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ANALYTICS, INNOVATION, AND ORGANIZATIONAL ADAPTATION

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ABSTRACT

With the advent of big data, organizations are integrating powerful computing tools in their organizational processes to drive efficiencies and improve service delivery. Yet, at the heart of this conversation lies the role of analytics and big data in innovation within and across organizations. In this article, we provide a stylistic model of the role of analytics in innovation and call for further research on the underlying processes, contingencies, and outcomes.

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Globus, a premier department store chain in Switzerland, is facing a challenge where consumers have become reliant on mobile devices and social media to make purchasing decisions. Fashion trends change when someone posts a new YouTube video, which requires Globus to identify consumer fashion trends and respond with updated pricing, marketing strategies and inventory management in nearly real time (SAP, 2014). With the help of in-memory analytics, Globus is able to generate slow-seller report in 17 seconds for its entire product line, saved 98% of waiting time for its employees to get needed information for better inventory decisions, so that they can cope with rapidly changing consumer preferences. Another example is Kaeser, an air compressor systems manufacturer in Germany, where its challenges come from the maintenance of its compressor system products which are sold to 91 countries. For performance and optimal usage purposes, air compressor systems need to be maintained properly, and customers simply cannot afford any unplanned system downtime (SAP, 2014). For Kaeser, it now uses predictive analytics-based maintenance together with Machine-to-Machine module which generates real time data like energy consumption, operational status and compressed air quality from customers' compressors around the world. This gives a clear solution to predict which equipment will need service, and by when. Whether it is Rolls Royce with its "pay by the hour" model for its turbine engines or McLaren tuning its Formula One racing capabilities, the underlying changes to business models and product or service delivery is driven by *analytics*, i.e., the capability to source, store, analyze, transform, visualize, and draw insight from large amounts of data.

Information systems (IS) have played a part in innovation among organizations for a few decades where the interventions were primarily of three types: innovations confined to the IS task; innovations supporting administration of the business; and innovations imbedded in the core technology of the business (Swanson, 1994). Over the past decade, the power of big data and analytics has transformed these efforts by organizations to better manage their manufacturing processes, introduce new products and services, and create efficiencies in managing customers (McAfee & Brynjolfsson, 2014; Pentland, 2014). Particularly striking is the speed at which new services and variations on concept ideas are tested and scaled. These nascent capabilities at collecting granular (big) data and analyzing them with new tools afforded by data science has allowed organizations at the digital frontier to adapt and evolve their business almost on a daily basis – raising fundamental questions on the underlying processes, routines, capabilities, and structures by which these firms innovate and adapt (George, Haas & Pentland, 2014; Schildt, 2017). Yet, analytics-driven innovation is not well-understood by scholars and executives alike, and opens up fertile areas for creative and practically relevant research (George, Osinga, Lavie & Scott, 2016). This raises the question: *how do organizations innovate and adapt in the digital-powered information age*?

A TYPOLOGY OF ANALYTICS-DRIVEN INNOVATION

Analytics is not only an information technology, it is also an enabler of an organization's innovation processes, organization design, strategy formulation, scenario planning and risk mitigation, and performance efficiencies in manufacturing and service delivery. Analytics captures status and changes within and outside of an organization, and beyond those; it can also provide real-time and predictive insight, where previously decision makers can only look backward on historical data. Analytics, however, is still a tool – its power and transformative capacity lies in its deployment and usage in innovation processes. Analytics, thus, has the potential to help organizations adapt at a faster rate by trialing new products or internal processes to enhance efficiency or performance. Next, we develop a taxonomy of analytics implementation models and their use in innovation.

We provide a simple 2X2 taxonomy using two dimensions: Analytics Focus and Innovation Focus. By analytics focus, we refer to the organizational effort and attention is focused on the analytics itself – here, the senior management would place primacy on the analytics implementation. This implementation could be either being modular (independent and possibly localized in specific functions) or integrated (interdependent and embedded in multiple functions). By innovation focus, we refer to the organizational effort and attention is focused on the innovation outcome – here, the possibilities are simplified as product and process. In Figure 1, we classify four different models of analytics in innovation.

Insert Figure 1 Here

Type I: Analytics as Innovation (Trials). In organizations where the managerial focus is on analytics implementation as a part of the innovation process but clearly demarcated and operationalized as a separate experiment, we term this model as “trials”. Here, analytics is seen as a way to innovate, and can be seen in three different types of experiments. First, organizations which are trying for the first time to adopt analytics solution into their main business process and decision making; second, organizations which are already using certain analytics systems but are going to use a new analytics functional module for the first time; and third, organizations applying analytics solution to a new area for the first time. It is likely that a majority of firms would fall within this category because analytics is still an emerging technological capability. For example, Alliander, a national grid operator for gas and electricity in Netherlands, adopted SAP’s real-time analytics solution, which is improving their operational performance: ‘including more accurate forecasting of energy demand, greater efficiency by automating manual tasks, improved auditing and reduced energy costs for customers.' (SAP, 2014)

Type II: Innovation on Analytics (Toolkits). In this model, organizations push for technological advances (innovation) in analytics, algorithms, products and implementation methodologies. Often seen in technology companies that are producing analytics products or in R&D organizations, such as universities and research institutes, as a source for developing novel ideas on analytics. Organizations that perform innovation on analytics as toolkits tend to have the requisite technological capability and human capital to make advances for the field. For example, in Oct 2015, Teradata launched two new analytics products: Teradata Listener and Teradata Aster Analytics on Hadoop; one is for Internet of Things data processing and analytics, and the other one is to use machine learning in Hadoop to do analytics (Teradata, 2015). Other examples are research advances published in data management conferences like SIGMOD and VLDB among others as sources of innovations on analytics theories and algorithms. In these organizations, they create toolkits for application by themselves or other businesses.

Type III: Analytics on Innovation (Testbeds). These organizations perform analytics on innovation related tasks: to collect data and results from innovation generation process and innovation implementation, to do analysis, visualization and produce deeper analytical insight. Analytics on innovation can help organizations build a stronger innovation mechanism, and can even help identify innovation diffusion within and across organizations, which provide decision makers support for collaborative work. Analytics on innovation can be applied to different innovation process and tasks, like new product development, business model innovation, business process optimization, management innovation amongst others – but the clear focus is on analytics as integral to the innovation process and its use as a testbed for novel ideas. For example, Sopheon's innovation analytics platform (Sopheon, 2016) and Nielsen's innovation analytics platform (Nielsen, 2016), both provide client firms the ability to do analytics on innovation processes.

Type IV: Innovation through Analytics (Transformers). Probably the most exciting, but difficult, space to occupy in the quadrant is to drive innovation through analytics – analytics is a transformer of the organization itself. Here, the innovation process is powered by analytics, and integrated in every step of the innovation processes to develop new products or services. Amongst the four types, innovation through analytics is challenging for organizations as it requires analytics to be seamlessly integrated into the innovation process. For example, Graze, is a UK-based e-commerce subscription service delivering healthy food by post. Leveraging its proprietary analytics platform, it develops push marketing strategies that customize healthy snacks based on customer preferences. The analytics dovetails seamlessly into production, and customers then receive perfectly tailored snacks for each day of the week based on their unique preferences (Charlton, 2016). Similarly, Netflix uses data analytics for customer modeling and user experience optimization. Based on customers' preference analysis and profile, it is able to recommend and rank videos for each individual customer (Gomez-Uribe & Hunt, 2016). Analytics has become a culture in Netflix's innovation process and tasks. In both Graze and Netflix, analytics is at the heart of business transformation.

ANALYTICS FOR INNOVATION AND ADAPTATION

Irrespective of the approach that organizations adopt for their innovation/analytics focus and where they fit within our taxonomy quadrant, each type is likely to reveal varying levels of success and failure. In this section, we portray a stylistic innovation process and show how analytics could influence elements within the process. In so doing, we develop new research directions for scholars interested in innovation processes, and how analytics could pose new questions for the organization of innovation and the adaptiveness of firms.

Using a systems control lens, we model the interaction of different functional components in an organization. An adaptive system is a system with the ability to identify how the environment changes and find a way to cope with those changes while maintaining system's performance or by making improvement to the system (Åström & Wittenmark, 1995; Landau, Lozano & M'Saad, 1998). There are four main components in an adaptive system: (1) s*ensor*: to identify and capture system status and changes; (2) *feedback loop and adaptation loop*: to inform status and changes; (3) *adjustment mechanism and controller*: to process the changes and generate reaction plan; and (4) *actuator*: to execute the action plan.

Insert Figure 2 Here

To enable an organization to be adaptive, we need all the above components to be available. In Figure 2, we present the framework for adaptation by deploying analytics in the innovation processes. Innovation is shown simplistically as consisting of two parts: *Idea Generation (Ideation)* and *Innovation Actuator (Prototyping)*. In the framework, *Analytics Hub*, together with local analytics modules and data points (where data is collected), serve as a sensor, which not only senses 'surface' data, but also digs into the deeper layers of the organization. *Adjustment Mechanism* has three constituent elements: *Scenario Modeling*, *Idea Generation* and *Cognitive Updating (Problem Framing)*. *Scenario Modeling* takes an organization's input and *Analytics Hub*' output as its input to scope out a scenario for the organization's current situation, its risks, and likely development pathways; *Idea Generation* draws results from the *Analytics Hub* and provides improvement suggestions to *Cognitive Updating* based on *Scenario Modeling*'s outcome, and generates updates for the controller which is the *Decision Making* module.

Decision Making module generates reaction plans. Actuator includes two parts: *Concept Testing*, *Innovation Actuator (Prototyping)*. By receiving the reaction plans, *Concept Testing* module first performs a test run or simulation to partially verify the correctness of reaction plan. If the plan passes concept testing, the *Innovation Actuator* then executes the plan and activates an updated *Business Process (Scaling)*, thus producing new outcomes. Feedback loop is formed by the link from *Analytics Hub* to *Decision Making* module. *Analytics Hub* together with *Adjustment Mechanism* forms the adaptation loop, where an organization's performance can be measured by analytics and compared with the desired performance. Differences can be sensed, and through the adaptation loop necessary improvement can be generated and applied. Whereas this model is based on a controls systems approach, social psychological and organizational theories of innovation are embedded in its components. Process components that include ideation and cognitive updating involve heuristics, creativity, and problem framing elements drawn from design thinking precepts (Gruber, de Leon, George & Thompson, 2015).

FUTURE RESEARCH DIRECTIONS

Our framework presupposes that analytics and innovation together can enable organizational adaptation in a fast changing environment. In order to design better mechanisms for adaptation, we developed a taxonomy based on analytics or innovation focus in the implementation of analytics within the firm. By using an adaptive systems logic, we developed a stylistic model of innovation processes and integrated analytics within the model as a driver of organizational adaptation. In so doing, we provide a few promising research directions and questions on the organization of innovation, structures and capabilities, as well as the inputs and outcomes of such interventions.

There are parallels to management theories on the creative processes underlying innovation, how feedback and cognition can deliver new insights and influence which problems are likely to be solved through new ideas (Haas, Criscuolo & George, 2015; van Knippenberg et al., 2015), and the links between creativity, idea generation, and implementation (Amabile, 1996). The roles that individual elements within the framework play in the process could vary within and across organizations and their units (figure 2). Doing so generates variety in how innovation processes are implemented with analytics either at the core or at the periphery of the business. For different types of organizations (e.g., small businesses *vs*. large corporations; single *vs.* dispersed locations; simple *vs*. complex products), what are the differences in their objectives and needs for using analytics and innovation to enable change? The strategic role of analytics within the innovation ecosystems could well be driven by our proposed taxonomy and the relative emphasis placed on analytics. Studies could examine, how and when organizations are likely to succeed through innovation by their adoption of analytics and their modular or integrative focus (figure 1).

Our model raises fresh questions on how organizations perform "course corrections" or create strategic flexibility, and the use of analytics to draw strategic insights for innovation. Given the nascent implementation of analytics, scholars could be well-positioned for research on the resources needed for building analytics as a dynamic capability, which enables adaptation and change. Our current models of innovation are primarily unidirectional where we make investments sequentially, perhaps analytics can transform innovation processes by reducing cycle times between concept and testing as well as prototyping and scaling? Schildt (2017) provides further research areas for exploration on the role of analytics in professional work environments and organizational design. Similarly, there are behavioral explanations for the use of analytics in innovation, including questions on how executives derive insight from data, how their attention is allocated across problems or environmental cues, and how employees accommodate changes in their creative work processes. These raise fundamental questions on whether we are at the crossroads of innovation processes itself.

REFERENCES

Amabile, T. 1996. *Creativity in context: Update to the social psychology of creativity*. Boulder, CO, US: Westview Press.

Åström, K., Wittenmark, B. 1995. *Adaptive control*. Reading, Massachusetts: Addison-Wesley.

Charlton, G. 2016. *How technology and data has driven innovation for Graze*. https://www.clickz.com/how-technology-and-data-has-driven-innovation-for-graze/100706/ (accessed October 12, 2016).

George, G., Osinga, E., Lavie, D., Scott, B. 2016. Big data and data science methods for management research. *Academy of Management Journal*, 59(5): 1493-1507.

George, G. Haas, MR., Pentland, A. 2014. Big data and management. *Academy of Management Journal*, 57(2): 321-325.

Gomez-Uribe, C. & Hunt, N. 2016. The Netflix recommender system: algorithms, business value, and innovation. *ACM Transaction on Management Information Systems*, 6(4): 1-19.

Gruber, M. Leon, N, George, G., Thompson, P. 2015. Managing by design, *Academy of Management Journal*, 58 (1): 1 – 7.

Haas, M.R., Criscuolo, P., & George, G. 2015. Which problems to solve? Online knowledge sharing and attention allocation in organizations. *Academy of Management Journal*, 58(3): 680-711.

Landau, I. D., Lozano, R., & M'Saad, M. 1998. *Adaptive control*. London: Springer.

McAfee, A., & Brynjolfsson, E. 2014. *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. New York: W. W. Norton & Company.

Nielsen. 2016. http://innovation.nielsen.com/innovationanalytics2 (accessed October 9, 2016).

Pentland, A. 2014. *Social Physics*, NY: Penguin.

SAP. 2014. *Real-time enterprise stories*. http://www.sap.com/bin/sapcom/en_us/downloadasset.2014-10-oct-13-21.sap-hana-real-time-enterprise-stories-pdf.bypassReg.html (accessed October 9, 2016).

Schildt, H. 2017. Analytics and organizational design. *Innovation: Organization and Management*, this issue.

Sopheon. 2016. *Innovation Analytics and Big Data for Innovation Success*. https://www.sopheon.com/innovation-analytics/ (accessed October 9, 2016).

Swanson, EB. 1994. Information systems innovation among organizations. *Management Science*, 40(9): 1069-1092.

Teradata. 2015. *Breakthrough Teradata Software Pushes the Analytic Edge with Internet of Things Data*. http://www.teradata.com/News-Releases/2015/Breakthrough-Teradata-Software-Pushes-the-Analytic-Edge-with-Internet-of-Things-Data (accessed October 8, 2016).

van Knippenberg, D., Dahlander, L., Haas, M., George, G. 2015. Information, attention and decision-making. *Academy of Management Journal*, 58(3): 649-657.

FIGURE 1
A Taxonomy of Analytics and Innovation

		Analytics Focus	
		Modular	Integrative
Innovation Focus	Process	Type I Analytics as Innovation "Trials"	Type III Analytics on Innovation "Testbed"
	Product	Type II Innovation on Analytics "Toolkits"	Type IV Innovation through Analytics "Transformers"

FIGURE 2
A Stylistic Model of Analytics, Innovation, and Adaptation