Organizational Learning in the Age of Data

Andrew D. Banasiewicz, Ph.D.
Director of Data Science & Analytics
Merrimack College
315 Turnpike Street
North Andover, MA 01845, USA
banasiewicza@merrimack.edu

Abstract

In information-driven economy, few organizational competencies are as important as the capability to systematically capture, synthesize and disseminate throughout the organization competitively advantageous decision-guiding knowledge. Traditionally, organizational learning has been viewed as a human-centric endeavor, but the rise of big data and advanced data analytic technologies are compelling a fundamental reconceptualization of the scope and modalities of organizational learning. Starting with a high-level overview of the genesis and the current conception of organizational learning capabilities, the article offers a revised and expanded conceptualization of that important organizational competency. Building on the foundation of explicit differentiation between episodic vs. ongoing learning inputs and new vs. cumulative learning outcomes, a new typology of organizational learning modalities is proposed. The new typology of organizational learning explicitly distinguishes between human reason-centric theoretical and experiential learning, and technology-centric computational and simulational learning modalities. By explicitly encompassing artificial intelligence, machine learning and other manifestations of technology-based learning, the proposed organizational learning typology offers a more comprehensive and timely framing of organizational learning. By expressly acknowledging the distinctiveness of human reason- and technology-based learning modalities, business organizations will be able to develop more robust and effective systems and mechanisms to support their goal of remaining competitive in knowledge-based economy.

Keywords:

organizational learning; learning modalities; experiential learning; theoretical learning; computational learning; simulational learning

Learning and Competitiveness

The widely used conception of organizational learning frames it as the process of acquiring, creating, integrating and distributing of information (Wang and Ellinger, 2011; Dixon, 1992; Huber, 1991). Clearly visible in that characterization is that the ultimate purpose of organizational learning is to enhance the informational efficacy of managerial decision-making (Mattox, 2016; Alegre et al., 2014; Greve, 2003); somewhat less obvious is the implicit assumption that learning is an inherently human endeavor (Savory & Butterfield, 1999; Ranyard et al., 1997). The latter, however, is gradually being called into question in view of the proliferation of self-learning algorithmic decision engines, commonly known as artificial intelligence (AI). Widely used to automate numerous routine business decisions, such as pricing of automotive insurance policies, eligibility approval for social or health services, or online product recommendations (Wright & Schultz, 2018; Wichert, 2014; Shi, 2011), AI decision engines are capable of independently learning from data in a manner that fits the established conception of organizational learning. And given the already substantial and still rapidly expanding role and value of those technologies to organizational functioning and competitiveness, it is important to expressly include technology-based knowledge creation and utilization in the definition of organizational learning.

Broadly characterized, AI can be seen as a manifestation of progressively better attempts at mimicking the functioning of human brain (Agrawal, 2014; Meyer et al., 2014), which suggests a number of similarities between human and machine learning, and some possible differences. For example, while AI systems can perform neural network-like processes that emulate the innerworkings of the human brain, those systems are still not self-organizing or adaptive (Zhang, 2010; Arbib, 2003); at the same time, machine-based capture and retrieval of information far exceeds the capacity of human brain (Krishnaswamy & Sundarraj, 2017; Stark & Tierney, 2014). When considered from the standpoint of organizational learning, that mix of differences and similarities is suggestive of some important considerations, further accentuated by informational realities of the Age of Data. Most notably, significant synergies can be realized by leveraging the combined effect of the adaptiveness and creativity of human learning with the virtually unlimited information processing and retention, and the nearly instantaneous recall of any and all captured information that characterizes machine learning[1]. In fact, it is difficult to think of organizational competitiveness without considering organizational capabilities to capture, ingest, synthesize and disseminate decision-pertinent information to decision-responsible organizational stakeholders at the appropriate time.

The Rise and Fall of Organizational Learning

The recognition of learning as a distinct organizational competency can be traced back to the 1960s and 1970s (e.g., Arrow, 1962; Cyert & March, 1963; Cangelosi & Dill, 1965; Argyris & Schon, 1978), but it was not until the 1990s that the topics of organizational learning spurred wider interest among researchers (Rebelo & Gomes, 2008; Bapuji & Crossan, 2004). The resultant rich and varied research streams (e.g., Denton, 1998; Popper & Lipshitz, 1998, 2000; Cohen & Sproull, 1996; Marquardt, 1996; Dodgson, 1993) included several popular books, such as the 1990 work titled *The Fifth Discipline: The Art and Practice of the Learning Organization*, which helped to popularize the notion of learning organization among practitioners. Unfortunately, the wider embrace of the idea of learning organizations has led to proliferation of 'tried and true' management solutions in the form of pre-packaged consulting frameworks chock-full of anecdotes and buzzwords, contributing a yet another chapter to management lore (Skeel, 2005; Neuhauser, 1998). Promising quick solutions to even intractable management problems, those templated conceptualizations, often accompanied by flawed axioms and other self-deceptive dictums,

[1] The idea of technological singularity, or the merging of human and machine intelligence giving rise to infinitely more capable superintelligence, can be seen as much stronger expression of that hypothesis.

became the de facto public face of organizational learning, effectively portraying an important organizational capability as yet another passing fad (Buckley et al., 2015; Robelo & Gomes, 2008).

False prophets, buzzwords and sage anecdotes aside, to remain competitive in knowledge-driven economy firms have to develop and deploy robust means of creating and leveraging decision-guiding knowledge. When looked at from the standpoint of organizational survival, institutional learning capability can be seen as a manifestation of organizational adaptiveness (Thomas & Vohra, 2015), enabling firms to fine-tune their behaviors (Templeton et al., 2009; Hult and Nichols, 1996), and cognitive functioning capabilities (Chiva and Alegre, 2005; Akgun et al., 2003). Within institutional setting, the behavioral and cognitive learning dimensions are shaped by a myriad of individual-level and system-wide influences, including organizational structure (Martínez-León & Martínez-García, 2011; Schreyogg and Sydow, 2010; Hinings et al. 1996; Gurpinar, 2016), culture (Yates and de Oliveira, 2016; Briley et al., 2014; Markus and Kitayama, 1991) and group dynamics (Lucas and Kline, 2008; Schein, 1993), as well as an array of latent psychological and emotional characteristics (Lucas and Kline, 2008; Schein, 1993; Wastell, 1999; Yanow, 2000), and even biological traits (Salvador and Sadri, 2018).

Equally important to developing sound organizational learning mechanisms are the volume and variety of what is to be learned, as well as the available learning modalities. The rise of Big Data and the proliferation of large-scale data analytic capabilities produce torrents of new information, created on ongoing basis. Consequently, establishing of valid and reliable means of assessing and synthesizing ceaseless flows of large volumes of information constitutes an important aspect of organizational learning. In a very pragmatic sense, the ability to separate the proverbial chaff from grain, which amounts to finding and institutionalizing decision-guiding insights often hidden in masses of comparatively trivial informational tidbits, is an important prerequisite of effective learning. Another aspect of the modern data-rich and technology-enabled informational infrastructure is that, within organizational setting, the very manner in which learning takes place is expanding, now not only encompassing the traditionally human-centric modality, but also the rapidly maturing artificial, or technology-based learning capabilities.

Organizational Learning in the Age of Data

Implied in the traditional conception of learning is that it is a human-centric process, and since organizations are essentially human collectives, at its core, organizational learning is also commonly viewed as a human-centric undertaking (Marcus & Shoham, 2014; Rasmussen and Nielsen, 2011; Dixon, 1992; Huber, 1991). However, the rise of big data along with progressively more advanced and automated data analytic technologies are beginning to cast doubt on the validity of the human-centric conception of organizational learning, with AI, and more specifically machine learning (ML) as the rather obvious manifestation of the already substantial encroachment of non-human learning modality.

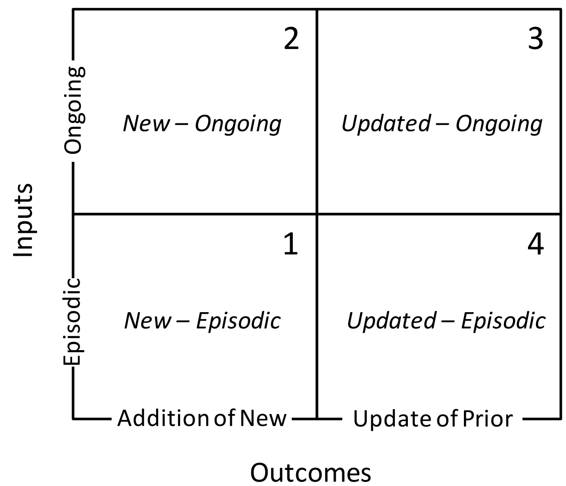
Reframing of the notion of organizational learning is important not only from the standpoint of the somewhat obtuse concept validity (Neumayer & Plümper, 2017; Locke, 2012), but also because development of sound decision-making competencies is contingent on identification and utilization of all available and pertinent information (Dezi et al., 2018; Jeble et al., 2018; Cox et al., 2017; Laux et al., 2017; Eva, 2015). Moreover, already considerable and growing share of organizational know-how resides outside of the human intellectual domain (Bolisani et al., 2018; Choi, 2018), as illustrated by online recommendation engines and similar technologies. It thus follows that reconceptualization of the idea of organizational learning should start with clear and explicit delineation of learning inputs and outcomes.

Learning Inputs and Outcomes

In the most rudimentary sense, learning can be seen as a proces of consuming inputs, in the form of various stimuli, with the goal of generating outputs, in the form of knowledge (Wang and Ellinger, 2011).

Broadly defined, learning process inputs can be either episodic, taking the form of ad hoc stimuli, or ongoing, manifesting themselves as recurring stimuli. Learning process outcomes, on the other hand, can take the form of incremental knowledge, or updates to existing knowledge. Consider Figure 1.

Figure 1
Learning Inputs and Outcomes

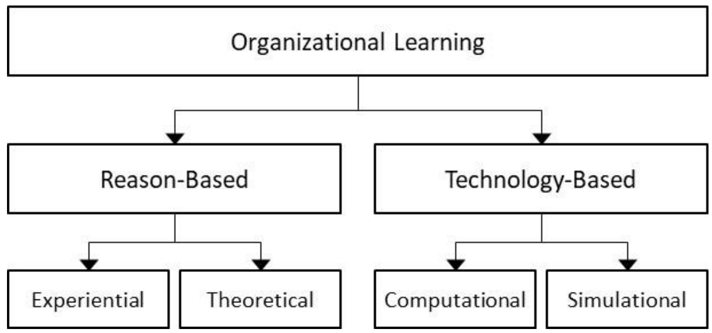


The resultant 2x2 organizational learning input-outcome classification yields four distinct learning scenarios: new knowledge produced episodically (quadrant 1), new knowledge produced on ongoing basis (quadrant 2), ongoing update of prior knowledge (quadrant 3), and episodic update of prior knowledge (quadrant 4). Jointly, those four dimensions of organizational learning capture the 'what' aspect of learning in the form of distinct types of knowledge assets derived from different informational sources and learning modalities, such as theoretical understanding of a new phenomenon of interest derived from the most recent empirical research findings (quadrant 1) or the most recent data-derived frequency of a particular type of insurance claims (quadrant 3). Essential to properly framing and contextualizing those distinct types of knowledge assets is a more in-depth detailing of the 'how' aspect of organizational learning, with particular emphasis on learning modalities.

Learning Modalities

In the most general sense, the basic tenets of human learning suggest that the ability to reason, conceptualized as the power of the mind to think and understand by a process of logic (Kahneman, 2011; Contreras, 2010) is most emblematic of human learning, while the ability to identify patterns in vast quantities of data is most descriptive of machine learning (Wright & Schultz, 2018; Wichert, 2014; Shi, 2011). That basic distinction is captured in two meta-categories of organizational learning: 'reason-based', which embodies individual and collective cognitive and behavioral knowledge, and 'technology-based', which embodies the capability of technological agents to autonomously translate patterns in data into performance of tasks. Each of the two meta-categories can be further subdivided into more operationally meaningful categories of 'experiential' and 'theoretical' for reason-based learning, and 'computational' and 'simulational' for technology-based learning. Figure 2 below offers a graphical representation of the resultant typology of organizational learning.

Figure 2
The Typology of Organizational Learning



Although outlined in Figure 2 as four distinct manifestations of organizational learning, experiential, theoretical, computational and simulational learning modes can also be thought of as progressively more sophisticated means of knowledge creation. From early man gazing at the stars and trying to make sense of natural phenomena (experiential learning), to early philosophers and scientists discerning the underlying laws of nature (theoretical learning), to modern data- and technology-enabled investigators identifying new and testing presumed relationships (computational learning), to the now-emerging means of simulating reality as a mean of learning that transcends experience and physical reality (simulational learning). And although experiential, theoretical, computational and simulational learning can be seen as progressively more sophisticated means of learning, it is important to think of them as complements, not replacements, in the same way that airplanes, automobiles, bicycles and simply walking are all different means of traversing distance.

Reason-Based Learning

At an individual level, learning can be broadly characterized as acquisition of new or reinforcement of existing knowledge (Giorgis & Johnson, 2001; Estes, 1956). The underlying process begins with awareness-arousing stimulus being encoded into short-term memory in one of two forms: iconic, or visual, and echoic, or auditory. The process of learning is then initiated: It starts with the formation of new neuronal connections, which is followed by consolidation, or strengthening and storing of remembrances as long-term memories, with distinct clusters of neurons being responsible for holding different types of knowledge (Ehrlich & Josselyn, 2016; Zull, 2002). Any subsequent retrieval of memories from long-term to active memory brings about re-consolidation, or strengthening of the stored knowledge, often referred to as remembering (Van Dam, 2013; Leamnson, 2000).

In a more abstract sense, learning can be characterized as adding new or modifying information already stored in memory based on new input or experiences (Kesner & Martinez, 2007; Jean-Marie & Tidball, 2006). It is an active process involving sensory input to the brain coupled with extraction of meaning from sensory input; it is also a fluid process, in the sense that each subsequent experience prompts the brain to (subconsciously) reorganize stored information, effectively reconstituting its contents through a repetitive updating procedure known as brain plasticity (Brynie, 2009; Moller, 2009; Kolb & Whishaw, 1998). Though generally resulting in improvements to existing knowledge, brain plasticity can nonetheless bring about undesirable outcomes, most notably in the form continuous re-casting of memories – in fact, that is one of the reasons eyewitness accounts become less and less reliable with the passage of time. All considered, the widely used characterization of learning as the ‘acquisition of knowledge’ oversimplifies what actually happens when new information is added into the existing informational mix – rather than being simply ‘filed away’ and stored in isolation, any newly acquired information is instead integrated into a complex web of existing knowledge.

Within the confines of reason-based learning, the most elementary knowledge acquisition mechanism entails immersion in, or observation of, a process or a phenomenon (Brito & Barros, 2005; Merav, 1999), commonly referred to as experiential learning. Subjective and situational, this mode of learning can be seen as a product of a curious mind driven to understand the nature of a particular experience, and it is built around systematic examination of sensory experiences, particularly those obtained by means of direct observation or hands-on participation (Douglas Greer et al., 2006; Braaksma et al., 2002; Blandin et al., 1999). Being entirely shaped by person-specific factors, experiential learning implicitly dismisses existence of innate – i.e., generalizable – ideas, resulting in knowledge that is entirely defined by individual learners (Gascoigne & Thornton, 2014; Rainbird et al., 2004). That mode of learning is particularly important in the context of specific tasks, such as underwriting of executive risk or managing retail customer loyalty programs.

Complementing the experiential learning dimension of reason-based learning is theoretical learning, which is focused primarily on common knowledge, or innate ideas that transcend individual experiences. It entails developing an understanding of universally true and commonly accepted abstract formulations and explanations, as exemplified by the axioms and rules of mathematics or the laws of nature (Brante et al., 2015; Karpov & Bransford, 1995). That mode of learning typically plays a very important role in the attainment of professional competence, as evidenced by numerous professional certification requirements (Blank et al., 2012; Sense, 2008).

Plasticity, Bias & Channel Capacity

In a very general sense, knowledge can be thought of as a library – a collection of systematic, procedural and episodic remembrances acquired via explicit and tacit learning (Kahin & Foray, 2006). However, as suggested by the notion of brain plasticity, unlike physical libraries, neural networks-stored 'collections' are subject to ongoing re-shaping, triggered by the process of assimilating of new memories. The resultant continuous re-writing of old memories means that an individual-level effective topical knowledge is ever-changing, and that the ongoing interpretation and re-interpretation of knowledge can exert a profound impact on individuals' perception and judgment.

While the ongoing re-shaping of knowledge affects the validity and reliability of individuals' knowledge, cognitive bias impacts the manner in which stored information is used (Caputo, 2016; Hilbert, 2012; Kahneman, 2011). Reasoning distortions such as availability heuristic (a tendency to overestimate the importance of available information) or confirmation bias (favoring of information that confirms one's pre-existing beliefs) attest to the many ways subconscious information processing mechanics can warp the manner in which overtly objective information shapes individual-level sense-making. To make matters worse, unlike machines that 'remember' all information stored in them equally well at all times, the brain's persistent self-rewiring renders older, not sufficiently reinforced memories progressively 'fuzzier' and more difficult to retrieve (Brynie, 2009; Moller, 2009). As a result, human recall tends to be incomplete and selective.

Moreover, the amount of information human brain can cognitively process in attention at any given time is limited due to a phenomenon known as human channel capacity (Benish, 2015; Woungang et al., 2010). Research suggests that, on average, a person can actively consider approximately 7 ±2 of discrete pieces of information (Massa & Keston, 1965; Miller, 1956). When coupled with the ongoing reshaping of previous learnings (brain plasticity) and the possibly distorted nature of perception (cognitive bias), channel capacity brings to light cognitively-biological human reasoning limitations.

Emotion & Motivation

Looking beyond factors that capture some of the brain mechanics related reasoning limitations, reason-based learning is also impacted by numerous attitudinal factors, most notably those related to emotions and motivation (Kahneman, 2011; Sessa and London, 2008). For instance, more positive experiences tend to manifest themselves in more complete recollections than negative events, and those events that occurred more recently appear to be more significant or thus more likely to recur. Moreover, desire to perform better has been shown to lead to deeper learning, even when time spent on learning, as well as learners' gender and ability were controlled for, highlighting the importance of intrinsic motivation to learning (Everaert et al., 2017). While commonly considered in the context of individual-level characteristics, emotion and motivation also have important group-level analogs, outlined next.

Group Dynamics

Contradicting conventional wisdom which suggests that groups make better decisions than individuals, research in areas of social cognition and social psychology suggests that groups do not necessarily outperform individual – rather, it is a combination of cognitive, social and situational influences that tend to determine the efficacy of decisions (Cristofaro, 2017; Mazutis and Eckardt, 2017; Bhatt, 2000). While group decisions tend to enjoy higher levels of confidence, that may not translate into higher decision quality because of a phenomenon known as groupthink, or a dysfunctional pattern of thought and interaction characterized by closed-mindedness and uniformity expectations (Russell et al., 2015; Schafer and Crichlow, 1996), and biased information search, characterized by strong preference for information that supports the group's view (Kopsacheilis, 2018; Rozas, 2012; Fischer et al., 2011).

A yet another important, organizational decision-making related aspect of group dynamics is group conflict (Katz et al., 2016; Stanley, 1981). As suggested by social exchange theory, which views the stability of group interactions through a theoretical lens of negotiated exchange between parties, individual group members are ultimately driven by the desire to maximize their benefits, thus conflict tends to arise when group dynamics take on more competitive than collaborative character (Li-Fen, 2008; Gould-Williams, 2005). Keeping in mind that the realization of group decision-making potential requires full contributory participation on the part of individual group members, within-group competition reduces the willingness of individuals to contribute their best to the group effort. Not only can that activate individuals' fears of being exploited, as well as heighten the desire to exploit others – it can also compel individuals to become more focused on standing out in comparison with others. Moreover, group conflict can heighten tendencies to evaluate one's own information more favorably than that others' (Arai et al., 2016; Van Swol, 2007), in addition to also evaluating more positively any information that is consistent with one's initial preferences (Faulmuller et al., 2010; Mojzisch & Schulz-Hardt, 2010).

Technology-Based Learning

The growing sophistication and proliferation of self-learning technologies, commonly referred to as artificial intelligence (AI), is beginning to challenge the traditional, human-centric conception of organizational learning (Lowe & Sandamirskaya, 2018; Betzler, 2016; Estes, 1956). Machine learning, a sub-category of AI that focuses on endowing computers with the ability to learn without being expressly programmed, enables algorithmic systems to discern patterns from available data, accumulate and synthesize the resultant arrays, which are then used as bases for executing specific tasks (Shandilya, 2014; Usuelli, 2014; Witten et al., 2011). In fact, as implied in the term 'artificial intelligence' AI systems are expressly designed to mimic the functioning of the human brain, perhaps best exemplified by neural networks, a family of algorithms modelled after human brain. Unimpeded by human limitations in the form of cognitive bias, fatigue or channel capacity, and taking advantage of practically limitless computational resources, AI is pushing the broadly defined ability to learn beyond the traditional limitations of human-centric information processing (Krishnaswamy & Sundarraj, 2017; Stark & Tierney, 2014). And in some context, most notably when performing routine, repetitive tasks, AI-based decision engines can in fact outperform humans. The primary reason for that is the very non-biological and non-reasoning essence of those systems: Being able to rapidly, tirelessly and nonjudgmentally ingest and summarize the often vast quantities of data enables those systems to systematically and objectively – or more specifically, unemotionally – assess decision alternatives in a way that is extremely difficult, if not outright impossible for human decision-makers (Usuelli, 2014; Witten et al., 2011).

It is important to emphasize that technology-based learning is a complement, not a replacement for human learning. When decisions are characterized as repetitive and structured, and the decision-making environment can be described as stable, technology-based learning can offer incremental value to the organization by enabling more exhaustive, expedient and unbiased utilization of available data. At the same time, however, there are many decision situations in which technology-based learning offers limited benefits, which is particularly the case in volatile environments or decision contexts, or when trend-discontinuing events materialize. Given that organizations tend to face a mix of repetitive-structured-stable and ad hoc decisions, technology-based learning should be considered an important aspect of the overall organizational learning strategy.

Also comprised of two complementing dimensions, technology-based learning can take the form of *computational* (Andreopoulos & Tsotsos, 2013; Suykens, 2003) or *simulational* (Hey et al., 2009; Wood et al., 2009) learning. While overtly quite similar in the sense that both modalities are built on the foundation of analysis of raw data using sophisticated data analytic tools and techniques, computational learning is primarily focused on the 'what-is' dimension of knowledge creation, while simulational learning explores the more speculative 'what-if' dimension of data analytic knowledge. More concretely, the former takes the form of informational summarization and pattern identification, while the latter is built around anticipatory, forward-looking data-based simulations of future outcomes of interest. Utility-wise, computational learning is invaluable to guiding recurring, routine decisions characterized by high degrees of longitudinal stability, as exemplified by managing insurance claims, while simulational learning is essential to infusing objectivity into non-routine decisions, as exemplified by emergence of disruptive technologies.

Interestingly, simulational learning can be thought of as machine equivalent of human reason-based theoretical learning. The reason behind that assertion is that simulational learning enables constructed reality-based knowledge creation, or discovery of universal generalizations within artificial representations of the world, broadly referred to as virtual reality, perhaps best exemplified by astrophysical research delving into the birth of our physical universe. Virtual reality-enabled learning makes possible generation of previously inaccessible insights (e.g., conditions that existed shortly after the Big Bang) because it enables simulation of impossible to experience in physical reality conditions, with which comes virtually limitless what-if type of scenario planning.

Overabundance

In the most rudimentary sense, data can be conceptualized as a mix of signal, which is potentially informative, and noise, which is generally non-informative (Subedi, 2013; Woodward, 2010). Hence one of the core aspects of data utilization is to separate signal from noise, a task that becomes increasingly more challenging as the volume and variety of available data expand (Jain & Sharma, 2014; Sinha, 2014). Walmart, the world's largest retailer, handles more than a million customer transactions per hour; by 2020, the aggregate volume of business-to-business and business-to-consumer transactions is expected to surpass 450 billion per day (Nadkarni & Mehra, 2018). And many of those transacting consumer, more than 5 billion as of 2018, are calling, texting, tweeting and browsing on mobile devices, all of which adds potentially informationally-rich pre- and post-purchase details (Fenwick & Schadler, 2018). However, given that the bulk of data available to organizations represents a product of passive recording of an ever-growing array of states and events (Wiggins, 2012; Tupper, 2011), finding the few organizational decision-related insights typically entails analytically sifting through vast quantities of non-informative noise.

The often staggeringly large quantities of available data are perhaps the most visible manifestation of the difficulty of finding meaningful signal in the sea of noise. However, within the confines of technology-based learning, epistemology, or the essence of validity and reliability of what is considered 'knowledge', poses an even more formidable challenge. Lacking the face validity, or 'does it make sense', aspect of reason-based learning, technology-based learning has to rely on generalizable decision heuristics to enable automated algorithms to independently and consistently differentiate between material and spurious patterns. Consider is common scenario: A computer algorithm sifting through data identifies a recurring association between X and Y – once identified, the association is 'learned' and subsequently used as a driver of algorithmic task execution. However, there is often a non-trivial possibility that what manifested itself as a recurring association between X and Y is erroneous, due to both X and Y being influenced by unaccounted for (i.e., not captured in the available data) factor Z, effectively rendering the presumed association illusory (Szatkowski & Rosiak, 2014). Moreover, even if the X-Y association is unaffected by the unaccounted for factor Z, the widely used statistical significance testing may produce falsely positive conclusions. One of the key culprits here is the well-known dependence of statistical significance tests on sample size – it can be easily shown (by varying the sample size while holding all else constant) that the often large number of records used in analyses can result in magnitudinally trivial effect size (Banasiewicz, 2013) being deemed statistically significant, which is typically interpreted as material.

Learning Outcome Assessment

While the development and deployment of robust learning systems and supporting mechanisms tend to be the focal point of organizational learning-oriented efforts, those learning enablements alone are insufficient to assure the desired outcomes. Especially within the confines of reason-based learning, cognitive bias, channel capacity, group dynamics in addition to more general emotional and motivational factors all can potentially impede the quality of organizational learning. Moreover, the relative newness of technology-based learning also affects the efficacy of the overall organizational learning efforts, as it often pits human experience against machine algorithms. All in all, assessing the efficacy of organizational learning efforts should be considered a core element of the broader organizational learning efforts (Cheung-Blunden & Khan, 2018; Arora, 2012; Benson & Dresdow, 1997).

As suggested by Hawthorne effect, when faced with formal learning assessment, learners are likely to engage more deeply in the learning process (Tuckman, 1988; Campbell & Stanley, 1966). However, to meet the objective of assuring the overall organization-wide assimilation and utilization of applicable knowledge, assessment needs to be situationally meaningful, with particular emphasis on the type and character of knowledge-based competencies. Given the diversity and the depth of organizational skill sets, that degree of learning outcome assessment customization needs to reflect not only the type of knowledge, but also the type or the depth of learning. For example, as 'doers', data scientists should be expected to acquire functional, i.e., theoretical plus experiential, knowledge of new machine learning algorithms, while those managing data science teams, or 'overseers', may only need to acquire adequate theoretical understanding of those algorithms.

Organizational Learning Transformation

Recognizing the transformative impact of data, organizations strive to make more data more readily available to more users by a variety of means, including embracing self-service business intelligence solutions (Alpar & Schulz, 2016); however, many quickly recognize that the bulk of prospective data users do not have the necessary data manipulation, assessment and analysis skills (Dubey et al., 2018; Hart & Hiltbrand, 2014). It is clear that data and data-related technologies are evolving and proliferating much faster than the overall workforce's readiness to embrace data-centric work, and merely making tools available to those who are apprehensive about 'jumping into data' is unlikely to bring about the desired organizational learning transformation.

The lack of the requisite know-how is but one of numerous impediments to broadening the utilization of pertinent information. Evidence-based decision-making also requires some degree of silencing of subjective intuition, which is difficult, even unnatural. A part of what make that challenging is that perception- and evaluation-warping cognitive biases are natural consequences of human brain's wiring (Hilbert, 2012; Kahneman, 2011; Contreras, 2010), thus considerable cognitive effort is required to overcome those natural mental impulses. At the same time, there is nothing natural about trusting data-derived conclusions, especially when those conclusions contradict one's intuition.

Lastly, making systemic organizational learning an operational reality also calls for structural 're-wiring' of organizations, especially those that reached operational maturity in the pre-data-everywhere period. Given that the main objective of organizational structure is to ensure that the chosen strategy is effectively executed (Gurpinar, 2016; Hinnings et al., 1996), learning-friendly structure needs to be evidence-, rather than managerial hierarchy-centric. Just adding tools and systems to an authoritarian organization where decisions are driven by a combination of organizational hierarch and the frequently biased subjective evaluations is unlikely to yield meaningful benefits, even if knowledge is created and disseminated throughout the organization. The ultimate goal of organizational learning is not just to be wiser, but to act wiser.

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