge the quality of the CV, when no specific feature of each CV can be explicitly responsible for the outcome. By identifying patterns and inferring non-obvious rules, the AI recruiter actually captures the tacit knowledge of those recruitment agents and can issue recommendations concerning new CVs in their absence, thus reducing their experience's volatility for the organization. By the same logic, the unsupervised customer segmentation system identifies patterns in past transactions between the organization and its customers. Here, it is the organization's experience in sales that is input into the system during training period. The patterns identified and the hidden structures found in this experience make the organization's knowledge of its customers' behavior more available for interpretation by the marketers. A typical scenario here is that the system, using past sales experience and existing customer information, suggests multiple ways of clustering these customers into segments. The marketer's role is then to go through the different clusters and judge which ones are the most meaningful.

In both supervised and unsupervised cases, the ML infers the tacit knowledge of employees who had performed the past experience recorded in training data and makes it available to a wider audience in the active context. However, there is more to this knowledge than the employees' tacit knowledge. In fact, ML is capable of discovering patterns and relations in the data that are not consciously known to employees. I refer to this process as discovery of tacit knowledge. The knowledge is tacit because it is not easily communicable (Lam 2000). As to the choice of the word *discovery*, it is guided by the fact that the knowledge was present – rather hidden – in existing data, but previously unknown to organizational members. The ML provides predictions based on both the *captured* and the *discovered* tacit knowledge. The problem with the latter is that it often involves complex relationships not readily understandable by humans. However, recent ML systems are increasingly moving away from their black-box reputation by providing explainability and interpretability with their decisions (Zhou & Chen 2018). This trend that primarily aims at increasing trust in ML (Bohanec, Robnik-Sikonja, and Borstnar 2017a) also facilitates the dissemination of typically non-sharable knowledge across the organization, which in turn enhances OL (Iyrngar et al. 2015).

Taking the example of the recommender system, the ML, through sustained interactions with customers, suggests new items and records the customers' responses, therefore learning about their preferences. This is neither based on salespersons' experience nor on the organization's experience with previous transactions. It is tacit knowledge built through direct and current experience with the customers. The dynamic knowledge base that is continuously built, refined and made available to the organization's members further enhances OL. While supervised and unsupervised *capture and discover* newfound tacit knowledge in existing data, reinforcement learning *creates* novel tacit knowledge never before present in the organization or its data. Indeed, the latter creates new knowledge based on new experience. This unique capability is associated with a major challenge when it comes to generalization from the experienced context to an unknown one. Indeed, the policies learnt in a reinforcement algorithm cannot be transferred to a context other than the one where they were generated. However, transfer can happen through other means. Certain Reinforcement learning algorithms that have an image recognition component are capable, when used in a DL architecture, of generalizing the knowledge they learn in one context to another (Aggarwal 2019). In other words, when the number of layers in a neural network is large enough, a system that learned image recognition from experiencing human faces can transfer this knowledge to a medical image recognition context. Another way to transfer knowledge is the use of Inverse Reinforcement Learning (IRL) to bootstrap initial knowledge, where the algorithm can learn actions, policies and rewards by observing past scenarios such as game replays (Shek 2019). Possible transfer to other reinforcement application contexts in addition to the aforementioned is the explainability now embedded in many reinforcement systems, which provides decision rationale and therefore facilitates the transfer of the newly created knowledge across the organization.

In brief, all three AI approaches, albeit in different degrees, improve the bottleneck of individual learning by enabling quick access to tacit knowledge. This allows members to build on each other's experiences and on the organization's, not only their own, thereby accelerating learning (Argote et al. 1990, Ransbotham 2017).

> *Proposition 1a*. Supervised and unsupervised learning have a positive impact on OL through their ability to capture, discover, and transfer tacit knowledge.

> *Proposition 1b*. Reinforcement learning's has a positive impact on OL through its ability to create and transfer new tacit knowledge.

"Learning does not always lead to veridical knowledge" (Huber 1991, p. 89). ML is no exception. For the learning to be trustable, data has to be of high quality, even flawless (Von Krogh 2018). Some of the most serious threats therefore to the reliability of supervised and unsupervised outcomes are the issues underfitting or missing relevant associations in the data, and of overfitting or accounting for noise from irrelevant minor variations in the training data set (Choy et al. 2018). This is particularly risky given the low interpretability and "black box" characteristic of AI (Brynjolfsson and McAffee 2017; Faraj et al. 2018). Since it is complicated for humans to understand how the learning is taking place, the resulting knowledge change, and hence OL, will highly depend on the training data they were fed and the way it is processed by the algorithm. It is important therefore to pay special attention to the data inclusions and exclusion on one hand and the variables considered by the algorithm on the other.

Taking the same examples, and starting with the supervised recruitment system, Amazon has recently faced a public scandal triggered by its AI recruiter, which taught itself that male candidates were preferable to female ones. Training data was based on previous hires, when tech jobs were highly male dominated. The algorithm, by identifying patterns in past hiring decisions, perpetuated the historic bias and eliminated qualified female candidates. Information such as being captain of a women's chess club or graduate of a women's college was interpreted as a cue to downgrade the CV rating (Dastin 2018). A remedy to unconscious biases of human recruiters is through proper examination and testing of training data and the development of algorithms that improve diversity (Alsever 2017). Having said that, and while this AI recruiter example illustrates a risk to learning, Amazon has still learned a lot from ML's *bad* learning by discovering the organization's embedded discriminatory bias, which might have otherwise gone undetected. Unfortunately, in cases where the bias is unexposed, learning can suffer long lasting consequences.

A similar bias risk can be found when using the unsupervised customer segmentation system. As cluster suggestions are based on the training data, only data that is collected by the organization on customers can be considered. Profiling is then based on variables which choice might reflect hidden biases of organizational members. The incompleteness of data can also lead to erroneous clustering or at least a less accurate one. In addition, customers with atypical behavior might be considered outliers and excluded from the profiling, resulting in lower levels of service provided to them.

As reinforcement learning does not rely on training data, it is released from a major source of potential bias (Von Krogh 2018). However, there is another significant source of bias particular to this learning approach. Reinforcement learning systems have a larger level of freedom than other ML types in the way they learn. This seemingly advantageous feature can also result in undesirable effects. More specifically, the reward-driven model of reinforcement learning gives it similar behavior to the human biological system, whereby the strength of learning by reward is coupled with the pitfall of learning "cheats" or "hacks" in an effort to maximize the reward even if unethically. In other words, the system can get greedy. An example – one that is rather innocent compared to possible darker scenarios in healthcare or other life critical settings – is that of a cleaning robot that might create a mess in order to clean it and increase its reward (Aggarwal 2019). An ill-posed reward function is not the only risk here; an ill-posed objective or an objective function that is too expensive to evaluate frequently can be as detrimental to the quality of learning (Amodei et al. 2016). Still, and with the advanced capabilities it now presents, relying on ML predictions reduces the complexity of an increasingly diverse environment. In an organizational context, striving for simplicity and for freeing humans from over-burdening can lead to delegating more judgement and control to the machine (Agrawal et al. 2019), which in turn can have unexpected greed-centric negative impact on knowledge and therefore on OL.

In general, for any ML type, bias brought by the system results in the dissemination of biased and therefore non-veridic knowledge. Having this knowledge embedded in the organization and repeatedly cycling as illustrated by figure 2 can be particularly detrimental to the quality of OL. This is not to say that the traditional OL did not suffer from its own impediments, but this paper emphasizes the risks introduced specifically by the introduction of ML, and any other risks are therefore outside its scope. It is for this reason for example that algorithm bias is not included as it is similar – although not identical – to program bias risk in traditional IT.

> *Proposition 2a.* Supervised and unsupervised learning carry a risk of bias stemming from both the training data and the algorithm, which can negatively impact the quality of OL.

> *Proposition 2b.* Reinforcement learning carries a risk of bias stemming from the objective or reward and their associated strategy, which can negatively impact the quality of OL.

Two forms of OL are exploitation of existing knowledge and known alternatives and exploration of new ones (Dodgson et al. 2013; Kane and Alavi 2007; March 1991). Piao and Zajac (2016) further differentiate exploitation into repetitive and incremental. They associate repetitive exploitation with March's (1991, p. 71) description of exploitation as "production", "efficiency", "implementation", and "execution", as it involves the organization repeating existing designs/products without significant modifications. Incremental exploitation on the other hand is associated with March's (1991, p. 71) description of exploitation as "refinement," "choice," and "selection", as it involves introducing new designs for its existing products. Supervised learning, through repeating the patterns in the training data in order to generate outcomes and predictions dictated by the labels, can be said to enable repetitive exploitation. Further, the repetition is one favoring successes as defined by the labels. This over-emphasis on successes might lead to what is referred to as superstitious learning (Levinthal and March 1993; March 1981). Indeed, by repeating the successful behaviors, organizations become better at them and increase their specialization in their areas of success at the expense of areas of failure. Organizations are then said to fall in the success trap and lose the flexibility to explore new options (Walrave et al. 2011). This is a good strategy assuming a stable environment. However, environments seldom are, which might lead to misplaced specialization in the event of a major environmental change (March 1981). Such behavior increases the risk of learning myopia, which Levinthal and March (1993) say can take three forms, namely the tendencies to ignore the long term, to ignore the big picture, and to overlook failures.

A consequence of repetitive exploitation and the resulting learning myopia is impeding exploration and therefore slowing down adjustment to environmental changes (Piao and Zajac 2016). The challenge in this case is in the ability of the ML to *unlearn* outdated patterns, referred to by Hedberg (1981) as a *discarding activity*. The time it takes a supervised system to unlearn the old patterns and learn the new ones depends on how often the model is updated with new training data and whether there is sufficient data for the update. This challenge is known as concept drift, which refers to supervised learning scenarios where models built based on past labeled data are no longer valid in a dynamically changing environment (Baier et al. 2019; Gama et al. 2014). Failing to address this concept shift can result in loss of validity of predictive services (Baier et al. 2019), Amazon's AI recruiter is a picture-perfect illustration of this issue. The repetitive exploitation of the existing recruitment patterns might have been efficient, but it has resulted in an over-emphasis on generating "successful" outcomes as dictated by the labels of the CVs in the training set. Subsequently, it resulted in missing the lack of diversity and the underlying gender discrimination in the recruitment process. While more women have been joining the tech world in recent years, the system was unable to sense this and prevented Amazon from adjusting fast enough to an important environmental change.

The second type of exploitation, incremental, is the closest OL process to unsupervised learning. The system generates new alternatives from existing data/experience. To illustrate this idea, the customer segmentation system learns from existing customer data and generates multiple alternative way of clustering them into segments. When incremental exploitation occurs, variations are increased as the organization identifies change opportunities, produces novel combinations of ideas, and acquires tacit knowledge. Repetition of existing patterns becomes less likely, making way for exploration of new ways and slow learning or selection of new alternatives, enabling organizational knowledge to grow (Piao and Zajac 2016). The alternatives in our example are the different ways in which segmentation can occur for a better targeting of the customers. Segmentation is the result of finding hidden structures and patterns in the training data. As customer behavior changes, its new data is input in the system and the cluster suggestions are regenerated. This is possible because the update of the model requires no human labeling effort; therefore, the bottleneck encountered in supervised learning does not apply here and the update can be performed frequently. Typically, these systems are set to automatically process new data at pre-set regular time intervals, which leads to continuous change (Brown and Eisenhardt 1997). The resulting dynamic segments enable the organization to adapt its marketing accordingly and stay aware of environmental changes.

Last but far from least is reinforcement learning. Its design is one of continuous exploration and exploitation. As explained in an earlier section, it is target-oriented and aims toward maximizing its reward function while pursuing the target. For the reward to be maximized, the system must favor repeating successful behavior or exploiting, but it also needs to explore how to improve its future actions (Sutton and Barto 2018). According to March (1991), exploitation restricts exploration, and while exploitation is praised for its efficiency and low uncertainty, a balance between the two is needed for better OL. Beyond balancing between exploration and exploitation is the concept of ambidexterity. Building on Duncan (1976), Tushman and O'Reilly (1996, p. 24) defined ambidexterity as the "ability to simultaneously pursue both incremental and discontinuous innovation and change." It is often referred to as the simultaneous pursuit of exploration and exploitation, requiring crossing the boundaries of the organization to include both internal and external knowledge processes. New knowledge is therefore integrated with the existing one creating a synergy effect for OL (Raisch et al. 2009). As a result of these benefits, an ambidextrous organization is expected to have superior performance and effective adaptation to environmental changes (Raisch et al. 2009; Gibson and Birkishaw 2004).

Going back to the recommender system example, continuous and simultaneous exploration/exploitation is pursued through suggesting products to the customer and adjusting future suggestions according to the response triggered. This is new knowledge about the customer that did not exist earlier. When combined with existing customer profile and purchase history, the synergy results in a better understanding of the market and of individual customers made available to organizational members. Continuous interaction with the external environment through recommendations and responses to them enables timely sensing of changes in customer preferences.

> *Proposition 3a*. Supervised enables repetitive exploitation, increasing the risk of learning myopia and impeding adjustment to environmental changes.
>
> *Proposition 3b*. Unsupervised enables incremental exploitation, leading to subsequent exploration and facilitating adjustment to environmental changes.
>
> *Proposition 3c*. Reinforcement enhances ambidexterity, facilitating adjustment to environmental changes.

Conclusion

Extant literature has long studied the relationship between IT and OL, but the recent shift in the sources and management of knowledge with ML calls for revisiting this relationship. In this paper, I have argued that it is essential to know where the knowledge is coming from before concluding on its organizational consequences. For ML, the sources of knowledge depend on the learning approach whether supervised, unsupervised, or reinforcement.

Contribution to Research

The first and foremost contribution this study makes to research is in unpacking the learning component of ML in relation to an organizational phenomenon and considering the influence of the different learning approaches within ML on OL. This perspective highlights the importance of understanding the internal learning processes of the machine before theorizing the external learning processes in the organization. It places a rightful emphasis on the unfolding of knowledge inside and outside ML for a better understanding of the learning.

A second contribution is to the IS literature as this study extends the rich body of literature studying the impact of technology on organizations in general and their learning in particular. It adds to the existing knowledge by arguing that ML is fundamentally different from other widely implemented technologies, and that therefore its influence on learning merits a special consideration. This is especially true since ML itself has learning embedded in it.

A third contribution is to the organization literature as this paper revisits OL concepts of experience, knowledge, and exploration/exploitation in light of the ML abilities pertaining to tacit knowledge. Learning can be seen from a relational perspective relating the machine itself and the organization.

A fourth contribution is in presenting a conceptual argument for multiple propositions that can guide future empirical research needed to test their validity in practice. Empirical research in ML in particular and AI in general is abundant in the computer science and engineering literatures; however, a bibliometric study of AI research between 1994 and 2014 found that only 3.3% of research in business related subject categories was on AI (Niu et al. 2016). There is therefore a need for more empirical research in the business and management disciplines such as IS, and I hope these propositions contribute to encouraging such enquiry.

Contribution to Practice

AI as a new technology is largely misunderstood. Von Krogh (2018) has called for management researchers to "help practitioners see through the "hype" and adopt an informed, prudent, and realistic approach to AI." I believe this study addresses primarily this particular concern. Managers can benefit from a better understanding of the effect that choosing a type of AI system can have on learning in their organization. In an ideal world, managers would be able to choose the type most appropriate for a particular application. However, this is rarely possible. There could be optimally a need for supervised for instance but unavailability of labeled data, which dictates an unsupervised system choice. By highlighting the potential benefits and risks of each type, this paper provides guidelines that can help managers leverage each ML type and mitigate its associated risks.

Moreover, this paper highlights the importance of the quality of data used in training the ML. Managers who pay closer attention to testing for bias increase their chances of a successful implementation. The aforementioned Amazon recruiter example shows how detrimental bias can be in terms of the system reliability as well as the image of the organization.

Limitations and Future Research Opportunities

The framework adopted in this paper allows for an emphasis on experience and knowledge, which lines with the way AI learning unfolds. There are however concepts in OL that were not considered such as transactional memory, and future research can be developed to address them in light of AI. Another limitation is the lack of context, as this study is a conceptual one meant to give a general perspective on the influence of multiple learning schemes within the machine on OL. Different specific empirical contexts can bring additional considerations and therefore call for modifying certain claims in the propositions. The need for considering the context when advising on OL is emphasized by Örtenblad (2017), further stressing that studies addressing the above propositions in actual settings are a valuable addition to this one's contribution.

When conducting such empirical studies, it is important to understand a key assumption made here, which is the pure form of ML types. In the interest of clarity, I have considered supervised, unsupervised, and reinforcement learning to be present in their pure form in all three running examples and have built the propositions around that separation to highlight the different influences of the learning approaches. In reality, tasks can be supervised or other, but a process flow in a system often includes a combination of types. The propositions still apply per task, but it is important to understand the more complex nature of a real setting to be able to perform proper empirical studies complementing this one.

Propositions	Examples of issues/questions raised
Proposition 1	1.1. How can OL measures be redesigned to account for the specific types of ML components used in an organization? 1.2. What implications do the different types of ML have on knowledge sharing and collaboration between humans? Between human and machine? 1.3. What is the role of time in the change to organizational knowledge? Is the temporality different for the different ML types?
Proposition 2	2.1. How can conflicts between machine decisions and human judgement be resolved and how do the learning approaches influence that? 2.2. What techniques can managers use to reduce the risk of bias for each of the learning approaches? For a mixed learning approach?
Proposition 3	3.1. How can organizations learn from failure with the help of the different ML types? 3.2. What is the impact of a specific type of ML on OL in a fast-changing environment (e.g. gaming industry, fast fashion, etc.)? 3.3. How do the different ML relate to agility in an organization? Does it facilitate it and how? Does it introduce obstacles to its success and how? What moderators and/or mediators can be identified?

Table 1. Future Research Opportunities

The propositions in this paper provide a starting point for many OL/ML potential studies. Table 1 lists some examples of issues that could be raised by each proposition. Studies addressing these issues can be very diverse using methodologies ranging from qualitative case studies (e.g. 2.1, 3.1) to quantitative ones (e.g. 3.3) with possible use of panels (e.g. 1.3) and even studies of method development (e.g. 1.1). Other related research opportunities are numerous as the diffusion of ML in organizations is still in its infancy and ML studies in business and management are scarce (Niu et al. 2016) not only in relation to OL, but also to other areas such as work and occupations, innovation, affordances of ML, and many others.

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