Organizational intelligence in the digital age: Analytics and the cycle of choice

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Organizational intelligence in the digital age: Analytics and the cycle of choice

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Abstract

In this chapter we investigate the taken for granted assumption that the use of analytics makes organizations more intelligent. We discuss how analytics influences learning from experience, one of the processes of organizational intelligence that informs rational choice. In particular, we revisit the cycle of choice, a fundamental framework in the field of organization theory, according to which organizations learn by making choices following a closed cycle of connections between the beliefs held by individuals, the individual behavior, the organizational choices, and the responses from the environment. We examine each case of possible breakdown in the cycle of choice and analyze whether the use of analytics could help avoid the breakdown. We conclude that while analytics may support learning from experience and avoid certain types of breakdowns, relying too much on analytics can also trigger new breakdowns in the cycle. We close the chapter with a reminder that while organizations indeed need to use tools that make them smarter, they also need technologies of foolishness.

Introduction

Analytics is said to be the key for organizational success in the digital era (Davenport and Harris 2007), helping organizations transition from myopic to holistic (Winig 2016), become smarter (Davenport, Harris, and Morison 2010) and gain competitive advantage (Ransbotham, Kiron, and Prentice 2015). While this sounds promising enough to put analytics on the top of CIOs' agenda (Gartner 2015) and to awaken the interest of researchers in the field of information systems (Chen et al. 2012) and management (George, Haas, and Pentland 2014), some prudence may be necessary before we all jump on the bandwagon bringing us straight to a data-driven wonderland. It is generally accepted that analytics, even though perhaps at a more mature stage, will be here to stay (Ghoshal, Menon, and Sarkar 2015). This implies a call to academics, to be more reflective about how the topic is studied and first of all to unpack assumptions that have given boost to its present popularity; in particular: *Does analytics indeed make organizations more intelligent?*

Going back to the behavioral theory of the firm (Cyert and March 1963) may help us in this inquiry. The behavioral theory of the firm has an enormous influence in the field of organizational intelligence, in particular through decision making and organizational adaptation. From this theoretical perspective, organizational intelligence has been related with making choices through two fundamental processes: rational calculation of alternatives and their consequences to choose the optimal alternative; and learning from past experience to choose among present alternatives (March and Olsen 1975). These two processes take place by processing information gathered internally in the organization and from the external environment. Rationality entails acting based on a thorough examination of alternatives and their consequences, which is done by gathering information, while organizational learning (i.e. modifying rules and actions) based on past experience (March and Olsen 1975) is used to replace or to augment the search for information while pursuing intelligent organizational action. Rational choice making as well as organizational learning involve inferences from information, and may therefore be imperfect if organizations are bounded by cognitive limits, time available to search for the information, and so forth (Levinthal and March 1993; March 1994; Simon 1976). Analytics is believed to reduce such boundedness by supporting a complete examination of the choice alternatives and their consequences and in making sense of past actions and their consequences, due to the information processing capabilities that it offers (Clark et al. 2007; Davenport 2010; Winig 2016). Thus, analytics is assumed to make organizations more intelligent by increasing rational action and adaptation to the environment based on past experiences.

We will investigate this assumption by using the cycle of choice framework as it has been developed by March and Olsen (1975). The framework is based on the ideal situation of full rationality and unboundedness in which intelligent organizations learn by making choices following a closed cycle of connections between the beliefs held by individuals, the individual behavior, the organizational choices, and the responses from the environment. However, given that information is seldom complete, difficult to interpret and often distorted, the steps that organizations take to learn are often broken down which results in organizations learning in a bounded and irrational way. If indeed analytics makes organizations more intelligent, this would mean that the use of analytics helps fixing the breaks in the cycle of choice. In this chapter, we take a closer look at this assumption.

The technology of analytics

With the term *analytics* we refer to the set of practices, skills, techniques and technologies, such as analyzing past behavior, predictive modeling and optimization, which are employed by organizations to extract actionable insights from data and steer decisions and actions (Bose 2009; Davenport and Harris 2007; Davenport et al. 2010). A common example of using analytics is the employment of market basket analysis (Kumar and Rao 2006) by Walmart, with the goal to learn from the purchase behavior of customers and to improve their sales promotions, store design, and so forth.

The vast development and use of various information systems and the increased digitization have significantly increased the amount of data that is available to organizations (McAfee and Brynjolfsson 2012; Constantiou and Kallinikos 2014). Unavoidably, analytics has been established as one of the most influential technologies in our era (Luftman et al. 2015), as it is considered indispensable to leverage the value of big data (Chen, Chiang, and Storey 2012) and to make organizations survive and succeed in highly competitive and constantly changing environments (Davenport and Harris 2007). Most enthusiasm has concentrated on the argument that analytics helps organizations become more intelligent (Clark, Jones, and Armstrong 2007; Davenport 2010; Kiron, Shockley, Kruschwitz, Finch, and Haydock 2012), and transform their ways of acting from myopic and reactive to holistic and proactive (Winig 2016). Some criticism has been expressed regarding organizations investing in analytics yet failing to transform their organizational processes and to act based on the data analytics insights, e.g. because of lacking management support, or insufficient appropriate skills and understanding for how to use analytics, or unsupportive organizational culture (Ransbotham et al. 2015). Nevertheless, the assumption is that if organizations overcome such barriers, they will be able to make better informed decisions and learn from their past experience more effectively, thus become more intelligent and succeed with analytics (Davenport and Harris 2007; Petrini and Pozzebon 2009).

Analytics is closely related to decision support systems (Arnott and Pervan 2014), which include techniques for providing an automated solution to a certain problem with a specified set of data and a specific model. It is also closely related to business intelligence (Chen et al. 2012), which focuses on techniques for accessing, reporting and monitoring information. The main difference with those (older) technologies is that analytics includes more fine-tuned data mining techniques customized to analyze various problems, to explain why things are happening in a certain way, and to project what will happen next (Sharma, Reynolds, Scheepers, Seddon, and Shanks 2010).

The study of analytics in organizations necessitates also studying the use of algorithms which are either included in commercial software packages such as SAS, or custom-made by data analysts in order to query, construct, pre-process and analyze the datasets. Acting based on analytics is related to an algorithmic way of managing the organization (Newell and Marabelli 2015), i.e. sensemaking, making choices and acting while adhering to the outcomes of algorithms. Such algorithms are often black-boxed, in the sense that they encapsulate the knowledge frames of the analysts that are not shared with the rest of the organization (Pollock and Williams 2011). As a result, organizational members have to sense make through representations (created by the algorithms included in the analytics code), and to follow actions based on analytics insights, without fully understanding how those representations and insights were created.

The technology of analytics brings along the need for new skills in the organization. It has even necessitated the new profession of "data scientist" (Davenport and Patil 2012), that requires highly analytical skills and the ability to extract the correct datasets and to apply the appropriate techniques with the goal to find patterns in the data. To succeed in analytics, organizations need to employ a variety of skills (Bose 2009) including data management, technology, statistical modeling and analytical, business knowledge, and communication skills.

Analytics and the cycle of choice

In the "Behavioral Theory of the Firm" Cyert and March (1963) view organizations as intendedly rational systems; i.e. organizations tend to learn and adapt their behavior based on past experience and experience of others (Levitt and March 1988). Building on this notion, March and Olsen (1975) introduced a model of "complete cycle of organizational choice" (p. 149), to analyze organizational learning by adaptation. The model assumes that ideally organizations can act as fully rational and make decisions based on "perfect" information. Specifically, the rational cycle of choice assumes that 1) individuals make interpretations based on complete information about the environment; 2) changes in individual actions follow from adapting fully to these changes in interpretations, 3) organizational actions are informed by these individual actions, and 4) actions of the environment in turn are assumed to be reactions to these changed organizational actions.

Let us introduce here an example of organizational learning that we will use in the rest of our analysis. Telecom is a telecommunications organization serving businesses with telephony and internet services. The Sales department of Telecom performs business-to-business sales by employing account managers. An account manager serves a set of business customers by being in frequent contact with them and making sure they are offered the portfolios that fit their needs. In the ideal situation, organizational learning in Telecom would take place while performing full cycles of choice: Each account manager would have complete information and could fully understand why certain customers churn to competitors, while others retain or even upgrade their contacts. This individual understanding would inform the way each account manager approaches the customers, as well as the pricing, portfolio roadmapping, marketing and other strategic activities that Telecom performs. The organizational actions would eventually influence a response from the customers (e.g. ordering a new portfolio), and this would feed back to the individual understanding of the account managers, and the cycle would continue.

However, adapting to experience based on "perfect" information is highly problematic, as organizations face bounded rationality (March & Simon, 1958). For example, in the case of Telecom, it is often hard to have complete information to understand the way its business customers behave, since there are various factors that influence a company's telecom & IT choices. March and Olsen (1975) consider several instances of incomplete learning, in which information processing is ambiguous. These cases of dysfunctional learning (Kim 1993) are represented by breakdowns in the cycle and include: role-constrained learning, audience learning, superstitious learning and learning under ambiguity. The cycle with the breakdowns is depicted in figure 1.

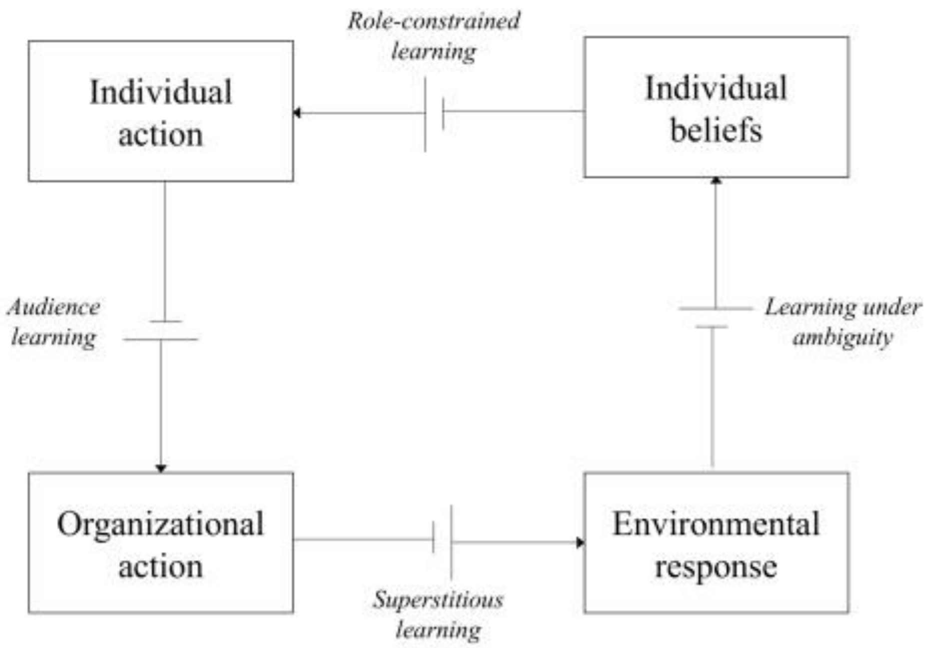

Figure 1. The cycle of choice with organizational learning dysfunctions

The breakdowns in the cycle of choice emerge because the organizations often face difficulties in acquiring or understanding information perfectly. Since analytics helps analyze vast amounts of data and produces valuable insights, it can be assumed that analytics may help reduce the occurrence of breakdowns in the cycle, and consequently make organizations more intelligent. In the next paragraphs, we unpack this assumption by investigating each case of dysfunctional learning, to examine whether analytics will help avoid the dysfunctions, or whether it may create new ones.

Learning under ambiguity

Learning under ambiguity happens when individuals learn and modify their understanding while being faced with ambiguity about what happened in the environment (March & Olsen, 1975). Individuals change their views and beliefs but without fully understanding what happened or why it happened. The modified beliefs drive their individual actions which then influence organizational actions. Consequently, the organization learns and adapts its behavior under ambiguity.

As analytics provides visualization capabilities and multidimensional analysis, it may support making sense of the environment (Chung et al. 2005), and therefore help reduce uncertainty in individual and organizational actions (Clark et al. 2007). In the example of Telecom, using analytics in Sales could help account managers have a more complete view about their customers' behavior, actions and preferences, and learn what approaches and actions are needed to keep them from churning to competitors, and to increase sales.

However, analytics may have a reverse effect if individuals rely too much on analytics: While in today's world the problems of computer illiteracy are gone, a new illiteracy is emerging, one that can be called algorithmic illiteracy: even if organizational members know how to use digital tools, they often remain unaware of the algorithms that are encapsulated in them. This could limit their interpretation of analytics insights. Getting lost in the translation of analytics insights into action yields learning under ambiguity.

Next to that, by creating an analytical model, people tend to treat it later as "objective" information, while there is a lot of subjectivity in the way models are constructed. However, quantitative methods also have their limits (Phillips 2003; Yoo 2015). "The factors that enter decision making are often so numerous and complex as well as individual specific that it is hard to conceive of a probability space large enough to capture all of the determining factors accurately" (Phillips 2003: C39). The algorithms for collecting, processing and analyzing the data are most often not created by the individuals who act upon them. This means that they may not encapsulate their own beliefs and experiences, but instead include rules based on the beliefs and biases of the data scientist who developed them (Nature Publishing Group 2016). By making sense of the environment only through data representations, individuals' own mental representations are eventually altered and their capacity to learn is reduced (Constantiou and Kallinikos 2014). Think of the example of Telecom's Sales department: the analytics algorithms often do not capture the personal relationship between account managers and their customers, while this is an important source for understanding customer behavior better. In that case, if account managers relied too much on the analytics, they would learn under ambiguity - even though they may not be aware of it. Overall, if organizations use analytics yet treat it as a black box, learning under ambiguity may increase, and may cause severe long term consequences.

Role-constrained learning

Role-constrained learning occurs when the link between individual beliefs and actions is broken down (March and Olsen 1975). That is to say, individuals learn and change their beliefs and interpretations, but they are constrained in modifying their individual behavior accordingly, because of their role descriptions, rigid bureaucratic rules, and standard operating procedure. Still, the organization in general learns, without knowing that the knowledge of individuals is different from what they put in action. This case of dysfunctional learning often results in organizational inertia. Let us go back to the example of Telecom and its Sales department: Account managers have direct contact with their customers and can therefore see what problems they face, when their preferences change and why this happens. Ideally, this should entail changing the services and prices that they offer to their customers, in order to make sure the customers remain satisfied and do not churn to a competitor. However, if the organization is organized in silos, most probably the account manager's job description does not allow for influencing how the offered services are structured into portfolios, or how they are priced. In that case, account managers realize that they need to change the way they serve their customers' needs, yet they are bounded in doing so. The individual has learned but cannot put this learning in action and thus limits the potential for the organization to adapt to individual local and situated experiences.

Analytics may help reduce role-constrained learning since it is expected to increase organizational agility and help fight inertia by providing timely information to the organization on how rules and routines need to be adapted (Davenport 2014). In a data-driven culture, if we assume that individual learning takes place with the help of analytics, the organization will be willing to adjust its structure, roles description and operating procedures, to reflect the changes recommended by the analytics insights. In that case, individual learning can be better aligned with individual actions and further influence the organizational actions. In the example of Telecom, we could assume that using analytics to analyze the customers would inform the organization that the account managers need to have more flexibility in the way they serve the customers the offers that they make to them, and would allow them to provide more customized portfolios.

On the other hand, by relying too much on analytics, a reversed situation might happen in which role-constrained learning is reinforced. If individuals are expected to act solely based on analytics, they may not be able to apply their intuition and beliefs drawn from their personal experience. Undoubtedly, the importance of intuition and personal judgment cannot be underestimated, especially in today's complex, uncertain and volatile environments (Abbasi, Sarker, and Chiang 2016; Constantiou and Kallinikos 2014). With the expansion of big data and analytics technologies, it becomes highly challenging for organizations to balance data with intuition, while it also raises questions of accountability. For example, there can be several cases when individuals are expected to act based on analytics, but their intuition suggests taking a different course of action. Also, this could have a long term impact on the individual knowledge, since the individual stops learning through direct experience. Even if analytics helps avoid one type of role-constrained learning, other types of role-constrained learning open up if organizations act fully based on the data analytics insights.

Audience learning

Audience learning occurs when individual action is not adopted or integrated by the organization (March and Olsen 1975). While individuals change their actions based on what they learned, this learning does not affect organizational learning. In the example of Telecom's Sales department, one account manager may see that a specific portfolio does not represent most customers' needs, and therefore focus on selling other portfolios. The account manager realizes that the organization is investing too much on a portfolio that is unsuccessful. However, due to the lower hierarchical status and the political interests of several managers who are at stake, the account manager cannot persuade the Marketing department to change the portfolios structure. Although learning has occurred on the individual level, the organization does not change anything. Next to being unable to influence management, it can also be just management itself that is blind to what is really happening on the work floor causing individual action being disconnected from the organizational action.

Analytics can help overcome audience learning in a number of ways: Individuals can use analytics to justify their actions to others. In a data-driven culture, analytics insights can be viewed as the objective information that bridges different viewpoints and brings more agreement in the organization (Davenport et al. 2010). In this way, individuals can influence organizational action by providing the figures that support their arguments and actions. Furthermore, analytics increases transparency in organizations (Fitzgerald 2016), by providing not only an analysis of what has happened in the past or what is happening in real time, but also by creating anticipations on what is likely to occur in the future (Hansen and Flyverbom 2015).

Nevertheless, analytics can also stimulate audience learning. First, it can easily be the case that people choose to use numbers and figures only when this data is aligned with the actions that they want to take (McAfee and Brynjolfsson 2012). This is an example of 'action rationality' (Brunsson 1982); people perform an action and later make a decision to justify the action. Individuals may choose to use the type of analysis that shows a pattern between an action and a reaction, but in practice they try to cover up the action that they would have performed anyway for other reasons. In the example of Telecom, account managers may choose to use analytics only when the sales predictions match with the approach that they wanted to take, and omit mentioning analytics insights that indicated collaborating with different partners, or contacting customers with whom they do not have a friendly relationship. In addition, people may even start playing numbers games and distorting the data that is stored in the information systems, in order to influence the analytics results so that they fit with their actions (Pachidi, Huysman and Berends 2016). For example, the account managers of Telecom may distort the figures regarding their sales opportunities, in order to get their bonuses easier. If the higher management of Telecom is blinded by using analytics to run the organization by numbers, they may remain unaware of the numbers games and introduce a bonus structure that does not correspond to the real sales actions of the account managers.

Superstitious learning

Superstitious learning occurs when information about the causes of environmental changes is incomplete yet the organization assumes that environmental actions are reactions to their own actions. (March & Olsen, 1975; Levitt & March, 1988). Superstitious learning thus can also be referred to as ego-centric learning: organizations adapt to a false interpretation of environmental changes since they do not take exogenous causes of environmental changes into account. In the example of Telecom, the management of Telecom believed that the significant increase in sales was driven by their increased investments in marketing and customer relationship management, and overlooked the fact that small-to-medium enterprises were paying for their services because the economy was good. After a financial crisis, Telecom suffered from significant losses, because their small-to-medium business customers churned to competitors with lower prices, despite the competitors' lack in marketing and customer relationship management.

Many studies have shown the effectiveness of analytics to provide valid insights from the analysis of data from the environment (Lilien, Rangaswamy, Van Bruggen, and Starke 2004; Tremblay, Fuller, Berndt, and Studnicki 2007). By providing more information regarding what is happening in the market, how competitors are behaving and how customers react, analytics has the potential to limit superstitious learning. For example, analytics can be used in the healthcare domain:

association rule mining on electronic health records has proved to be effective for identifying relevant and accurate associations between symptoms, diseases and treatments (Chen et al. 2012).

However, too heavy reliance on analytics could also reinforce superstitious learning. If the organization keeps using analytics solely to understand what organizational actions caused an environmental response and adapt accordingly, they may start focusing only on actions that have proved to be successful. Behaviors, patterns and discriminations that are inscribed in the analytics algorithms (Newell and Marabelli 2015) will be reinforced, while other patterns and parameters will be ignored (Yoo 2015). Next to that, it does not seem possible that analytics can capture all aspects of the environment. It is possible that certain types of patterns are not coded into algorithms. For example, in the case of Telecom, if the organization relies only on analytics to understand the changes in sales, they may ignore tacit information that cannot be coded into the algorithms, such as the plans of the customers to expand their businesses to new locations. Thus, by relying too much on analytics, organizations risk becoming path dependent, ego-centric and bounded by their very own information producing devices.

Organizational intelligence by analytics: Closing the cycle or keeping it open?

In this chapter we have taken a more reflective approach towards analytics, in order to examine the taken-for-granted assumption that it reduces organizations' boundedness by facilitating better information to make choices and learn from it. Organizations are embracing analytics as if it is the holy grail of perfect information that will reduce uncertainty and increase rationality in their decisions and improve their learning (Clark et al. 2007), seduced by the lure to being perfectly rational (Cabantous and Gond 2011). However, as organizations use analytics to act and learn more rationally, they run the risk of becoming even more bounded. We returned to the roots of the conversation on using technologies of rationality in order to improve learning from past experiences. For this, we revisited the cycle of choice framework developed by March & Olsen (1975), which is helpful to analyze learning from experience and its tendency to dysfunction as a result of making adaptations to imperfect information about individual beliefs and individual actions, the organizational actions and the responses from the environment. We argued that even though the use of analytics can indeed improve decision making, in case organizations rely too much on analytics, those dysfunctions in learning will be reinforced or reappear in different ways. This is the lure of analytics: while organizations think that by using analytics they become unbounded, they risk becoming even more bounded. A summary of our analysis is provided in table 1.

Table 1. The effect of analytics on organizational learning dysfunctions

Organizational learning dysfunction	**Definition**	**How analytics can close the cycle of choice**	**How analytics can break down the cycle of choice**
Learning under ambiguity	Individuals learn and modify their understanding while being faced with ambiguity about what happened in the environment.	Analytics helps make sense of the environment, e.g. through visualization techniques and multidimensional analysis.	Relying too much on analytics while treating it as black box results into more ambiguity, as the mental representations of individuals are ignored.
Role-constrained learning	Individuals learn and change their beliefs and interpretations, but they are constrained in modifying their individual behavior accordingly, because of rigid role	Analytics may help reduce role-constrained learning, since it is expected to increase organizational agility and help fight inertia, by providing timely information to the	If individuals are expected to act solely based on analytics, they may not be able to apply their intuition and beliefs, and eventually stop learning through direct experience.

	descriptions, bureaucratic rules and standard operating procedures.	organization on how rules and routines need to be adapted.	
Audience learning	Audience learning occurs when individual action is not adopted or integrated by the organization.	Individuals can use analytics to justify their actions to the organization, while analytics also increases transparency regarding what is happening on the work floor.	Organizational members may use analytics only when the data is aligned with the actions that they want to take, or may even play numbers games. Management can be blinded by analytics and overlook what actually happens on the work floor.
Superstitious learning	Information about the causes of environmental changes is incomplete yet the organization assumes that these changes are caused by its own actions.	By providing more information regarding what is happening in the market, how competitors are behaving and how customers react, analytics has the potential to limit superstitious learning.	By relying too much on analytics, organizations risk becoming path dependent and bounded by their very own information producing devices.

Whether analytics increases or decreases organizational intelligence, it is questionable anyway why we would want to develop organizations that learn perfectly and act fully rationally. Acting based on analytics by definition entails employing a technology of rationality, i.e. acting upon a model-based assessment of the likelihoods of possible future ends and of pre-established preferences among those ends (March 2006). However, in order to innovate and to survive in highly volatile environments, organizations also need to apply technologies of foolishness (March 1988), i.e. being open to new alternatives by employing playfulness, trial and error, and improvisation. Acting irrationally can sometimes lead to great outcomes for the organization. The organization needs to have some Don Quixote's, the people who may seem crazy by deviating from the expected behavior and remaining open to unexpected consequences (March and Weil 2009). By acting solely based on analytics in the hope to close the learning cycle, organizations risk losing the occurrence of outliers to learn from, the success of the unexpected, the plurality of different viewpoints, the generous insights by Steve Jobs and all other less known Don Quixote's out there. Thus, not only should organizations reduce their high expectations regarding what analytics brings to organizational intelligence, it would be smart to include technologies of foolishness when engaging in learning. To cite March: "Individuals and organizations need ways of doing things for which they have no good reason. Not always. Not usually. But sometimes. They need to act before they think." (March 1988 :259) Hence, even though with the use of analytics the cycle of choice can be closed to a certain degree, aiming for a closed circle would be counterproductive.

One thought before closing this chapter concerns our choice to use the cycle of Choice (March and Olsen 1975) as an analytical framework while thinking about analytics. This framework corresponds to the most popular assumption taken by the proponents of analytics, regarding making organizations more intelligent. Analyzing historical data collected from internal and external (to the organization) information systems is assumed to increase rationality and learning from experiences, and thus to perform complete cycles of choice. It was useful to examine whether this is true, in order to be more reflective about the enthusiasm by scholars and practitioners in advocating analytics as the holy grail to achieving organizational intelligence. We found the cycle a useful analytical framework for scholars and practitioners to think about analytics, and we believe that it could be revisited and used as a framework to think about other similar technologies. Further than that, revisiting this old framework brings back the never ending discussions regarding rationality and foolishness in organizations, and the balance between exploration and exploitation. It refreshes the conversation on the information processing perspective, which has become taken-for-granted in achieving organizational success.

Our analysis questions basic assumptions regarding why and how information systems should be used in organizations, and serves as a reminder that we need to develop technologies that not always make us smarter, but also afford some foolishness. Acknowledging that we do not want to fully close the circle of choice, we hope to see future research investigating how technologies such as analytics and big data, so far approached with the goal to increase rationality, could increase creativity and innovation. For example, scholars should consider how we could use data mining techniques to experiment with the outliers, or how we could use big data to play with novel, unanticipated insights (George et al. 2014; Pentland 2014). We hope that our reflection triggers the readers to stop thinking about analytics solely as the means to organizational intelligence. Instead, it is time to explore how analytics can make organizations more rational but also more foolish.

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