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Trust, Organizational Decision-Making, and Data Analytics:
An Exploratory Study

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ABSTRACT

The use of data analytics of all kinds is making inroads into almost all industries. There are many studies that explore the usefulness and organizational benefits of these tools. However, there has been relatively little attention paid to the other issues that accompany the implementation of these tools, namely the level of trust felt by the consumers of the information products of these tools and the changes in decision-making caused by the introduction of data analytics. It is important that the level of trust these decision-makers have in their analytics tools be understood as that will have great impact on how these tools will be used and how the firm will use them to build value. This study examines the level of trust organizations have in their analytics tools and how these tools have changed their decision-making processes. This study will add to the broad understanding of how and where data analytics tools fit into the data-driven organization.

KEYWORDS

Data Analytics, Organizational Decision-Making, Qualitative Methodology, Trust

INTRODUCTION

The use of some form of data analytics has become commonplace in a growing list of industries around the world. While the manner of application, the specific tool used, and the very definition of data analytics varies widely across firms, industries, and countries, there are a few common themes that deserve investigation. Within some tolerance for individual interpretation, the underlying reason for employing these tools is to help the organization make better, faster, and less expensive decisions (Davenport, 2013). However, even though these decisions are supported by sophisticated technology, the underlying core ingredients of decision-making must still be in place: suitable information and appropriate knowledge. The information being made available by analytics tools is increasing in sophistication, relevance, and depth very rapidly. Likewise, the knowledge to make decisions is becoming more abundant in both the human decision-makers and, in an increasing number of cases, in the software being implemented to take over the decision-making task. Disruptive changes such as these will likely be met with concomitant organizational reactions, and it is these reactions that this paper seeks to understand.

One of the most important, but somewhat understudied, characteristics of the information used by decision-makers is that it be trusted (Söllner, Hoffman, & Leimeister, 2016; Bruneel, Spithoven, & Clarysse, 2017). Trust can be defined as "the subjective expression of one actor's expectations regarding the behavior of another actor" (Baba, 1999). The evaluation of information as a trustee (with the organization as trustor) might refer to its accuracy, its validity, its provenance, or any other

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aspect of the information or its creation that an information consumer might find important. Up until the recent past, information was provided through a relatively easy to understand process that was, if not completely transparent, understandable to the typical manager or decision-maker. This basic understanding of how the data were collected, processed into information, and presented for use is what enabled the information consumers to trust the data enough to use in making decisions. However, the increasing use of externally sourced data, remote or contract information systems (IS) support, and other factors that muddy the provenance of the information has served to reduce the trust placed in the information available. The introduction of tools like predictive and prescriptive analytics and the proliferation of data analysts who create the models have created even more distance between the information and its user. This study explores the impact this changing information environment has on the trust that managers place in the information they consume.

Just as there is no single definition of data analytics, there is no single definition of a data analytics tool. In this study, the concept of a data analytics tool is necessarily broad because the variety of data analytics tools used by the firms in this study is very broad. Some are using very advanced prescriptive decision-support and decision-making tools, as in the case of the financial services firm, and some are using only entry-level data visualization tools, such as the university. And, some are using a broad mix of tools across the analytics spectrum, such as the insurance firm and healthcare organization. Therefore, the term "data analytics tools" will be used to represent the spectrum of tools in use at a specific organization. It will be left to further research to make an analysis of the issue of trust in terms of specific classes of analytics tools.

Some authors consider trusted information to be an essential input to the decision-making process (Browne, 1993). As such, the level of trust given to analytics-derived information leads into the second goal of this research, to determine if the implementation of analytics tools has changed the manner in which organizations make decisions. This is very broad, since the concept of changes in the decision-making processes might include the actual analyses performed, the location in the organization in which the decisions are made, or even the type of decision being addressed. In fact, it could encompass a combination of all three characteristics, or more. As this is an exploratory study, part of the results will be to determine which of these decision-making characteristics are affected by analytics and in what manner.

LITERATURE REVIEW

There is a large body of literature surrounding both the issue of trust (Pirson, Martin, & Parmar, 2017; Huang & Wilkinson, 2013) and how trust relates to the use of information (Ebrahim-Khanjari, Hopp, & Iravani, 2012; Denize & Young, 2007). This literature review will focus on the latter in the first subsection as that is a more relevant topic. Likewise, there exists a very large body of work surrounding the act, and art, of making decisions, and a somewhat smaller body surrounding the part played by analytical tools in making decisions (Verhoef, Kooge, & Walk, 2016; Hardoon & Shmeuli, 2013). The second sub section will focus on the role of analytics in making decisions as a more fruitful path toward locating the present study.

Trust and Information

The literature describing the linkage between trust and information falls into a few categories. Sacha et al (2016) suggest that the trust placed in the data being provided by an information system is a factor of the type of user consuming the information. Whereas a subject matter expert might accept a relatively large amount of variation and unexpected results from an analysis, novice users are more likely to be thrown off by unexpected activities within the system, thus damaging whatever trust had already been built. Muir (1987) points out that this trust, once lost, is very difficult to rekindle. Sacha et al (2016) also deal with the situations in which the user is aware of uncertainties in the system. The existence of uncertainty leads to a reduced level of trust by the user. Only when the user is convinced there are no major uncertainties, even if this belief is mistaken, will the user's trust in the system be considered high.

Provenance is the key to having trust in information according to Lemieux (2016). Though various definitions abound, she defines provenance as "the description of the origins of a piece of data and the process by which it arrived in a database." The author points out that in the current technological environment, provenance of information is often much more complicated due to the distributed nature of data capture, storage, and processing.

Trust in data is often tied to the user's trust, or lack thereof, in the technology providing the information. Walker (2016) suggests that e-commerce participants have more trust in the system and its activities when they feel like they are sharing information with the system rather than "surrendering" their information. She describes a process and level of transparency that promotes a more equitable usage and distribution of information as being one in which the user is less likely to feel at the mercy of the system. She also points out that for many users, trust is taken for granted until it is violated. A similar pattern emerges in Ho, Ocasio-Veláquez, and Booth (2017) in which they find that a user's perceived riskiness of cloud computing has a significant effect on their intention to trust the technology and its handling of their data, which in turn will affect their willingness to adopt a cloud solution.

One last view of data trustworthiness centers on the perceived quality of the data. Certainly, definitions of data quality will vary widely across the spectrum of information consumers, but Goetz (2015) suggests that whatever the specific user's definition of high quality data is, if it is not met then those data, and the information derived from them, will likely be given a lower impact in the decision-making process, if they are considered at all. Data quality is linked directly to the transparency of the processes that capture and treat those data and the degree to which the information derived from those data are aligned with the needs, both tactical and strategic, of the user.

This subsection of the literature review demonstrates that the decision-maker's trust in the information provided has many roots and that the user's perception of the quality of the information and its underlying data is what drives its perceived usefulness. The underlying theme is that the propensity to trust information might vary with the type and experience of the user, but the major driver is an understanding of the provenance of the data, the transparency with which it is handled, stored and transformed, and the degree to which the user understands and trusts the underlying technologies providing the information.

DECISION-MAKING WITH ANALYTICS

Decision-making within a data analytics-driven environment differs from "ordinary" decision-making in that the expectations are usually heightened in terms of decision time, quality, and even scope (Davenport, 2013). Decision-makers and their immediate customers/supervisors might have inaccurate preconceived ideas about what analytics-enabled decision-making will be able to do for the organization. However, as Bartlett (2013) makes clear, the decision-making framework in an analytics-driven environment is much the same as the pre-analytics world: Frame the problem, execute the analysis, interpret the results, and make the decision. While advanced analytical capabilities will likely modulate how these steps are accomplished and by whom, they are still required to be done.

It is widely understood that a steady supply of high-quality data is a prerequisite for successful analytics and decision-making (Shorfuzzaman, 2017) and that data empowers decision-making (Monino, 2016). There are many challenges that must be addressed and overcome in order for the analytics-driven decision-making process to be successful. The data, models, and underlying model parameters are much more dynamic in most analytics environments in order to respond to increasingly rapid changes in those environments (Liu et al., 2016). Therefore, the effort put forth to continually deal with these conditions often require much more effort than in a more traditional decision-making environment. Without this vigilance, models age and become less and less relevant and useful, thus making them less able to create sustainable competitive advantage. The very unfortunate result is not simply a decrease in decision-making capabilities, but that these handicaps often go unnoticed by decision-makers until they have been in place for some time (Bartlett, 2013).

In order for the value of analytics to be realized, the organization must develop or adjust their decision-making culture by, for example, increasing the collaboration between the various actors in the decision-making process (Frisk & Bannister, 2017) and expanding the scope of people involved. In some advanced organizations, this scope expansion might include both human and autonomous systems working collaboratively (Hirsch, 2018). Of course, in order for this increase in collaboration to bear fruit, the people involved must be properly prepared, and this includes the managers who oversee the processes (Badiru, 2017). This becomes especially important when the character of many contemporary decisions is examined. Rarely is there but one decision variable to consider. In most cases involving significant increases in organizational value, or when dealing with business issues of considerable import, many decision criteria are involved. Multiple Criteria Decision Making (MCDM) has been an important field of study for many years (Zionts, 2000) and requires a much fuller understanding of the decision-making milieu (Ramanathan, Ravindran, & Mathirajan, 2017) as well as the tools available to the decision-making staff. Even though many tools exist that do not require a deep understanding of the underlying mathematics to use, interpreting the output of these tools does require both an understanding of the math involved as well as a significant understanding of the business situation in which the results are to be applied.

There are, as this section of the literature review points out, many aspects of the decision-making environment that must be considered by those designing the organizational processes within which the decision-making takes place as well as those making the decisions. It also points out that there is a strong relationship between the decisions being made, the person or people making them, the data/information being used as input, the decision-making processes, and the technologies employed. It should stand to reason that, all other things being equal, a change to one aspect of the decision-making environment, for example the people involved, would have some impact on the decision-making results (i.e. speed, accuracy, scope, etc.) and if this aspect of the environment is substantially changed, there must be a concomitant change in other aspects of the environment (or the decision quality). In the case of data analytics, significant changes are being made to the information being consumed, the data that underlies it, the processes being used to convert the data into information, and the technologies used to perform those transformations and present the results to the decision-maker. Each of these changes if taken individually would be considered significant. However, in many cases they are all being made simultaneously, and that is the basis for this research.

RESEARCH QUESTIONS AND METHODOLOGY

Research Questions

The literature reviewed in the previous section demonstrates the importance of a user's, and an organization's, trust in their data and information resources. This trust is the product of a number of important ingredients coming together properly, not the least of which are the sources and methods used to gather the data and process it into information (provenance), the quality of the data (which is often driven by capture methods and measurement tools), and the systems that deliver the information to the user. In the present study, it is that delivery method (data analytics) that is under scrutiny. Conventional information systems such as spreadsheets or relational databases are well accepted from a technological standpoint so the information delivered by these platforms does not suffer from technologically-driven trust issues. However, with many decision-makers, their level of familiarity with analytics is often lower than with the legacy systems they replace or supplement. This fact, combined with a lack of understanding of the underlying mathematical and statistical activities, especially in upper management, might lead to a lack of trust in the results of the data analytics tools. Therefore, the first research question approached with this project is:

Research Question #1: Do organizations approach data analytics tools, and the information they provide, with the same level of trust as with legacy information technology?

The second reason for this research is to understand the impact the current analytics tools have on the organizational decision-making process. Since information is one of the basic inputs to decision-making, and the quality of the information (including its accuracy, format, and relevance) is an indicator of the quality of the decision, then it is important to understand whether the implementation of data analytics has had an impact on how decisions are made. Moreover, it is important to understand if other aspects of decision-making have changed such as who makes the decisions and where they are located in the organization, what types of decisions are being made, and whether the quality of the decision (however that is measured by the organization) has changed. Thus, the second research question is:

Research Question #2: Does the implementation of data analytics have any impact on the decision-making process or the characteristics of the decisions being made?

Methodology

Because of the exploratory nature of this project and the fact that there have not been any similar inquiries made yet, a qualitative methodology was chosen as the appropriate approach to these research questions. In this case, a set of semi-structured interviews were performed with managers from six organizations representing five industries: financial services, health insurance, manufacturing (2), higher education, and healthcare. The diversity of industries is intentional and provides an opportunity to explore many different types of analytics installations. There is also significant diversity in the length of time the analytics tools have been in place, ranging from fifteen years (financial services) to still being in the implementation phase (higher education). Within each firm, the participants were drawn from the ranks of the IT management, ranging from the Chief Technology Officer (CTO) of the financial services firm to IT Director at the manufacturing firms, to IT Manager at the university. The participant from the health insurance firm, besides being a member of the IT management team, is also an SAP Analytics Coach. IT management roles were selected because they have the most comprehensive perspective on the use of data analytics tools across the organization. From this vantage point, they are in a position to assess the interaction between the technology and the organization and thus address the research questions posed above.

Before discussing the specific research procedures, a discussion of sample size is necessary. Sample size with reference to qualitative studies, specifically interviews, is not well standardized or easily calculated as with quantitative studies (Marshall et al., 2013). The generally accepted guideline of performing interviews until no new data is collected is easy to understand, but often difficult to operationalize. Another difficulty is to determine how many interviews to conduct after the researcher identifies the point of no further data being collected (Patton, 2002). In attempting to recruit research participants for this study, forty-two potential participants in thirty-eight different organizations across multiple industries were contacted, but only six full-length interviews were completed. However, the level of redundancy in the data was reached rather soon, so the suggested criterion for limiting the sample size was likely reached even with the challenges encountered (Boddy, 2016).

The interviews were conducted either over the phone or in person and the average length was approximately 55 minutes. The interviews were semi-structured and included questions exploring the types of data analytics tools in use, the length of time they have been in place, and organizational reactions to the implementation of these tools including changes in decision-making processes and the level of acceptance of the results of their output. In keeping with the suggestions of Glaser and Strauss, (1967), Glaser, (1978), and Glaser, (1992), the data analysis began immediately and continued in an iterative process throughout the period of data collection and analysis. This process of "constant comparison" is one of the keys to the grounded theory methodology (Urquhart, Lehmann, and Myers, 2010). Through this process of open coding, concepts of interest are identified in the data, in this case aligned with the research questions noted above, and are categorized based on the data. As more data are collected and compared with existing data, certain themes emerge and are analyzed for relationships. This is accomplished using "selective coding," or coding that focuses on constructs that help to explain the interactions between categories (Glaser, 1978). Finally, "theoretical coding" takes place with the aim of creating inferential statements that help to describe the phenomena under study. These relationships will form the basis for any theoretical statements that can be made from the data (grounded theory).

FINDINGS

Trust in Information

It oversimplifies the findings to suggest that there are only two types of organizations: those that trust their data and those that are more skeptical. On the surface, however, that is exactly what happens in this study. Led by the financial services firm, there is a majority of the organizations in the study that have few worries over using the information provided by their analytics tools. The CTO of the financial services firm suggested that analytics are "endemic" in his firm, and indeed in his industry. The question by employees is not whether analytics will play a role in a particular process, but rather "Yeah, what analytics are we using?" The CTO dates the beginning of the "analytics age" in the financial services industry to approximately 2005, so this organization, a major presence in the industry and a driver of analytics, has had a great deal of time for its employees to become comfortable with the tools and for a "data culture" (Torbeck, 2011) to mature. As such, there is significant trust in both the information provided by the tools as well as the tools themselves. For instance, many of the departments in the firm that utilize analytical tools to support decision-making have begun moving their analytic tools to various cloud providers. While the "public" reason for this shift is given as cost savings and/or increased flexibility, the CTO suggested that it is also a tool used to gain or maintain internal influence by demonstrating to upper management how efficiently a department can develop proper analytical capabilities.

Following the financial services firm in experience and comfort with analytics is the health insurer. A major entity in their industry as well, they have undertaken a major effort in the past 5-7 years to embrace advanced analytics to support decisions ranging from coverage options to the amount paid on various types of claims. As with the financial services firm, they have actively promoted their data culture and built a substantial analytics architecture and support system. Their level of enthusiasm extends to the identification of individuals within the firm who are designated as leaders or coaches to play the role of promoters of an analytics-based decision-making environment. The trust that management has in their information emanates from two primary sources: they have a well-developed data quality plan in place and they were involved with the selection of many of the analytics tools that have been implemented. This is especially true of the data visualization tools that are the primary analysis tool of upper management. They were given the opportunity to gain a level of familiarity with the tools prior to full scale implementation, and this coupled with an understanding of the underlying data quality characteristics of the input data gives management an understanding of what the information provided by the system can be counted on to represent, and what its limitations are. In turn, they have great confidence in the information passed to them by their subordinates: "your senior directors and directors with their better data that their tools and their stats bring them are more confident in recommending the decisions that the folks [upper management] should make."

The healthcare organization, which includes a group of hospitals and various outpatient facilities, has a similar level of trust in the information provided to their decision-makers, though for a somewhat different reason. The upper management has had a great deal of visibility on how the various "home-grown" analytics tools have been developed over the years and this, combined with the ability to perform certain manipulations and drill-down beneath the processed information provided by the system, gives them a certain level of comfort that they can rely on the information provided: "We had a good level of trust in our in-house stuff that we've built over the years and I think that comes from the ability to drill down right down to the individual event with a patient and a doctor." Though it is a regional healthcare system, there is relatively little organizational distance between the decision-makers in the administration and the IT leadership and staff. With this proximity there is ample opportunity to build a high degree of trust in the tools, the staff that develops them, and the information they provide.

This is not quite the case with the analytics built into the medical records software implemented within the last two years. This system, like most commercial off-the-shelf (COTS) tools such as this, come with many vendor-supplied analytic tools that, while useful, do not enjoy the same level of confidence as those developed internally. As stated by the IT manager: "So, I think you get that initial distrust when you see something that you're not used to." Therefore, they require more explanation about how they work and, consequently, their adoption and absorption into the organization has been much slower.

The manufacturing firms in the study have a slightly different relationship with the output of their analytics tools. These firms have been in the analytics space for less than five years each. The information provided tends to revolve around the various internal activities of the firms and their purpose is to provide a deeper insight into the internal processes as well as the characteristics of the products they create. They are not creating new information as much as they are providing a more complete picture of the data they already collect. Historically in one of the manufacturers, the IT department has had a large role in the creation of reports and other documents that represented the information required to make decisions, but with the new analytics tools there is more opportunity for "DIY" information creation, and therein lies the root of the trust issues that reduce the management's enthusiasm for the new tools. In order for the management to utilize the datasets made available to them by IT, they require the IT management to "certify" that the information has been properly created. However, as more capability has been provided to the user, IT has begun requiring the users, or owners, of the information to check it and make sure it is what they wanted. There is some question about whether the management groups that have taken responsibility for information checking are actually performing all of the necessary checks ("A lot of times they sign it off, but really did you sign off on it?"), resulting in a somewhat disorganized information ownership environment.

Finally, the level of trust in the information provided to the decision-makers in the university is very high. The administration, starting with the new president, is anxious to see the information these tools can provide. Currently, they are limiting their implementation to visual analytics tools, but the expectation is that they will eventually expand to some form of predictive analytics. The process of selecting that tool is taking place within a multi-disciplinary committee that includes members of the IT and administration community. While they appear to have settled on a specific tool, they continue to debate the functionality required and other technical issues. They have yet to address the processes that must be in place that are typically necessary to engender trust in the information. For example, they have not dealt with data quality issues or data governance beyond what was in place prior to the analytics implementation. Whether they believe that the current processes are sufficient or these issues have just not entered the conversation yet is not clear. However, these discussions appear to be unnecessary because the administration seems to have complete trust in the information that will eventually be provided. According to the IT manager interviewed for this study, the president's office is "looking forward to having that API where I can just create a dashboard and every month – viola!"

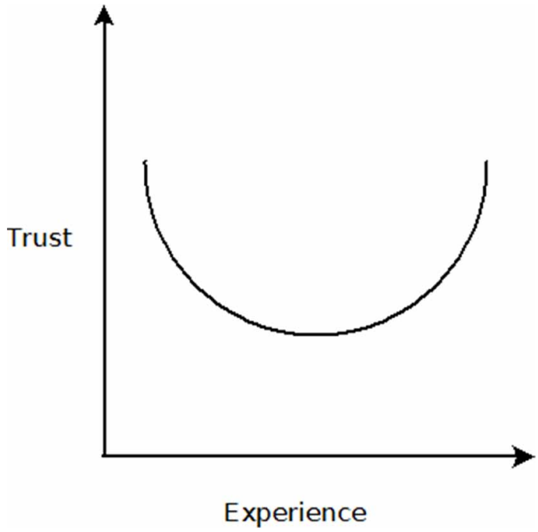
These results can be viewed through a few different lenses, the first of which is the length of time that the analytics tools have been used in the organization. For those firms with a long history of using data analytics tools such as the financial services firm and, to a lesser extent, the healthcare insurance firm, there has built up a relatively high level of trust in the tools and the information they provide. This is likely due to the confidence they have gained in the tools as their results continue to bring value to the organization. As the level of experience decreases, the level of trust within the ranks of the information consumer begins to decrease, as with the healthcare organization, and to an even greater extent, the manufacturing firms. These firms do not have the same level of experience and confidence in the tools, and so they still approach their results with some level of trepidation. This might not be globally true within the organization, as is the case with the healthcare organization that has a high level of trust in their internally developed tools, but less so in their COTS products. Finally, the level of trust rises again when the university is considered. This organization is still in the implementation process and thus has not yet spent a great deal of time working with the tool and finding its capabilities and shortcomings. They might also still be working with, and believing, the marketing information being sent to them by the vendor and, in this case, the IT group who are leading the charge for a particular vendor's tools. Thus, the relationship between the length of time the tool(s) have been in service and the level of trust the various organizations have in its results is shown in Figure 1.

The second lens through which these findings can be viewed is that of the organization's regulatory environment. The financial services, health insurance, and healthcare organizations all exist in highly regulated environments. In each case, the need to collect, store, transform, and act upon their internally generated, and sometimes externally captured, data is crucial to their continued success. For example, the financial services firm must maintain certain capital reserves to protect against insolvency due to risk or economic variables. The insurance and healthcare industries have similar requirements. These requirements drive the organization to become more data centric and therefore drive their data culture. The manufacturing firms have no such data requirements and therefore their data analytics implementations are driven strictly by competitive pressures. While these are obviously important influences, they depend largely on the competitive environment and the characteristics of the competitive advantage sought by the firm. In the case of these manufacturers, they are both in relatively stable industries with little dynamism, substitute products, or new entrants (Porter, 1990). Thus, they have the "luxury" of not being "forced" to use analytics. Last, the university is implementing their analytics tools for strictly internal purposes. They are in a stable competitive position and have no regulatory or accreditation-related reasons to use them, thus they are not under the same pressures to make them work that the other more heavily regulated organizations are. The relationship between the level of trust and the intensity of the regulatory environment is shown in Figure 2. This relationship is the result of firms in the more highly regulated industries being forced to use certain analytical techniques to maintain compliance with certain financial and operational requirements, thus they are compelled to develop and acquire tools that they have trust in. Those firms that adopt these tools for strictly internal purposes can be more skeptical of them until they gain sufficient experience.

The final lens through which these findings can be interpreted is whether the tools in use have been developed within the organization or were purchased from a vendor. It appears that those firms with an internally-focused development process such as the financial services and healthcare organizations tend to have a higher level of trust in the systems and their output than those that depend on external sources of analytics systems such as the manufacturing firms.

There are a few outliers to deal with, however. First, the health insurance firm does not develop its own systems but still has significant trust in their output. It could be that the effort they put into successfully implementing these tools, to the point of creating IT staff positions to act as coaches, might have overcome the issues associated with tools developed outside the firm. It might also be that the data culture in the firm is strong enough to enable it to move beyond the natural mistrust of new systems. Also, the analytics tools are primarily provided by their legacy Enterprise Resource Planning (ERP) vendor, adding additional reason to trust them. The second outlier is the university that has yet to fully implement their analytic tool and, by this relationship, should be highly distrustful. Yet, they are very willing to trust the outputs of the system. This could be due to their inexperience or willingness to believe the marketing information. Further research is needed in this area to gain a fuller understanding, but at this point the data broadly suggest that the trust placed in an analytics tool and its output decreases as the location of the system's development moves outside the firm (Figure 3).

Figure 1. Relationship between trust and analytics experience



The findings detailed in this section demonstrate that the trust felt by various organizations in the information provided by their analytics tool is the product of a number of factors such as the amount of experience they have with the tools, the regulatory environment in which they operate, and possibly where the system was developed. Other possible factors include the level of competition in their industry sector and the type of architecture the system runs on (i.e. on premise vs. cloud), but the data do not support making these assertions. In the next subsection, the findings regarding the impact analytics have on the decision-making processes are presented.

Decision-Making Processes

The data collected pertaining to the effect the implementation of data analytics has on the organization's decision-making processes shows much less order. These organizations display a wide range of responses to the introduction of these technologies. Without a doubt, the financial services firm, and presumably a large swath of the industry, shows the largest, most extreme departure from pre-analytics decision-making processes. The research subject (the CTO) used the loan approval process as an example. As the analytics tools were being implemented, they were perceived to be decision aids for the loan granting decision makers, usually the bank or branch manager. The rollout of the system was planned for two years, but after six months the upper management saw how well the system worked and changed the process completely. Instead of acting as an advisory tool, the decision was now made by the system and the manager had the opportunity to appeal those decisions that were deemed incorrect. This change took the authority to make decisions away from the human and placed it squarely with the technology. The CTO pointed out that the results of this might be better decisions and a larger net profit, but it comes at the expense of a decrease in the decision-making skills of the employees: "They're being trained to use the system, not to make decisions." Certainly, this brings with it various potential organizational issues, not the least of which is a decreasing skill base, a reduction in middle management, and a less satisfied employee cohort.

Other organizations saw a decentralization of decision-making once the analytics tools were implemented. One of the manufacturers noted an increase in the formation of committees that were charged with using the analytics tools to identify opportunities and formulate plans to capitalize on them. These were both internal and external opportunities. The committees were usually ad hoc in nature, but some continued to exist well past the point of being considered temporary. These teams

Figure 2. Relationship between trust and regulatory intensity

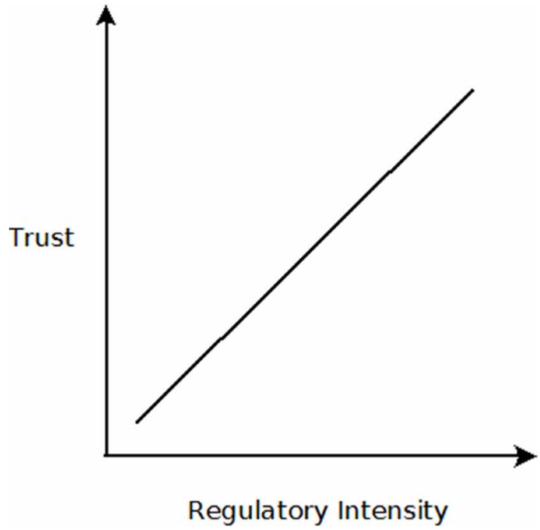
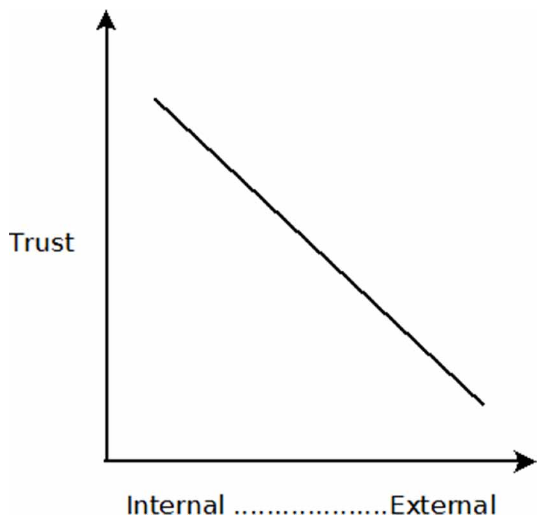


Figure 3. Relationship between trust and location of system development



centered on the self-service analytics tools that allowed them to create their own information, with IT assistance. In many cases, IT support was embedded in the team. But there are still significant growing pains because "Nobody understands the changes taking place in the business… They're struggling and trying to understand themselves what works."

The higher education institution in the study can already see that there will be significant decentralization of decision-making once the tools are fully implemented, though many in the organization approach this with a fair amount of trepidation: "But other people are thinking, oh, if we give a tool, they don't need us to crunch the numbers." There is significant concern regarding changing roles, loss of purpose, and general upheaval of the organization. At this point in the implementation, no direction has been forthcoming from the administration regarding how the organization will be adjusted to deal with these new technologies. The IT manager is not worried for her position, but the uncertainty was communicated to her by a number of people from across the university.

According to the insurance and healthcare organizations, there have been no significant changes in either the location or method of decision-making in the time since the tools were introduced. The health insurance firm noticed an increase in the speed of decision-making and also noted that the staff assigned to support the upper level decision makers was more confident in their recommendations. The IT manager from the healthcare organization pointed out that administration was better able to identify and attend to their strategic goals, such as developing new areas of specialization or balancing their capacity with the demand in various geographic locations.

DISCUSSION

The definition of trust noted earlier (Baba, 1999) was aimed originally at interpersonal conceptions of trust, but it fits equally well when applied to the organization/analytics environment. Each organization gets to make its own evaluation of whether and how much to trust the information being generated by the system, and this study suggests that there is a wide range of trustworthiness applied to these systems. Whereas the financial services firm seems to have a deep trust in their analytics tools, others such as the manufacturing firms and the healthcare organization are less convinced.

The findings of the study suggest that the type of user (position, experience, education, etc.) does not play a significant role in whether the tool is trusted. However, the data partially confirms that newer tools are more trusted than the legacy methods. This is certainly the case in the financial services firm, but in the healthcare world the internally developed legacy solutions engender a higher degree of trust. As noted, this has more to do with where the solution was developed than what it does. The healthcare organization also confirms the importance of data provenance in that it was more comfortable with tools that allowed it to examine the pathway by which the information provided was created. This was also the case at the manufacturing firm, except that the information consumers were content to allow the IT group to provide this assurance rather than confirming the data provenance themselves.

In other cases, the trust between the organization and the system seemed unconditional, even in cases where the system had yet to be completely installed and truly evaluated, such as the university. In these cases, the trust between the organization and the system is partially an artefact of the trust between the various organizational actors (Schoorman, Mayer, and Davis, 2007). At the university, the system is new and untested, but the relationship between IT and administration is strong. Even though the president of the university has only been in the position for about a year, the administrative staff has been there much longer and has developed a working relationship with IT to solve many problems that span the continuum from administrative to educational. Thus, they were willing to take the word of IT when they recommended the tool to be implemented, and did not even consider the many alternatives available. The same can be said for the healthcare organization. A strong IT/administration relationship easily overcame the unfamiliarity that many decision-makers had with the incoming technological changes. This is confirmed by the much different reception given to the tools that were not developed locally.

Schoorman, Mayer, and Davis (2007) also point out that the quality of data produced internally is often more highly trusted than that provided from sources outside the firm. One of the reasons that the financial services firm has such trust in their analytics tools, besides the long track record of performance, is that it largely deals with internally generated data, which the firm can control in terms of collection and processing. This confidence in the integrity of their data, as well as their trust in their (largely homegrown) systems, allows them to confidently make decisions and take risks that their competitors might not feel comfortable with. In essence, the trust they place in their analytics tools allows them to pursue more aggressive strategies in obtaining a competitive advantage.

As demonstrated in Figure 4, the level of trust placed in the analytics tools by the organizations that participated in this study is driven in part by their level of experience with analytics, the intensity of the regulatory oversight in their industry, and the location of the system's development. Certainly, their exist other organizational or industry-level drivers that also influence the level of trust that a particular firm places in its analytical tools but they were not uncovered in these data. It is also possible that, through further examination, these drivers will be seen to represent multiple facets of organizational characteristics that, when taken together, appear as one of these influences. For example, the level of experience that the firm has with analytics can also be seen to be a measure of how deeply the decision-makers in the firm understand the underlying mathematics and technologies as well as the methods involved in building the applicable analytical models. This model can be a basis for further study of these and other drivers of organizational trust in analytics tools.

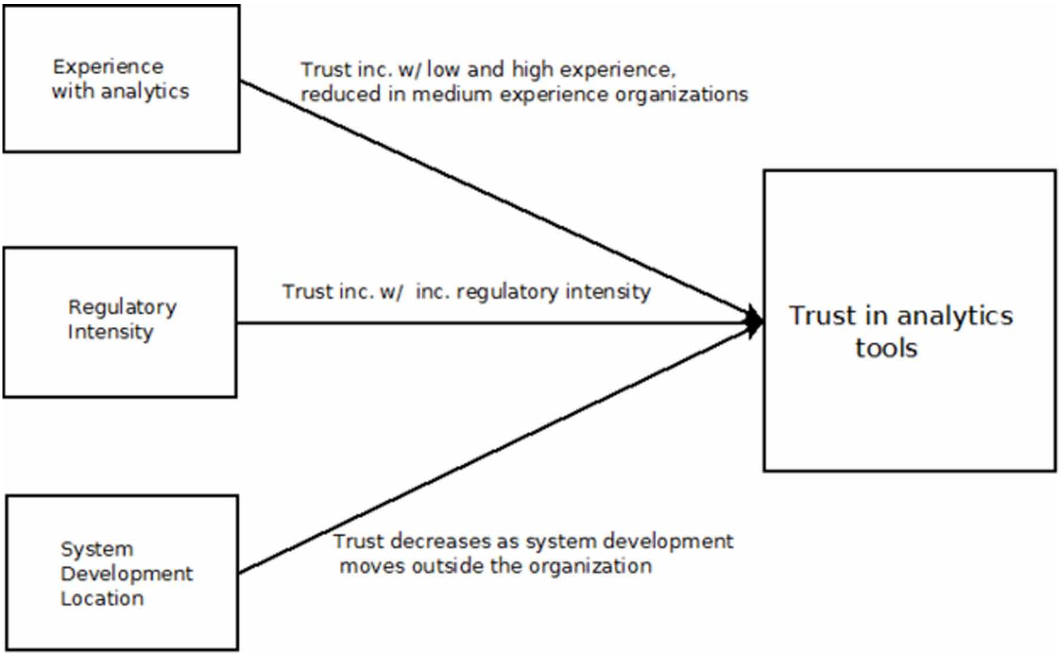
It must be pointed out that even though there were widely varying levels of trust placed in the information provided by the various analytics tools discussed by the study participants, not one of them had any distrust in the information. There is evidence of a great deal of prudence, especially on the part of some organizations, but that does not always equate to a lack of trust or distrust (Yamagishi, Kikuchi, and Kosugi, 1999). Simply, prudence stems from an understanding that there might be some aspects of the situation at hand that are yet to be understood and must be approached with a certain amount of caution. Likewise, lack of trust does not equate to distrust. While some organizations might exhibit a lack of trust in some aspects of their analytical suite, these misgivings often evaporate in the face of increased usage and understanding. However, distrust stems from the belief that the system at hand is either inferior or provides incorrect information not associated with a user's or an organization's unfamiliarity with its use. Distrust is a more systemic and serious issue, and takes a much greater effort, and a much longer time, to cure (Baba, 1999).

Two organizations in the study responded to the implementation of innovation by forming teams or increasing, or planning to increase, their level of collaboration, thus addressing the second research question. The manufacturing firm saw an increase in the use of teams and a decentralization of decision-making as the availability of self-service analytics grew. The university understood that, even at the preliminary stages of analytics implementation, the organization would become more team-oriented and that the ability to take on various tasks in the team format would increase significantly. These organizational responses were not the result of managerial intent. Rather, they occurred because of the increased availability of information and the tacit approval of management. The increased amount and quality of trusted information, coupled with the ability to create self-directed, multi-functional teams, allowed the employees to tackle problems previously thought too difficult. With these ingredients (increased information, management approval, and employee collaboration), these organizations will be able to create incremental innovation (Jones and Hooper, 2017).

CONCLUSION

This exploratory study has opened a door on a little-considered aspect of data analytics. Much of the literature concerned with data analytics centers on the benefits of analytics in terms of organizational performance, cost cutting, and marketing efficiency. However, little has been done to understand how well these tools, and their information products, are trusted by the organizations that adopt them, what factors affect this level of trust, and how these tools impact the way that decisions are made. There is certainly much more to be done in these areas of inquiry. The current study is exploratory and has limited generalizability. Future studies should expand the industries examined and apply additional analysis tools to enhance our understanding of these issues and continue the process of understanding whether, and why, these tools are trusted by the organization's decision-makers. As the number of organizations depending on analytics to gain a competitive advantage increases and the types of decisions that can be assisted, or made by, analytics grows, we should be aware of how the employee base sees these tools and how we can better coordinate these two valuable assets to

Figure 4. Drivers of trust in organizational analytics tools



create even more effective and efficient organizations. The results of this study and those that follow should help organizations select tools and acquisition protocols that better match the tool to the organizational environment as well as provide an understanding to management that the trust given to the results of analytics tools can be improved by understanding the various relationships described in this paper as well as creating a substantial data culture within the firm.

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