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From Big Data to Thick Information: Revisiting the Process of Information Production in Organizations

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Research-in-Progress

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Extended Abstract

We are living at the cusp of an 'information age' (van Knippenberg et al. 2015), which can be characterized by the new epistemic technologies - tools that play a key part in the ongoing construction of knowledge (Anthony 2018) - such as big data analytics (BDA) as well as advancements in the existing epistemic technologies such as machine learning algorithms (referred to as 'algorithms' for simplicity).

Facilitating "informating" role of the information systems (Zuboff 1988), these epistemic technologies bring promising propositions to the organizations in enhancing descriptive as well as prescriptive power of decisions (Agrawal et al. 2018; Brynjolfsson et al. 2016). To leverage these promises, several large incumbent firms in long-standing industries have started using new epistemic technologies as key elements of organizing practices over recent years. However, before this promise could be leveraged, organizations need to align their decision-making processes (Shrestha et al. 2019) and researchers need to understand how these changes manifest in practice (Faraj et al. 2018).

To understand the phenomenon holistically, it is important to understand the nature of such epistemic technologies, which rely on the production of data and information - both purposeful and unpurposeful (Constantiou and Kallinikos 2015) - as well as the application of algorithms to make sense of data in "rational" ways (Lindebaum et al. 2019). The increased reliance on data and algorithms poses unique challenges for organizations and has given rise to several debates in the academic community (Günther et al. 2017). This calls for a better understanding of distinct digital practices that are enacted as organizations actually leverage such technologies in practice (Baiyere et al. 2017)

This study responds to such calls of examining the use BDA and algorithms in organizational context by drawing on and contributing to the information systems and organizational theories. A central theme of the Carnegie School tradition (Cyert and March 1963; March and Simon 1958) is the role of information processing (Gavetti et al. 2007) focused on the managerial cognition manifested in social setting. Information (or insights) is treated as one of the key inputs in decision-making and accordingly focus has been in describing how information is processed in organizations and how these processes influence decisions.

On a slightly different terrain, a limited scholarship in organizational theory as well as information systems has focused on the processes that contribute to production of information and insights before the insights are processed and used in decision-making by managers. For instance, Feldman & March (1981) provide a succinct account of decoupling between information and decision-making in organizations. There are conspicuous features that hinder instrumental use of information, that include: "First, ordinary organizational procedures provide positive incentives for underestimating the costs of information relative to its benefits. Second, much of the information in an organization is gathered in a surveillance mode rather than in a decision mode. Third, much of the information used in organizational life is subject to strategic misrepresentation." (p. 175).

Parallelly, beyond the managers and decision-makers, a distinct group of professionals – analysts - play a vital role in information production. , Schultze (2000) depicts an account of three categories of knowledge workers –competitive intelligence (CI) analysts – about their practices of information production. In functioning as internal consultants, these analysts endeavored to be perceived as impartial and objective by the business users. Feldman (1989) in her study of bureaucratic analysts depicts how these analysts produce information and how these processes influence policy-making in the government agencies. These policy analysts have hard time valuing the kind of work they do as they follow problem solving and rational perspective. "Analysts do represent their offices and the positions supported by their office. However, they are not simply mouth-pieces… they not only represent what their bosses want to have in a report, but they also have responsibility of informing and persuading their bosses about the proper position for the office to take." (Feldman 1986, p. 73-74).

This study extends this line of research around information production to the context of new epistemic technologies and emerging profession of data analytics. It does so by asking the research questions: how data analysts generate insights from (big) data and how such insights influence the decision-making processes in large incumbent firms?

Following the qualitative case study methodology, the study is grounded in the context of banking industry with three large industry incumbents as research sites. All the sites have incorporated their new analytics units hosting a team of data analysts to cater to their need to become data-driven over last 3 – 5 years. These units share their insights with business users and managers in other departments (e.g., marketing, credit, retail assets, etc.), who in turn use the insights in making decisions. The data sources include semi-structured interviews, archival records, as well as observations including shadowing, meetings, and informal discussions.

While the fieldwork for the study is still going on, some of the initial observations are reported herewith. Overall, the data analytics units perform two key tasks: one is providing solutions to the requirements (problems) raised by the business users (e.g., marketing team, retail assets team, cards team) and the other is generating data-driven insights without a specific problem in mind. The first task could range from data extraction to automation of dashboard using visualization tools to building complex machine learning models to solve a business problem. For a typical modeling problem, the business analysts from team are the first point of contact with the business users. They iteratively exchanges thoughts with the business users to understand the problem. Once they believe they have a good grasp of the problem, they involve the data scientists in the team to work on the problem. Data scientists will make series of choices in generating insights from the data. The insights are then shared with business users with help of business analysts, team leads and sometimes the visualizers. The process will iterate until the solution gets accepted by business users and taken to the execution.

Parallelly, data analysts also allocate a portion of their time in conducting exploratory data analytics. This is one of the reasons of setting up such departments in many large organizations. The organizations believe that they are sitting on a huge pile of data which they have never been able to incorporate in their decision-making, and now they want to make use of it for better outcomes. In this process, the data scientists don't generally have a specific deadline. They slice the data in diverse ways, chose from several algorithms, run models, and try to interpret the results. They iterate until they feel they are onto something interesting and important. They generally try to generate several alternative scenarios which then are shared with potential business users with the help of business analysts and visualizers. From there, sometimes some of the insights proposed find a home with a business team who is ready to implement it. Depending on the success of such implementation, the insights sometimes are also shared across other business teams.

Initial qualitative coding of data around these two tasks imply some emergent themes. First, a large part of what data analytics professionals do is solving the problems of business users / managers. This process affords them limited ability to bring data-driven logic as they are constrained by the mental models of business users, both in defining the problems as well as dictating the parameters of interest to be considered in modeling. While solving such business users-induced problems, sometimes the data analytics professionals also undertake exploratory data analytics and generate new insights. These insights work as solutions to the problems which business users did not conceive before. In this process, they have much more freedom in deciding the parameters of interest, the domain of priority, the algorithms to apply and so on. Hence, the process is contingent upon what data analytics professionals are, what they know, and what are their mental models. Together, the two processes, business users-induced problem solving, and exploratory data analytics are intertwined in a recursive loop and influence the organizational attention in intended as well as unintended directions. In a way it also demonstrates the extent to which the new epistemic technologies affords organizations to become data-driven against the backdrop of intuition based decision making processes.

Second, there are distinct mechanisms through which the insights generated by data analysts get consumed by business users in their decision-making. For instance, when data analysts complete one project with a particular business team (e.g., Personal Loans), it travels through the evaluative spillovers (Bechky 2019) as well as "brute-force spillovers" to other business teams (e.g., Consumer Loans) in form of success stories. The role of reporting dashboards depicts another set of mechanisms. Automation of dashboards using visualization tools (e.g., Tableau) is one of the lowest hanging fruits the data analytics teams do to establish their identity in the organizations. In the process, the data analysts use dashboards as a tool to influence the attention span of business managers highlighting the specific gaps which they wish to address with analytics. Hence, the extent to which there is a tight coupling among the reporting analysts / visualizers and the data scientists within the team, determines the fate of insights being consumed in business decision-making. However, this tight coupling also results in some unintended consequences.

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