# Organizational Learning in the Age of Data

Andrew D. Banasiewicz(✉)

Cambridge College, Boston, MA 02129, USA
andrew.banasiewicz@cambridgecollege.edu

**Abstract.** 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. Building on the foundation of explicit differentiation between episodic vs. ongoing learning inputs and new vs. cumulative learning outcomes, this article proposes a new typology of organizational learning modalities, which explicitly distinguishes between human reason-centric theoretical and experiential learning, and technology-centric computational and simulational learning modalities.

**Keywords:** Organizational learning · Computational learning · Simulational learning

## 1 Introduction

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 and 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 and 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 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, AI systems can perform neural network-like


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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 and Sundarraj 2017; Stark and 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.

### 1.1 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 and March 1963; Cangelosi and Dill 1965; Argyris and Schon 1978), but it was not until the 1990s that the topics of organizational learning spurred wider interest among researchers (Rebelo and Gomes 2008; Bapuji and Crossan 2004). The resultant rich and varied research streams (e.g., Denton 1998; Popper and Lipshitz 1998, 2000; Cohen and 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, buzzwords, stories of great success, and other forms of 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 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 and 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 and 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

[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.

and Martínez-García 2011; Schreyogg and Sydow 2010; Hinnings 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 mechanism 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.

## 2 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 and 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 machine learning (ML) and artificial intelligence (AI) as two obvious manifestations of the already substantial encroachment of non-human learning modalities.

Reframing of the notion of organizational learning is important not only from the standpoint of the somewhat obtuse concept validity (Neumayer and 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.

### 2.1 Learning Inputs and Outcomes

In the most rudimentary sense, learning can be seen as a process the process 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 Fig. 1.

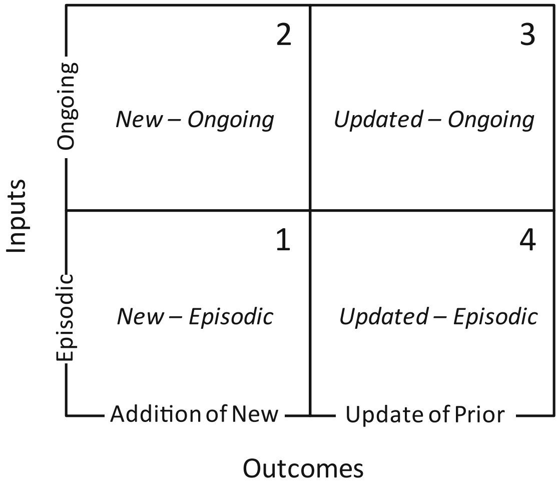


**Fig. 1.** Learning inputs and outcomes

The resultant 2 × 2 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.

### 2.2 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 and 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 efficacy of the broadly defined informational infrastructure to autonomously perform specific, typically routine, organizational tasks. Each of the two meta-categories can be further subdivided into more operationally meaningful categories of tacit and explicit, and computational and simulational learning, for reason- and technology-based, respectively. Figure 2 below offers a graphical representation of the resultant typology of organizational learning.

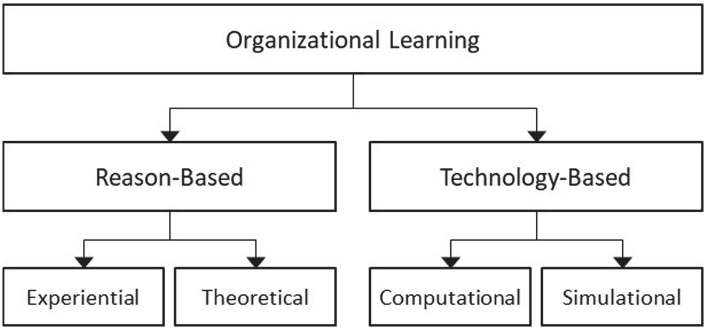


**Fig. 2.** The new typology of organizational learning

Although outlined in Fig. 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 progressive more sophisticated means of learning, it is important to think of them as complements, not replacements, in the same way that planes, 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 existing knowledge (Giorgis and 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 and 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 and Martinez 2007; Jean-Marie and 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 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 and 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 and 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 and 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 and Bransford 1995). That mode of learning typically plays a very important role in the attainment of professional competence, as evidence by numerous professional certification requirements (Blank et al. 2012; Sense 2008).

*Plasticity, Bias and 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 and 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 (which is why eye witness accounts become less and less reliable with the passage of time), 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 $7 \pm 2$ of discrete pieces of information (Massa and 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 and Motivation.* Looking beyond factors that capture some of the brain mechanics related reasoning limitations outlined earlier, reason-based learning is also impacted by numerous attitudinal factors, most notably 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 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 instead suggests that hat groups do not always outperform individual, and that a combination of cognitive, social and situational influences are ultimately stronger determinants of the quality of decision-making (Cristofaro 2017; Mazutis and Eckardt 2017; Bhatt 2000). Higher levels of confidence often associated with group decisions may not yield 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 and Davies 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 compel individuals to become more focused on standing out in comparison with others. That can activate tendencies to evaluate one's own information more favorably than that others' (Arai et al. 2016; Van Swol 2007), and also to evaluate more positively any information that is consistent with one's initial preferences (Faulmüller et al. 2010; Mojzisch and 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 and 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, discern patterns from available data, accumulate and synthesize the resultant knowledge, and then execute specific tasks using self-discerned decision logic (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, as illustrated by one of the more commonly used artificial learning approaches represented by a family of algorithms known as neural networks. 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 and Sundarraj 2017; Stark and Tierney 2014). And in some context, most notably when performing routine, repetitive tasks, AI-based decision engines can in fact outperform humans, primarily because those systems can rapidly, tirelessly and objectively infer from the often vast quantities of data decision alternatives that exhibit the highest probability of desired outcomes (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 is characterized as stable, technology-based learning can offer incremental value to the organization by enabling more exhaustive and objective utilization of the available data. Conversely, there are many decision situations in which technology-based learning offers considerably less beneficial, as is the case when available historical data have limited predictive value, and/or decision environment is highly volatile. That said, organizations typically face a mix of repetitive-structured-stable and ad hoc decisions, suggesting that 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 and Tsotsos 2013; Suykens 2003) or simulational (Hey et al. 2009; Wood et al. 2009) learning. While overtly quite similar in the sense that both learning 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.

Simulational learning can be thought of as machine equivalent of human reason-based theoretical learning. More specifically, it 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 the creation of possible but not-yet-observed situations, and 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 and 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 and 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 informationally-rich pre- and post-purchase details (Fenwick and Schadler 2018). However, given that the bulk of data available to organizations represents is 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 separating information from 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 the reason-based learning, technology-based learning has to rely on generalizable decision heuristics to enable the automated algorithms to independently and consistently differentiate between material and spurious conclusions. Consider is common scenario: A computer algorithm sifting through data in search for material patterns pinpoints a recurring association between X and Y – once identified, the association is ‘learned’ and subsequently used as a driver of the algorithm-enabled decision-making. 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 and 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. More specifically, the often large number of records used in analyses can result in magnitudinally trivial effect size, such as a correlation coefficient, being deemed material, or statistically significant, because of the well-known dependence of statistical significance tests on sample size (Banasiewicz 2013).

## 3 Conclusions and Recommendations

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. Historically viewed as a human-centric endeavor, organizational learning is being re-defined by the rise of big data and advanced data analytic technologies, all of which is compelling a fundamental reconceptualization of the scope and modalities of organizational learning, and research summarized here 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, which explicitly distinguishes between human reason-centric theoretical and experiential learning, and technology-centric computational and simulational learning modalities. By expressly 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 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.

As is the case with all conceptual frameworks, the conceptualization offered here needs to be subjected to theoretical and application scrutiny. Does the new typology of organizational learning summarized in Fig. 2 exhibit the necessary MECE (mutually exclusive and collective exhaustive) characteristics? Is the said typology practically meaningful, or stated differently, does the use of the new typology of organizational learning lead to measurable gains in organizational learning efficacy? Those and related questions need to be answered to ascertain both the theoretical and practical values of the proposed framework.

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