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Key Issues of Predictive Analytics Implementation: A Sociotechnical Perspective

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ABSTRACT

Developing an effective business analytics function within a company has become a crucial component to an organization's competitive advantage today. Predictive analytics enables an organization to make proactive, data-driven decisions. While companies are increasing their investments in data and analytics technologies, little research effort has been devoted to understanding how to best convert analytics assets into positive business performance. This issue can be best studied from the socio-technical perspective to gain a holistic understanding of the key factors relevant to implementing predictive analytics. Based upon information from structured interviews with information technology and analytics executives of 11 organizations across the US, this study identifies the socio-technical components that are key to organizations' implementation of predictive analytics and offering actionable recommendations.

Keywords: predictive analytics; socio-technical framework; structured interviews

INTRODUCTION

Business analytics (BA) is defined as “the techniques, technologies, systems, practices, methodologies, and applications that analyze critical business data to help an enterprise better understand its business and market and make timely business decisions.” (Chen et al., 2012, p. 1166). The applications of BA have been broadly categorized as descriptive, predictive, and prescriptive analytics that respectively address the following three questions (Sun et al., 2017): what happened, what is likely to happen, and what are the best and worst outcomes under uncertainty? Among these applications, predictive analytics (PA) has particularly captured the attention of organizations due to its proactive rather than reactive approach. This ability provides organizations with significant potential for uncovering new opportunities and enhancing performance. As businesses acquire an increasing volume of data through their enterprise systems and gain access to myriad external market datasets, they find new and innovative ways to utilize this data to predict customer behaviors, market demand, employee churn, economic shifts, etc. (Chen et al., 2012). This capability significantly enhances organizations’ ability to make decisions about the future and the bottom line (O’Flaherty & Heavin, 2015). An IDC study found that implementation of PA yielded an average 5-year return on investment (ROI) of 431% (IDC, 2002). Consequently, organizations are increasingly investing in PA technologies and solutions. A McKinsey study found that nearly fifty percent of the executives surveyed mentioned big data and advanced analytics as one of their top three strategic and investment priorities (McKinsey, 2014). PA has shown its versatility across various domains, such as meteorology (e.g., Raval, et al., 2021; Garg & Krishnamurthi, 2022), health and medicine (e.g., Kumar, et al., 2021; Mishra & Kumar, 2021; Xiong & Green, 2022; Hernandez & Zhang, 2017; Venkatesh, 2019), education and human resources (e.g., Gkontzis, et al., 2022; Singh, et al., 2022), marketing and sales (e.g., Yedilkhan, & Mukasheva, 2022; Dubey, et al, 2018, Papagiannopoulos & Garcia Lopez, 2018), supply chain management (e.g., Schlegel, 2014; Lawless, 2014), business operations (e.g., Hashimzade, et al., 2016; Rudolf & Doelle, 2016; Risse, 2018; Saadat, et al, 2022; Turkbayraqi, et al., 2022), and information systems research (e.g., Shmueli, & Koppius, 2011). This widespread adoption highlights the growing significance of PA in various public and private sectors. With each passing day, new opportunities are being discovered, and existing applications are being expanded to apply PA to addressing complex and diverse challenges.

Despite increasing capabilities and investments in PA, primarily in the form of technology investments such as data warehouse, cloud services, analytics and statistical modeling software, and hiring of IT, data science, and analytics talents (Sun et al., 2017), there is a paucity of research devoted to understanding the

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necessary conditions and factors for successful implementation of PA. The process theory suggests that investments in technical assets do not generate business value automatically unless they are successfully integrated into the organization's business functions and effectively utilized (Soh & Markus, 1995; Trieu, 2016). Therefore, the subsequent logical question to ask is: which factors affect an organization's ability to leverage PA assets to create a positive business impact? This is the primary question that motivates the current study. The approach we take to address this issue is through the sociotechnical lens. The sociotechnical systems theory posits that any production system is composed of both the social and the technical subsystems and that the interaction between the two subsystems creates the conditions for system performance (Cooper et al., 1996; Walker et al., 2008). In our realm, PA systems/applications represent the sociotechnical systems, and the extent of their business effectiveness is influenced by the dynamic interaction of the social and technical subsystems in an organizational setting. Therefore, it is essential to investigate which social and technical factors influence effective implementation of PA. The main objective for this study is to identify the most salient factors in implementing PA and then categorize these factors into either the social or technical subsystem for a comprehensive framework for understanding, planning, and implementing PA in organizations.

Data for this research is gathered through structured interviews with information systems or analytics executives at eleven U.S. organizations engaged in PA projects. The structure of this paper is as follows. The next section examines the existing literature on key issues relevant to business analytics and PA implementations. This is followed by a discussion of the sociotechnical theory and the ways it is applied to this study. The subsequent section discusses the research methodology. Then based upon the results of the structured interviews, a sociotechnical framework of the salient issues germane to PA implementation is presented and discussed. Finally, this study concludes with recommendations and future research directions.

BUSINESS AND PREDICTIVE ANALYTICS IMPLEMENTATION LITERATURE

BA's ability to improve business decision making has been widely documented. However, limited research effort has been devoted to developing a holistic framework on how to best implement BA and predictive analytics. Existing literature in this area tends to focus on the technical and algorithmic issues, and this has led to organizations' biased emphasis on only tools, systems, and data skills,

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which limits organizations from reaching the full potential of PA as a business value creator. For example, like several other popular books on PA, McCarthy et al. (2022) offers a practical approach to implementing PA from the technical, data, and algorithmic perspectives, focusing on the big three PA techniques (i.e., regression, decision trees, and neural network) and their variations. There is a paucity of literature that addresses the issue of how to utilize PA assets for optimal business impact. For example, Davenport (2006) suggests that three factors are key to successful implementation of analytics, and they are: widespread use of modeling and optimization, an enterprise approach to data management and sharing, and senior executive advocacy for analytics. The work of Taylor (2011) emphasizes the development and sustainability of decision management systems powered by predictive analytics. It focuses on creating systems that are more agile, analytic, and adaptive than traditional passive operational systems. While primarily technical and process-oriented, the work also addresses some organizational elements (such as people, process, and technology enablers) that are crucial for enhancing the success rate of these initiatives. Using case analysis, Rathore et al. (2014) identify 12 critical success factors for successful implementation of BA including strategic planning, dealing with resistance to change, visualizations, data sharing, data collection, phased adoption, what-if analysis, competitive analysis, implementation timing, environmental concerns, loss forecasting, data security and privacy, and data integration. However, these attempts still largely focus on the technical and data issues and only briefly touch upon organizational and managerial issues. A couple of relatively recent studies address issues beyond technology investments and provide some valuable insights. The qualitative study by Parks & Thambusamy (2017) suggests that BA success is a function of organizational culture (BA skills, and BA resources), process (business-IT alignment, BA measurement, BA best practices), and technological (data management, BA techniques, and BA infrastructure) dimensions. However, the study fails to provide concrete recommendations on how these dimensions should be jointly optimized to create the condition conducive for analytics success. Yet in another study, Chen and Nath (2018) propose the concept of BA maturity as a way of measuring the success of an organization's analytics efforts. Using empirical data, the study verifies the positive relationship between BA maturity level and self-reported BA success and identifies the following factors of BA maturity: BA integration, management support, process-level benefits of BA, and technology and data analytics capabilities. While these studies provide a more holistic view of BA implementation beyond just the technical issues, they stop short of developing a comprehensive and theoretically sound framework for analytics implementation, therefore, offer limited guidance to analytics researchers and practitioners. This study will draw upon the sociotechnical theory as the theoretical underpinning in the search for factors that influence the success of PA implementation. The next

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section provides a brief overview of the sociotechnical theory and how it is applied in the PA context.

THE SOCIOTECHNICAL PERSPECTIVE

The sociotechnical theory was first presented at the Travistock Institute in London in the middle of the 20th century (Cherns, 1976). It suggests that any organization or its work system consist of two interdependent subsystems – the social and the technical subsystems. The technical subsystem focuses on “the processes, tasks, and technology needed to transform inputs to outputs,” whereas the social subsystem is concerned with “the attributes of people (e. g., attitudes, skills, values) and the relationships among people, reward systems, and authority structures” (Bostrom & Heinen, 1977, p. 17). The following diagram (Figure 1) describes the interacting variable classes within a work system – technology, tasks, structure, and people.

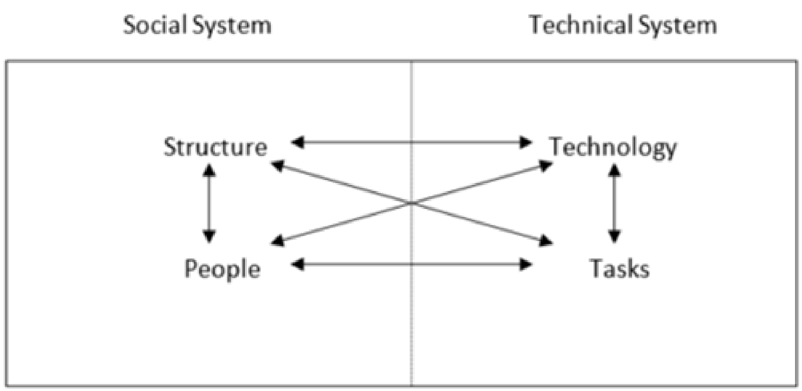

Figure 1. The Interacting Variable Classes within a Work System (Adapted from Bostrom and Heinen (1977))

The sociotechnical theory implies that social and technical systems cannot be viewed as independent of one another. The efficiency and effectiveness of the organization depend on the synchronization of the two systems. The premise of the social and technical theory is that the social and technical systems must be optimized together to provide the organization with the best overall outcomes. This perspective also posits that computer-related technology is essentially neutral and that failure to recognize the social system associated with the design and use of technology is the reason why many new technology adoptions fail (Bostrom & Heinen, 1977). The traditional viewpoint tends to approach new system

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implementation by first configuring the technology and then expecting the social system to adapt to the change. In contrast, the socio-technical theory believes that any redesign of an organization through the adoption and use of information systems (IS) must involve careful upfront design to meet the requirements of both the social and technical subsystems simultaneously (Rouse & Baba, 2006).

Past IS research has adopted the sociotechnical approach as the preferred method for computer-based system analysis, organizational work design, studying the diffusion of new technologies and measuring IS quality (e.g., Cooper et al., 1996; Palvia et al., 2001; Sawyer et al., 2003). Similar to any IS, implementation of PA also induces techno-changes that drive potential improvements in organizational performance, and therefore, its interdependence with other social and technical components must be recognized for the sake of achieving maximum benefits. As a catalyst for organizational changes, IS use must be accompanied by a fit between the technology solutions and sociotechnical elements such as infrastructure, business processes, organizational strategy, culture, and incentives to be successful. Therefore, the principles of the sociotechnical perspective provide the theoretical foundation for identifying the factors that contribute to successful implementation of PA from a holistic perspective in the current study.

RESEARCH METHODOLOGY

To obtain the relevant perspectives regarding the current practices in PA implementation, structured interviews were conducted with information technology and/or analytics executives from 11 organizations in several metropolitan areas across the United States. Five organizations are headquartered in the Midwest, while two are based in each of the Western, Eastern, and Southern states, respectively, creating a relatively balanced sample geographically. A convenient yet representative sample was used. The interviewees were recruited through the researchers' personal and professional networks. To ensure that the interviewees would speak candidly about their organizations' PA implementations, participants were promised anonymity. The interviewees' job titles include Chief Information Officer, Chief Data Officer, Director of Analytics, and Business Insight Manager. The interviews were conducted either in person or over the phone by the researchers using a structured list of questions. This list of questions was compiled based on business and PA literature in order to encompass all aspects of PA from organization structure, culture, and leveraged technologies. These questions are listed in Appendix A. Also included was a question asking the executive to rate their organization's predictive analytics efforts using a 10-point scale (1 = Not

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successful at all; 10 = Highly successful). The interview sessions lasted between 30 minutes and 60 minutes. All interviews were recorded and transcribed. Profiles of the 11 organizations are provided in Table 1. As the profiles show, sufficient variation across the organizations regarding the industry (one organization per industry type), size, and self-reported success level is achieved for theoretical replication. One organization reported “NA” for self-reported success because the interviewee felt it was too early to assess the outcomes of her organization’s PA efforts. The average success score of 5.9 indicates a need for improvement across the participating organizations. The finding is actually encouraging for the researchers, as our primary interest lies in uncovering common challenges, concerns, and frustrations through the interviews. Furthermore, it motivated us to encourage the interviewees to suggest strategies that could enhance their PA efforts.

Table 1. Profiles of Interviewed Organizations (n=11)

Organization Number	Industry	# Employees	Self-Reported Analytics Success (1-10)
1	Sports Analytics	430	5
2	Entertainment	4,332	7.5
3	Consumer Electronics	1,100	7.5
4	Banking	4,500	8
5	Transportation	12,784	3
6	Engineering	10,000	NA
7	Railroad	42,000	6.5
8	Education	2,250	5.5
9	Construction	22,000	5
10	Telecommunication	9,659	6.5
11	Technology	5,000	4.5

Using the grounded theory approach (Glaser & Strauss, 1967), the researchers first coded the transcripts independently to identify key concepts that emerged from the interviews. This initial phase of coding was extensive, with each researcher developing over 40 preliminary codes to capture the diverse ideas and themes present in the scripts. After the individual coding phase, a reconciliation process was conducted for researchers to compare the codes that were independently developed. Differences in coding were discussed and analyzed to reach a more refined and comprehensive understanding of the data. The team employed the technique of constant comparison, where codes and their associated excerpts were continually compared to find similarities and differences. This reconciliation process helped the team reach a consensus on the codes and ensured the consistency

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and validity of the research. Through axial coding (Corbin & Strauss, 1990, Strauss & Corbin, 2008), the researchers collaboratively grouped the agreed-upon codes into broader concepts based on correlations among the codes. Finally, the concept groups were assigned to various sociotechnical variable classes after the researchers carefully considered how each group fit into the broader framework of the sociotechnical theory. The research team continuously referred back to the original data throughout this process to ensure that the assignment of the concept groups to classes accurately reflected the realities captured in the interviews.

RESULTS

This section explores the multifaceted aspects of PA implementation within a sociotechnical framework. They are presented as four cohorts of issues dealing with people, structure, technology, and task. Table 2 lists the elements of the social and technical subsystems of PA implementation uncovered during the interviews.

Table 2. A Socio-Technical Framework of PA Implementation

SOCIAL SUBSYSTEM	TECHNICAL SUBSYSTEM
People: • Desired Skills and Qualities • Recruitment, Training, and Retention • Resistance to Change	**Technology:** • Fast Changing Technological Needs • Data Accessibility and Quality
Structure: • Measuring PA Success • Culture and Mindset • Funding and Prioritization • Organizational Challenges	Task: • Utilization of Analytics • Aligning PA with Organizational Goals • Data Storytelling

In this section, we delve deeply into each concept group of the framework to explain the key findings and best practices as identified by the interviewees. For added clarity and context about the industry and organizational size, each quote from the

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interviewees is accompanied by a reference number. This number corresponds to the organizational numbers displayed in Table 1.

PEOPLE

The people elements of the sociotechnical framework pertain to the values, attitudes, knowledge, and skills employees bring to the workplace. The interviewees reveal that recruiting and retaining the right people is a critical but challenging aspect of acquiring the necessary skills for PA. Organizations seek individuals who have the appropriate technical backgrounds, strong communication skills, proactive/creative mindsets, and the ability to adapt to rapidly changing technical and business environments. Furthermore, developing formalized recruitment, training, and retention programs for analytics and reducing the organization’s resistance to changes prove effective to achieving PA success.

Desired Skills and Qualities

All the interviewees acknowledge that PA requires employees who possess technical expertise as well as strong communication skills to succeed in understanding data and conveying the benefits of analytics to stakeholders. Instead of focusing on the obvious need for technical skills, the interviewees tend to emphasize more on the importance of non-technical skills such as communication and business understanding. Technical jargon and verbiage surrounding data and predictive analytics are complex and confusing; therefore, hiring employees who can communicate results in simple terms to individuals coming from a non-technical background, including clients, executive management, and stakeholders, becomes extremely important. As described by one interviewee, “data scientists...have to be very effective in delivering [their] message...or [they] will miss that bridge between what they’ve done in the predictive model and its application to the business. [3]” If analysts cannot clearly communicate the benefits of predictive models to other members inside the organization, they will lose the prioritization and support that PA requires to grow in the business. For effective communication, analysts must have a sound understanding of the business so they can convey the value of analytics in a business framework. More importantly, analytics professionals must understand the business and its processes to identify business problems and utilize PA to solve them. One executive has this to say, “even the mediocre students from schools know how to [do] coding, but really what we’re looking for is a business insider [who has] a good understanding of data and also [has] good knowledge of the business [so they] can link them together to solve business problems. [10]” Solely analyzing the data from the technical or statistical

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perspective is not enough; analysts must understand and effectively convey the business value behind data to institutionalize real changes for the organization. Furthermore, employers seek individuals who are proactive with data and "actually passionate about predictive analytics". As described by one interviewee, "it can be a real opportunity to advance your career [and] show management that you took something that looked like it was separate and had no relationship and created something that we can use to run our business better. [9]"

Further, organizations desire employees who can readily adapt due to the rapidly changing nature of the PA field. Organizations would rather "employ someone who can learn new things" than someone who is restricted to a single software or commercial vendor. As PA technology and data are constantly evolving, businesses require their analytics professionals to adapt to new data, tools, and methodologies to keep up with these fast-paced changes. On a larger scale, it is important for organizations to recruit individuals with varying backgrounds to create a strong and diverse team dynamic. As described by an executive, "I always want to hire someone that is smarter than I am because if they don't know anything more than what I already know, that's not going to help out the team...I want someone who brings something different to the team so that we can take on new challenges that we haven't been able to do yet. [3]" The interviewees recommended that employers strive to foster diverse PA teams so that they can expand their perspectives and overcome new challenges.

Recruitment, Training and Retention

Many organizations face the universal challenge of finding individuals with the required PA expertise and skillset. One interviewee states, "there is a shortage of skills in the labor force right now, [so] it's a big challenge to find people who can do the kind of work we need – both the technical and non-technical skills to bridge the gap between the technology and business in our projects. [5]" The talent shortage is primarily due to the newness of the field. For example, one interviewee describes, "five years of experience, which would be considered as little experience in most fields, is a lot of experience in this field. [2]" As previously stated, PA requires experienced individuals with a wide range of skills, which many candidates in the workforce do not yet possess, and this poses a serious challenge to organizations. This challenge is greater for companies located in regions that are not traditionally technology hubs such as the South and Midwest of the United States, where technical talents are less accessible than the coasts, making recruitment a consistent challenge for companies. Smaller companies also have greater difficulties because they are competing for the same talents with larger and more established corporations that are more likely to attract talents and willing to

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offer attractive compensation packages. At the same time, several interviewees see a tendency of job candidates over-representing their skills and experience during the interview process by claiming "being experts in technologies while they are not," causing companies to lose productivity due to ineffective hires.

Due to the shortage of talent in PA, companies should place a greater emphasis on their hiring, training, and retention process of analytics professionals. However, the great majority of the organizations interviewed do not currently have a formalized process for doing that, which may be due to the limited sample size of this study. As one interviewee says, the success of PA hinges on "getting the right resources through training [and] hiring, because without the proper human resources, data and analytics technology lose their value. [6]" The interviewees debate the pros and cons of hiring professionals with developed skills and hiring candidates with high potential to learn and develop expertise internally once at the company. The decision seems very situational and dependent mostly on the financial resources the company has as well as the urgency of deploying analytics talents. The interviewees tout that a key benefit of hiring less experienced candidates with the potential to develop skills via internal training and development opportunities, is that the employees are more satisfied, and their retention rates appear higher. One executive alludes to this phenomenon, "over time, we've found that when you intern in-house, and build this kind of talent, they (employees) tend to stay longer and perform well. [11]"

Therefore, investing in human capital development of analytics professionals is just as important, if not more important, as aggressive recruiting efforts. One interviewee describes a training program for analytics professionals in his company that includes both education on technical topics and rotations across various business areas to help their analysts "gain a broad knowledge of the overall business and get a very deep insight of data analytics. [4]" This also provides new employees the opportunity to practice PA before fully immersed into their roles because "even the best analytics person requires a few months to really understand the business and data. [4]" Moreover, because of the technical nature of PA, it is crucial employees stay up to date with the necessary skills in advanced data tools and technologies to achieve quality PA results. As noted by one interviewee, "from a big data movement, the concerns are the newness of it and lack of existing skill sets, [so] you have to train a lot of folks, both new and current employees.[3]" Without a structured training program, newly hired analysts may lack a thorough understanding of the data and its business context for adding business value. Also, current employees may not fully realize and appreciate the potential that PA affords, and they may also resist changes brought on by PA.

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Alongside adequate training, it is important for organizations to create an environment where employees are challenged by their work and able to grow professionally. To foster a stimulating environment, employers should provide projects that are meaningful and have a visible, positive impact on the business. To this effect, one interviewee notes, "people are more likely to stick around if the work that they're doing matters...and really has something to it. [4]" If employees are not stimulated by their work or unable to see the positive differences they are making, they are more likely to experience dissatisfaction or be allured away by attractive offers from other companies. When organizations can retain their analytics talent, they save valuable resources that would otherwise be spent on recruiting and training, maintain effective teamwork, and create a consistent company culture, and all these ultimately lead to a more productive organization.

Resistance to Change

One of the greatest challenges organizations face with the implementation of PA comes from people's innate resistance to change. Because its use is still an emerging trend and commonly depicted as being used by large corporations, many are skeptical about its usefulness to their own organizations. One interviewee said, "a lot of people will say, I can see how it works really well at Google or Facebook to do big data stuff, but how does it work in my industry? [7]" Some employees may consider PA as "too fancy" or "too early" for their organizations as they simply want to continue working within the existing framework and focusing on the day-to-day operations. As one executive describes it, "in some cases, it can take more than 2 years to take a larger sub-segment within our organization and move them up to the predictive component. [5]" In other situations, PA can "uncover faults in existing [business] processes [that have] existed for 15 or 20 years," as one interviewee points out, "and that's when you are going to run into problems with owners of those processes and need an entire stack of support from executives to overcome the resistance. [9]" Most traditional organizations do not view themselves as a "technology-native" enterprises and therefore must overcome a lot of legacy mentality and behaviors before embarking on PA.

Resistance to PA is even witnessed among information technology professionals. The PA methods and technologies are dependent upon data, statistical algorithms, and machine learning, which are continuously evolving because of technological and methodological advances. And, because of this fast-evolving nature of PA, keeping up with this change requires IT staff to constantly adapt to newer and often unfamiliar technological environments. Consequently, there is often resistance on the part of the employees to this new paradigm. This is how one executive describes it: "Folks I see are divided into two camps - like 'Yeah, awesome, let's learn this

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new stuff' or like 'no, I'm not doing this … what do you mean I have to learn this new technology,' so the more folks of the first camp you have, the better chances for success in [PA]. [4]" Employees frequently resist changes because of their attachment and familiarity with the tools they use. One interviewee highlights this "situations where [they] brought in new technology [and]...an engineer or analyst [will say], 'I have been using the current tool for 10 years, and I am the in-house expert for that tool.' [2]" When IT professionals become too comfortable with the current technology, they develop antagonistic views against changes that would require them to learn new skills or threaten their job security. Furthermore, some employees may perceive the supplanting of old technologies by the newer PA platforms as being wasteful in terms of prior financial investments and learning efforts. This point is reinforced by the comments of another executive who adds, "a lot of people who used to consume the products being gotten rid of were very concerned and voiced: "well first, we invested a bunch of money into this...why are we now changing? ...we have all these technologies - why would you want to buy another one? [7]"

If an organization fails to manage user resistance against the changes as a consequence of PA efforts, the likelihood of a successful transition to informing business decisions by analytics would be slim. One executive suggests that one strategy to reduce resistance is to demonstrate that PA presents "a real opportunity to advance careers." "What I found is that people that like [predictive analytics] are some of our best employees because they think two steps ahead, and they are passionate about what we do. We are trying to hire or promote people with this aptitude – they say I may not be an expert at PA today, but I want to create something that we can use to run our business better, [5]" says another interviewee.

STRUCTURE

Broad organizational issues are examined for the structure construct of the socio-technical framework in this study. The issues revealed through the process of the interviews include measuring the success of PA efforts, changing the culture and mindset of organizational players, prioritizing and funding PA projects, and navigating the various organizational challenges.

Measuring the Success of PA

The value of PA has been widely documented and illustrated in literature. However, most organizations we interviewed have not developed an effective mechanism for

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measuring the success of their PA efforts. As a relatively new initiative at most organizations, companies are still trying to determine how to accurately measure the success of PA. Many firms currently rely on traditional measures such as return on investment (ROI) and annual business performance through revenues, profits, and costs, but these instruments tend to be affected by a wide range of factors and fail to measure the long-term effects or intangible benefits of PA. Without a defined measure of success, it is difficult to understand PA's impact on the business or to identify new opportunities and which aspects of it require improvement. Moreover, by measuring success accurately, analysts can better articulate and communicate the benefits of PA to executive management and thus garner their support for future investments. The interview data suggests that the success measures of PA should include a combination of both the quantitative and the qualitative elements.

Quantitative elements include financial analysis of models, ROI, efficiency ratios, cost savings, etc. Although it is tempting for analysts to present the accuracy statistics of their predictive models such as the accuracy rate, sensitivity, specificity, or root mean square error (RMSE) to validate their work, it is more meaningful to convert the value of these models into dollars and tangible benefits that are easier to understand by businesspeople. The data from the interviews recommend using quantitative measures along with baselining to better demonstrate the impact of PA on business performance in terms of revenue generation and cost savings.

Qualitative elements that can be used in assessing PA success may include its strategic importance to the organization's decision-making processes, stakeholder feedback, customer satisfaction, etc. To begin, PA can be evaluated based on the degree to which it influences business decisions. For example, if PA models provide highly valuable input and help drive evidence-based decision-making in the organization, then the firm's analytics efforts would be viewed as successful. As one interviewee observes, "PA has become such a crucial part of our processes to the extent that we can't survive without it. [2]" Qualitative feedback from stakeholders on how PA have changed and improved their decision-making capability and confidence, extent to which its findings are incorporated into the final decisions, and new opportunities that analytics capabilities present to the business, are all important gauges of the PA success. User satisfaction has often been used as a benchmark for IS success, and it can be leveraged to measure PA success as well. One interviewed executive mentions that when seeking managers' feedback regarding the impact of analytics, they use questions such as "Are you happy with what you're getting? Do you feel like you're making decisions driven by data? Do you desire more support from the analytics group? [1]" in their survey instruments. Similarly, some organizations measure customer satisfaction with business actions informed by PA findings. One interviewed organization utilizes

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"text mining to analyze themes and topics [with] what's being said in surveys and compare that to the results from previous years [3]" to measure whether customer satisfaction has improved as the result of implementing decisions driven by PA.

Thus, using a combination of various quantitative and qualitative measures allows organizations to better assess their PA success and develop a more holistic view of its impact on the business. The interviewees also suggest that better metrics of PA success help in garnering additional management buy-in and better support from various business units.

Culture and Mindset

The culture and mindset topics emerged from the interviews emphasize organizational structure over individual issues. They highlight the need for a shift in organizational culture towards a data-driven approach, underscoring the importance of changing management practices and leadership styles. Many interviewees call for institutional changes and advocate for an environment that rewards innovative data use. Overall, these issues underscore the necessity of systemic changes in organizational operation and decision-making, rather than addressing specific individual employee concerns. Therefore, in this study, we categorize culture and mindset issues as part of the structure variable class.

From the interviews, organizational culture emerges as an important determinant of whether PA would be successful. As one individual puts it, "implementing PA requires a different mindset, not just new toolsets or technologies. [8]" Organizations must answer the question of whether they are ready to embrace the data-driven culture to transform the business. Consider the following comments from another interviewee: "I think the biggest issue right now is gaining support from leadership. Well, gaining support from anybody. We have a few data champions in the company that are big-believers, and they want to adopt it, but then you get some people that always want to make decisions based on gut instinct or whatever you want to call it. [5]" "There is just, you know, 'hey we don't need to do anything fancy, we just need to process transactions accurately,' but a lot of [our] business is turning to quality, value-based engagements, and in those situations, you have to use PA to identify opportunity to improve. [10]" Management is reluctant to abandon their old habits of relying on their experience and intuition and often ignoring data-informed PA business solutions especially if they go against their gut feelings. When analytics brings insights that are counterintuitive to "what your gut tells you, the hardest part is getting the buy-in [from managers] to try something new, [10]" says one interviewee. If the management cannot learn to trust the data, PA will not be supported or valued in the organization. In addition to changing the

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management mindset about analytics, some executives we interviewed brought up the importance of cultivating a data entrepreneurship temperament in the organization. One interviewee explains data entrepreneurship as "an open culture surrounding analytics that gives employees access to organizational data and rewards innovative use of data that lead to business improvements. [6]" Organizations that have cultivated the data entrepreneurship mentality "simply [view] PA as part of the business process – no one even questions why we need it. [2]" The data entrepreneurship culture may also help mitigate challenges related to data access and ownership, which will be further explored later in the discussion of the technology variable class.

However, to gain the trust of the managers and start changing the culture, PA must first provide business validation as one interviewee notes, "just everywhere there is a shortage of people who really understand how data and analytics can create value, and [for the organization] to transit into a culture of seeing data as an asset, it is our role as a predictive analytics team to explain to people and show results. It is a big shift but has been happening rapidly in the last few years. [1]" The interviewees acknowledge that it is "an iterative process of gradual learning and teaching the organization that there is value in PA and that you can do away with the gut feel. [6]" When people start to see the benefits, buy-in would come; therefore, the point about being able to measure success earlier becomes an important issue. Our data also report that through business validation, there has been an increased awareness of the value of analytics and greater interest in using it to make business decisions, pushing analytics towards becoming a priority in organizations.

Funding and Prioritization

Resource allocation has always been a contentious issue among the members of an organization as some businesses consider PA as research and development efforts and are not ready to take that "leap of faith" to make the initial investment. This is emphasized by one of the interviewees, "one of the shortfalls we have is that there is not a lot of appetite for R&D activities, and [top management] views a lot of PA projects as R&D. You have to be willing to dedicate some budget and some overhead costs to that to explore the possibilities. [11]" Often, the lack of funding constraints what the PA teams can accomplish. One company executive bemoans that the short-sighted management is not willing to allocate more resources in terms of hiring and project support to the analytics team despite the interest the team has generated with some early success. "Until we get funded, we don't have the resources to address the needs of all the internal clients, [9]" declares the interviewee. Even in organizations where a formal budgeting process exists,

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obtaining funding for PA projects can be difficult when the management does not agree or see the value of what these analyses can do.

Some organizations have success in securing funding for their PA projects, and they assert that the key to funding or at least a priority in funding boils down to "justifying the need and value of what you plan to do". "Communicating the importance and the future ROI [of PA] compared to all the other business initiatives and proving that it's just as important as them so that PA doesn't get deprioritized. We often have too many initiatives in progress in parallel, so it's easy to lose sight of why we should fund analytics, [10]" suggests one interviewee. One company we interviewed ensures that members of their analytics team actively engage with executive management to understand key business goals and drivers and discover where and how PA can be integrated. Interactions between different business functions and management levels can promote collaboration and help include PA as a priority when setting organizational goals. Some of the organizations we interviewed use a "chargeback" system to fund PA efforts. "We're tracking our spending based on projects and business segments, and then the spending and analyst time get allocated to the business units who 'fund' our project, [3]" says one interviewee. While these PA teams are better at aligning their efforts with business needs, they also see large fluctuation in their funding due to business cycles and the needs of the business units, making budgeting and funding activities that are not directly tied to client projects (e.g., training and technology purchases) more challenging.

Organizational Challenges

Other organizational challenges related to the role of the analytics function are gleaned from the interview data. These challenges include whether PA should be a top-down or grass-roots initiative and whether its structure within the organization should be centralized or decentralized. There is no consensus among the interviewed executives regarding whether PA or analytics initiatives in general should be implemented as a top-down mandate from the top management or as a grass-roots movement initiated within the functional areas. In some organizations, at this point, PA is entirely a grass-roots effort as one interviewee mentions, "our function was instrumental in bringing the team together and changing the direction towards more PA. This has caught some steam and is generating interest among the senior management as we talk about what we are doing and [what] we can be doing. [5]" Yet in some organizations, the efforts are top-down as their executives (e.g., CEO and CFO) are characterized as "fairly data-driven". Even within an analytics function, there exist divergent perspectives as to how the efforts (projects) are initiated. Several interviewees note that in their organizations, there is a mandate

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from the upper management that high-quality data be made available to the entire enterprise, but the analytics efforts were mostly grassroots driven depending on "what the functional areas do". While there is no consensus on how PA projects should be initiated, there is agreement that securing top management support is essential for ensuring sufficient funding and getting PA elevated to a strategic level.

Another contentious debate among organizational members is deciding on if the PA function should be centralized or decentralized in an organization. With a centralized structure, there is only one "analytics" group that serves as an internal consultant to other functional areas, whereas in a decentralized structure data analysts are embedded within each functional area. Clearly, the decentralized structure improves responsiveness to meet the myriad business analysis needs, but it also results in a fragmentation and dispersion of analytics efforts within the organization. Consequently, it leads to duplication of work and resources, especially when there is a lack of communication across teams. This point is emphasized by one executive who states, "sometimes you get teams going in different directions…So it can be difficult to rally everybody together to go after something – especially a large analytics project. [3]" Some companies using the centralized approach are also coping with trust issues, says one executive, "the centralized analytics group has to make sure that it is trusted, understood, and welcomed into the groups that it is working with. Data is a very scary thing sometimes, so if there isn't real trust between the groups, there can be risks here. [5]" Here, the key to building trust is to maintain ongoing communication between the analytics team and various business units. One executive points out that the analytics team should not wait until it has the answers to start communicating with the stakeholders. "Over the course of the project, we must touch base regularly – talking, checking in, and ask the client 'Is this still the right direction?' 'Does this make sense?' 'What else can we be doing here?' [8]" says the executive.

A model of decentralization with a data champion is also seen in some organizations. One executive from a large financial institution says, "we spread analytics capabilities going across the organization but there is a large concentration of that within the consumer banking group, and other areas come to us for expertise and leverage. [4]" Often, the decision to centralize or decentralize is highly situational and fluid as one interviewee puts it, "these things are not very cut and dry. Over the last year or so, our businesses have hired analysts in every department. That didn't use to be the case. Prior to a year ago, [analytics] was all part of IT. [11]" Another interviewee mentions that whether the analytics function should be centralized or decentralized "is probably the biggest unknown" as businesses debate the pros and cons of the two approaches and whether predictive analytics should even be part of the IT function. "The decision to centralize or decentralize will

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continue to be controversial until the role that PA plays in the business can be better defined, [6]" suggests another interviewee.

TECHNOLOGY

The technology component of the sociotechnical theory includes devices, tools, and techniques needed to transform inputs into outputs. While implementing PA would inevitably involve many technical issues related to hardware and software engineering, the scope of this study precludes those topics but focuses instead on technology management issues. The main issues relevant to PA implementation involve keeping up with fast-evolving and disruptive technologies and ensuring user data accessibility and quality.

Dealing with Fast Changing Technological Needs

Every organization interviewed is struggling with how to deal with the rapidly changing technology landscape in the field of PA. The interviewees admit that they can only foresee "one or, at most, two years down the line" about which analytics technologies their companies would need and focus on "picking the right tools for the moment [1]". Companies struggle to keep up with the fast-paced changes that occur within the field with respect to technology, procedures, and policies. For example, a business that mostly uses traditional data types in their analysis may be considered behind the analytics curve due to the current use of non-traditional data (e.g., textual, audio, and video data). At the same time, the interviewees caution not to "chase the technology" or let the PA efforts be "led by new technologies". One executive notes, "…while the buzz words like 'machine learning' and 'AI' sound sexy, these technologies may not be what you need. You will only get distracted from the important business questions that benefit your organization if you get too deeply stuck in cool technologies. [4]" Another interviewee points out the danger of the hype around the tools: "[The vendor] can oversell the capabilities of the technology … if someone spends a lot of money on the technology and doesn't get any results, [the management] thinks that's all snake-oil and smoke and mirrors … So, they foreclose the possibility of the real valuable stuff that may not be as flashy but can have good impact. [8]"

All organizations in our sample emphasize the importance of investing in the data infrastructure both in-house and in the cloud that would allow data to be easily accessible and integrated with one another before jumping into fancy tools such as machine learning software. As one individual says, "we've made a large investment [in the data infrastructure] to make sure that's not something that holds us back.

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[3]" Without a robust data infrastructure, PA will encounter insurmountable difficulties down the line, especially when the organization tries to access and analyze data across multiple business lines or over a long period of time. Therefore, managing data resources in both the legacy environment and the more contemporary Hadoop ecosystem simultaneously while maintaining services for both in-house and cloud data storage remains a top technical priority for organizations. Another executive adds, "…we've got every other database imaginable. Our challenge has been the prevalence of so many different data technologies that different business units use, and we have to make tough and expensive decisions about what to keep and what to retire. [9]"

Some organizations struggle with determining whether packaged or custom software solution is best for them in this fast-changing environment. While packaged solutions are quick to implement, but as one executive explains, "…I don't think you can find a piece of software or an analyst in a box that will do everything for you as a company. [2]" Therefore, this executive recommends organizations analyze their own organizational needs and prioritize which capabilities they require before determining which software solutions best meet their needs. In most cases, even with a packaged software solution, there is a need for either software re-configuration or process re-engineering in the business. Customized software is developed to complement the business needs of the organization. However, developing custom PA software, either internally or by a consulting firm, can be costly and time-consuming. Several organizations cite costs of technology as a major hurdle and therefore choose to implement open- source solutions. Finally, no matter how the organization acquires the technologies for PA, the need to gain the skills to harness the powerful technologies cannot be overstated as one interviewee notes, "…so I can buy the best software, I can get the data, and then I can predict the wrong thing. [3]"

Data Accessibility and Quality

As the need for analytics grows, so does the demand for data. "A good predictive analytics tool is only one dimension…limited by the data we have," one interviewee comments, "we like to democratize data so that every single person in our company has access to our data warehouse. [3]" Although this is an ideal situation from the analytics point of view, it is not feasible in every industry because of the data ownership, security, and information privacy perspectives. For example, some organizations interviewed have data retention policies required by regulations, and others have mandates requiring that certain data to be purged periodically. The latter requirement would limit the availability of historical data. While a robust data infrastructure enables data access across various systems, organizations are constantly trying to balance the desire for more access with the legal frameworks and business traditions that restrict collection, distribution, and analysis of data. Some executives mention that data accessibility is a political rather than a technical issue. One interviewee states: “There are some people in our organization that don’t want to unlock that box and think they are the only person set up to make good decisions [with] that data. When you ask for access, they scream, ‘why are you messing with my back yard?’ [7]” Therefore, he recommends the establishment of data access policies and procedures “to liberate that data both technologically and culturally”. Instead of being caught in this perpetual conflict, the analytics team should work closely with the business units and legal teams to develop policies and procedures for data accessibility that meet the requirements of their respective industries. In some of the organizations in our sample, an enterprise governance process for information acquisition, use, and sharing has been formally developed and managed by a unit separate from the analytics team to ensure compliance.

In addition to data accessibility, poor data quality issues also are prevalent in many organizations. A few executives caution against going for “too much” data. “Finding useful data and variables in the enterprise data is like finding a needle in a haystack,” points out one of the interviewees, “most of the data are just noise. You got to be very choosy [about data]. [2]” Yet another interviewee says: “Sometimes there’s so much data that you can’t find what’s real and what’s false. The worst scenario is that you drive business decisions based on predictions that aren’t real. [5]” The use of legacy enterprise systems exacerbates the problem, and the quality of the data stored in these systems tends to erode over time if they are not meticulously maintained. One executive notes: “I think our biggest issue is the adage garbage-in, garbage-out. It’s a huge concern to us that we don’t have the data that has actually been vetted and can be sure it’s legitimate. [10]” In light of this, therefore there is an urgent need for establishing accountability for data quality and standardizing data acquisition, storage, and retrieval processes. In addition to producing inaccurate results, poor data quality can taint the reputation of the analytics team and foreclose the prospect of ever making PA as a strategic organizational initiative. One interviewee explains: “I think the data quality controls are lacking [in predictive analytics], and you can really poison the well in the minds of the decision-makers who want to rely on the results you are providing. [2]” Nine of the eleven interviewees brought up the topic of improving data quality control, suggesting that prior to conducting any PA, the company ought to spend sufficient time and efforts to understand the data and get an unbiased assessment of data quality. Furthermore, some executives suggest that a data governance structure should be implemented in order to hold users and custodians of data assets accountable.

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TASK

The task construct of the socio-technical framework examines the specific tasks that enable organizational changes brought on by the technology. The issues germane to this construct are the role of PA in organizations, aligning PA with the organizational goals, and data storytelling.

Utilization of Analytics

The goal of PA is to develop actionable strategies for improving organizational performance; therefore, the process of implementing and validating analytics findings must be institutionalized. Several individuals in our study mention that the most challenging part of PA is to operationalize and implement the insights informed by the analysis. The resistance can come from both the analytics team and the business units. One interviewee states: "Analysis paralysis is a common phrase in the [analytics] field where the analytics team ends up studying the data set forever and never gets to a conclusion. We need to provide analysts with some direction as to what we are trying to accomplish and get everybody aligned around that to focus on getting it completed. [3]" Thus, it is crucial for a team to produce analytics that are cohesive and can equate into action in order to have a positive impact on the organization. If the analytics deliverables are unclear and/or do not provide actionable results, then the analytics efforts are for naught, and the PA project is likely to lose stakeholder support. This point is emphasized by one interviewee who states, "… if we do things that aren't actionable, people start to question where the value of these interesting research projects is. [2]" Another interview notes that it is often difficult to get the necessary commitment from the business units to operationalize the analysis findings: "My team could build out models all day, but we can't do anything with those models until the business units are willing to do something about them. The biggest challenge is to understand what that inflection point needs to be, how to implement it right, how to do it on scale, and [how to] manage the process. [9]" There seems to be confusion on whose responsibility it is to convert analytics results into actionable business strategies. The analytics team cannot simply immerse itself in analyzing data because the project is interesting and cool, and then hand the findings over to the relevant business units hoping that something would be done. Successful PA projects require the analytics team to work closely with the business units throughout the entire process starting with the business questions, choosing the right data and variables, and eventually discussing the results and actionable solutions. Ensuring business unit participation early in the process helps improve the likelihood that the PA findings are utilized. On executive notes: "[The PA team] must make the business units feel that they are driving the process, not the other way around, and work hand-in-hand with them to

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find the best ways to utilize the results. When [business units] feel that they are involved, they will be committed to implementing the changes. [3]"

Aligning Predictive Analytics with Organizational Goals

Certain business units within an organization are more data-driven than others, and therefore they require greater analytics support. The most common data-driven business units as identified by the interviewees include marketing, customer relations, operations, and engineering, but many interviewees agree that the scope of analytics in their organizations should expand beyond these "usual suspects". Most of the organizations in our sample at the time of this study do not have a formal process of aligning PA efforts with organizational strategies, goals, or objectives. This may be due to the relative nascence of the discipline. As mentioned before, at many businesses, PA still operates as a grass-roots movement without the support and visibility at the highest level of the organization. As one interviewee comments: "What we're trying to do is to eventually work on corporate initiatives. The plan right now is to complete some successful pilot projects at the functional level to gain the confidence of the management to trust us with serving the whole company. [10]" Some companies have started a more formal process in leveraging the scope of PA. One executive states that his company is in the process of prioritizing PA efforts based on corporate objectives: "We're in the process of defining this now by getting together the key stakeholders to talk about the different projects that matter the most to them to see where there may be overlaps that the PA group can coordinate and work on first. [4]" Aligning the PA work with corporate strategies, goals and objective would help generate more visible business outcomes, secure funding, and avoid duplicate efforts by different business units. However, building business validation is a key to inspiring business confidence to let PA be a part of the strategic decision-making process in the organization, concludes one executive. Having a voice to advocate for PA at the corporate strategic meetings would help keep analytics relevant in the long run. Also, defining the long-term roadmap for PA that aligns well with the company's strategy, goals, and objectives should be viewed as a priority to ensure success. One executive puts it very succinctly, "It can be addictive for [the analytics team] to work on fast projects, but in the long term, the function will stay up better if there is kind of a roadmap for PA internally. [6]"

Data Storytelling

Storytelling is the ability of the analytics professionals to communicate and explain the highly technical concepts and jargons related to analytics to the individuals with non-technical backgrounds. Most of the interviewees admit that their PA teams are

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diligently working on how to communicate the complex data results and their meanings in a simplified way to the non-technical groups such as the business executives and the clients. One executive provides the following perspective on bridging this gap: "It is a challenge to convert things back to simple terms and communicate the results so that [managers] can make good decisions based on the analysis. I think a good way to accomplish that is to focus on visual metaphors in your presentation … because most decision-makers don't have the time to learn statistics. [1]" Another executive that we interviewed states: "Analytics people must express things in a non-technical manner and being able to position it in the points of business value or ROI to the customer on what the value prospect is to them. [11]" Hiring analytics experts with good communication skills should be a prerequisite stated during the personnel recruiting process. This point is made by one interviewee: "In addition to a technical skill assessment, we interview around the candidate's ability to explain analysis to a non-technical audience. One of the tasks [during the interview] is to present something that he or she has done. We bring people who don't know anything about it and ask them if the presentation makes sense to them. [3]" All the interviewees agree that for PA to "have an impact," the analytics team must be able to explain the findings in a way non-technical people can understand. Many companies in our sample proactively provide communications training to their technical staff and have regular briefing meetings that require technical analysts to explain their work to business managers. Data storytelling also entails the methods of using enticing visualizations, metaphors, and anecdotes to help a non-technical audience comprehend the business implications revealed by complex data analytics projects. "We name our function 'Business Insights' instead of 'Data Analytics' so that my analysts know that they need to speak the language of business not statistics and that the businesspeople know we are approachable and here to help, not to make them feel dumb with all the technical jargons, [4]" says one interviewee.

RECOMMENDATIONS AND DIRECTIONS FOR FUTURE RESEARCH

While still in its infancy as far as implementation is concerned based on the limited sample of this study, PA is receiving increasing interest from businesses that seek to improve decision-making through the use of data. This study explores the key issues that must be addressed while embarking on a PA implementation project. The structured interviews of executives revealed many issues that would influence the success of an organization's PA efforts within the sociotechnical framework. Based on the analysis of the interviews, we offer the following recommendations for improving the success of PA implementation:

1. Emphasizing None-Technical Skills: Hiring employees with not only technical expertise but also strong communication skills and business understanding is crucial. This helps in effectively conveying the benefits of PA to stakeholders and ensuring analytics are aligned with business needs. Furthermore, developing structured recruitment, training, and retention programs to maintain an analytics workforce comprised of individuals with strong communication skills, a proactive and creative mindset, and the ability to adapt to rapidly changing environments.
2. Cultivating a Data-Driven Culture: Garnering management's support in fostering a culture that values data-driven decision-making is essential. This includes changing mindsets from intuition-based to data-informed approaches and encouraging a culture of data entrepreneurship, which can lead to free flow of data across functional areas and innovative data uses.
3. Addressing Resistance to Change: Managing resistance to change, particularly among IT professionals and employees directly affected by PA, is key. This involves demonstrating the career advancement opportunities that PA offers and integrating PA into the organization's strategic initiatives.
4. Aligning PA with Organizational Goals: PA efforts should be aligned with organizational strategies, goals, and objectives. This alignment helps in securing funding, support, and in ensuring that PA initiatives are focused on delivering tangible business value. Furthermore, the alignment would ensure that PA success is measured and quantified for improving resource development and allocation in the future.
5. Supporting a Blended Structure: The organization should support a blend of centralized and decentralized analytics structure, allowing both top-down and grassroots analytics initiatives. While the PA resources (i.e., human and computing resources) may be centralized to achieve cost-efficiency, consistency, and professionalism, there should be flexibility to allow these resources to play embedded roles within various business units. This approach promotes collaboration, and at the same time, allows the resources to specialize and understand the unique strategic roles they play in each initiative.
6. Ensuring Data Accessibility and Quality: Establishing policies and procedures for data accessibility and maintaining high data quality are vital. This ensures the reliability of PA outputs, reduces political roadblocks, and helps leverage data effectively across the organization. However, these data accessibility channels need to remain within the legal and industry standard requirements.
7. Adapting to Rapidly Changing Technologies: Organizations face challenges in keeping up with the rapidly evolving technology landscape in PA. It is

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important to focus on selecting the right tools and technologies that are most relevant to achieve the business objectives, without getting distracted by the latest trends or buzzwords that may not directly contribute to addressing key business questions. Caution should be exercised to avoid being led astray by the allure of new tools that may not yield practical outcomes.

Using the grounded theory approach, this study identified a wide range of PA implementation issues within the sociotechnical framework. The framework led to recommendations that encourage organizations to view PA implementation holistically, rather than focusing solely on technical issues, thus increasing the likelihood of successful data leverage for business gains. Consequently, this study has made significant theoretical and practical contributions to the field of business analytics. The issues illuminated in this study warrant more in-depth investigation and point to many fruitful avenues of future research. First, while this study employs a qualitative research methodology, future studies could use quantitative methods such as survey-based research from a larger sample of companies to validate the issues that have been identified here. Second, in-depth case studies of how organizations, both successful and unsuccessful, address the identified PA issues would further provide valuable insights. Third, as cultural differences are known to influence organizational behaviors, understanding the extent to which culture affects the sociotechnical issues would be useful in articulating future research in this area. Finally, the PA issues should be investigated in international settings to see if there are any significant differences.

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APPENDIX A. INTERVIEW QUESTIONS

1. In your organization, which business areas and/or applications are supported by predictive analytics (e.g., areas: human resources, marketing, logistics, customer relationship management etc.; applications: fraud detection, response modeling, customer segmentation, demand forecasting, etc.)?
2. Does your organization have a dedicated Business Analytics/Business Intelligence group that supports company-wide predictive analytics initiatives? Or are they embedded in various business units?
3. What kind of technologies/technical infrastructure investments have you made to support predictive analytics efforts in your organization (e.g., data warehousing, big data infrastructure, analytics software/systems, etc.)?
4. What are the key technical/managerial/organizational issues facing your organization in supporting and using predictive analytics? And, how are they addressed?
5. Do you feel that organizational culture is conducive to successfully implementing predictive analytics? How can this be improved?
6. From your perspective, what are the critical success factors to achieving success in predictive analytics (This includes technical, managerial, organizational, and cultural issues.)?
7. Does your organization have a formal process of recruiting, training, and retaining analytics professionals? Any issues/difficulties related to recruiting, training, and retaining analytics professionals?
8. Does your organization have a formal process of aligning predictive analytics efforts with organizational strategies, goals, and objectives? How are predictive analytics efforts funded?
9. Is predictive analytic viewed as an organizational strategic initiative in your organization? How much top-level managerial support/emphasis on predictive analytics do you see in your organization? Or is predictive analytics mostly a grass-root movement in your organization?
10. Does your organization have formal policies/procedures on the use and acquisition of data for analytics purposes? How concerned are you about the use of analytics results when it comes to issues of privacy, security, or any other ethical/legal considerations?
11. Have business processes been impacted/changed/improved, in your organization, because of predictive analytics?
12. How does your organization measure the success of predictive analytics efforts (e.g., business performance, customer satisfaction, ROI, etc.)?
13. What are the main concerns you/your organization have/has about predictive analytics and the big data movement?

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14. What challenges are you facing in communicating results to non-technical managers/executives? Have you found any approaches that work?
15. On a scale of 1 to 10, how would you rate the success of your organization's predictive analytics efforts? (1 = Not successful at All; 10 = Highly Successful)

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