Developing highly effective Business Analytics: an information processing perspective

David Lopez (d.lopezberzosa@surrey.ac.uk)
University of Surrey

Roger Maull
University of Surrey

Fabrizio Salvador
I.E. Business School

Abstract

Business Analytics is central to large firms' value creation, yet empirical support for how it is developed by companies is still needed. Prior results adopt a resource based view whereby the performance of business analytics is contingent on the availability of some well-known capabilities and organizational resources. Empirical evidence however has been only weakly supportive. Addressing this gap, we explore how business units within firms develop high performing business analytics. Our research suggests that a universalistic, best-practice, approach is limited in power and that the development of business analytics is appropriately viewed as a co-evolutionary, emergent, process.

Keywords: business analytics, information processing theory

Introduction

Business analytics is a phenomenon of considerable theoretical and practical importance (George et al. 2014, DalleMule and Davenport 2017, Chen et al 2012). By business analytics we mean the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions (Davenport and Harris 2007).

From a practical perspective, business analytics is increasingly acknowledged to be a source of competitive advantage in a myriad of sectors (McAfee et al. 2012, Anderson-Lehman et al. 2004) including manufacturing.

In the classic structure, a manufacturing business is divided into functional units that enjoy substantial autonomy and integration across them happens largely through the business unit leadership team and through the design of formal processes for product development, supply chain management and order processing among others. The emergence of smart, connected products, however renders this classic manufacturing model obsolete. The need to coordinate across product design, cloud operation, service improvement, and customer engagement is continuous and never ends, even after the sale.

GE Aviation, for example, is now able to provide more services to end users directly—a move that improves its power relative to its immediate customers, the airframe manufacturers.

Information gathered from hundreds of engine sensors allows GE and airlines to optimize engine performance by identifying discrepancies between expected and actual performance (Iansiti and Lakhani 2014).

From a theoretical perspective, business analytics is a focus of theories including resource based view (Davenport 2007, Kiron 2011, Ransbotham et al. 2016), information processing view (Kiron 2017, Cao et al. 2015) and process theory (Hindle and Vidgen 2017, Lycett 2013). These theories suggest several reasons why firms are embracing business analytics such as improving decision making and strategic planning, more effective pricing, customer selection and financial performance (Wixom 2013) as well as data-driven product innovation (Kiron 2017).

Creating value from data, the main purpose of business analytics, is not straightforward. Replicating the success of firms such as Google, Facebook, Amazon and GE is elusive (Iansiti and Lakhani 2014). Despite the strategic relevance of Business Analytics, scholars lack a process theory of how firms create high performing business analytics. We address this research gap by asking: How do executives develop high performing business analytics in their organizations?

Given the theoretical and empirical limits of prior theories, we take a theory-building approach (Eisenhard 1989). We compare how different business units in different companies developed high-performing business analytics. In total we consider 9 business units from 3 different firms.

We contribute to organizational theory (Van de Ven 1995) by suggesting a process-based theoretical framework describing how firms develop high-performing business analytics. Our research suggests that a universalistic, best-practice, approach is limited in power though and that the development of business analytics is appropriately viewed as a co-evolutionary, emergent, process.

Theoretical background

Resource Based View theory of the firm provides a useful theoretical perspective on business analytics. An initial study was Davenport and Harris' (2007) landmark research that linked business analytics and performance in large firms. In a rich case study they observed that firms with highly effective business analytics share common traits such as the existence of highly specialized resources, an enterprise approach to the development of these resources and a strong leadership from top management.

Further studies expanded on these findings. Kiron (2011, 2017) investigated which analytic-oriented resources and capabilities produce competitive value. A large scale survey-based study finds that successfully competing on analytics requires competences in the management of information, analytical expertise as well as a strong top management commitment to develop a data-oriented culture that uses analytics as a strategic asset throughout the organization.

Resource based view models assumes the existence of a set of resources and capabilities which, if properly nourished, will lead to effective BA. Recent studies however have raised concerns about the universal validity of best practice-based approaches to the development of business analytics as: (1) managers' perceptions of ideal BA are shown to be contingent on organizational variables thus lending support for a contingency approach to BA development, (2) firms with different strategic orientations (e.g. customer versus operations) and market context (highly regulated versus highly competitive) achieve BA performance through different alternative routes thus suggesting a complex undertaking which entails co-evolutionary change involving alignment of business, IT and human resources (DalleMulle and Davenport 2017, Hindle and Vidgen 2017).

The information processing view of the firm offers a second theoretical perspective on business analytics by conceptualizing firms and its constituent business units as information processing systems facing uncertainty. Galbraith's (1974) seminal research observed a direct relationship between the complexity of the task to be performed and the amount of information that must be processed by decision makers during the service execution in order to achieve a given level of performance.

Further research extended this information processing view by developing a conceptual model for organizational design and structure around a basic structural problem: how to design business units and relations between them in a manner to be capable of dealing with information processing requirements faced during task execution (Rogers 1999).

From this perspective a basic function of the organization's structure is to create adequate configuration of business units (as well as the linkages between them) to facilitate the effective collection, processing and distribution of information.

Effective information processing is understood as the collection of appropriate information, the movement of information in a timely fashion, and its transmission without distortion. Effective information processing also implies the ability to handle needed quantities of information according to these criteria.

Tushman and Nadler (1978) outline that a basic design problem is to balance the costs of information-processing capacity against the needs of the service and hypothesize that Organizations will be more effective when there is a match between information processing requirements facing the organization and information processing capacity of the organization's structure.

Overall extant theory on Business Analytics implies that (1) a corporate-centric process, (2) driven by top management nurturing (3) a data-oriented culture for the purposes of (4) coping with the information needs of the organization is likely to yield high performing Business Analytics.

Critical issues remain however. First, the prevalent view seems to be that the universal BA model –taken as a unified packages of resources and capabilities – is valid although difficult to implement. Second, developing highly effective BA entails strong collaboration between business units, thus suggesting a need for empirical studies adopting the business unit as the unit of analysis in order to provide insights on the pathways followed to develop information processing capabilities and the challenges, technical and organizational, faced by managers of business units.

Research Methods

Given limited theory about how firms develop high-performing business analytics we relied on inductive theory building using embedded multiple cases (Yin 2013). Our embedded design using several units of analysis (i.e. business units within a common firm) improved the likelihood of rich, accurate theory (Voss et al. 2002).

The setting is large firms operating in service-intensive industries such as education, healthcare, digital media and ecommerce. We select firms opting for mass customization as a strategic choice (Salvador 2008,2009); responding to customers' unique demands and expectations, and doing so in near real time, results in large information processing needs and subsequently demanding large information processing capabilities in terms of volume, variety and speed. The firms selected operate in highly competitive contexts, thus forcing them to excel in their operational performance. This allows better empirical grounding.

The research focused on two for-profit firms and one non-for-profit institution each with multiple business units. All firms are market leaders in their respective industries: education, digital media and healthcare. This combination of multiple industry sectors should improve the robustness and generalizability of the results (Yin 2013).

For each firm under consideration several business units were observed. We use several criteria to define a business unit. First a business unit was defined as a distinct and separable organizational entity with authority over key BU-level decisions, including resource allocations. Second, it delivered distinct services that customers could acquire independently of those offered by other BU in the same firm. Third it presented unique information processing needs. Fourth, it was managed by a general manager with an executive team.

For each firm we identified instances of business units with high-performing business analytics in preliminary interviews with general managers. We asked these executives to summarize the objectives, importance, challenges, resources and alliances they faced during the development of business analytics. We then proceed to interview middle managers, data scientists and IT professionals on the challenges and issues they had to overcome along the process. Table 1 summarizes characteristics of the focal firms and our data collection.

Table 1. Overview of the Focal Firms

Firm/Market segment	**Market dynamics**	**Revenue (2016, euros)**	**N. of employees**	**N. of informants interviewed/ Informants interviewed by type**	**N. of Business Units**	**N. of services deliveries**
SKY PLC. Digital Media	Highly competitive (BT, Virgin, Netflix, Amazon)	13.5 billion	30000	5. Middle Management (2), Data Scientists (2), IT (1)	2	2
IE Business School. Education	Highly competitive (FT rankings). Premium graduate education segment	180 million	1200	8. General Management (3), Middle Management (2), Data Scientists (2), Professor (1)	4	3
Spanish agency for organ donation. Healthcare	Competitive (worldwide leaders in organ donation)		600	4. General Management (2), data scientist (1), IT (1)	3	2

Data Collection

We relied on several data sources: face to face interviews, surveys, follow-up emails, phone conversations and archival data. Triangulation of data sources provides more accurate information and improves the robustness of the resulting theory (Myers 1997). The primary data source was 12 semi structured interviews with both open and closed ended questions conducted over 6 months.

We interviewed relevant informants at several levels in the hierarchy: the general manager of each participating business unit, two managers and at least one technical person involved in the development of BA for that Business Unit. We then used snowball sampling to identify other informants who were directly involved with a focal collaboration.

We began the development of each case by asking informants background questions about their industry, their firm's corporate and business strategy and their role in their firm. We then asked informants to relate the chronology of the development of business analytics in their business unit as well as the current status of their projects and on-going concerns.

In the interests of gaining complete information we prompted informants to provide more details when their descriptions were brief or when novel strands of narrative emerged. We ended each interview with closed ended questions on the performance of business analytics. All interviews were recorded and transcribed.

Potential bias was addressed in several ways. First, we interviewed informants at multiple hierarchical levels. Second we used open-ended questioning of highly knowledgeable informants focused on the development and use of Business Analytics to limit recall bias and enhance accuracy. Third we used "courtroom questioning" that focused on factual accounts of what informants did or observed others doing (Martin & Eisenhard 2010). Fourth we triangulated data from multiple informants and archival sources and factual evidence.

Data Analysis

Following recommendations for multiple case theory building (Eisenhard & Graebner 2007) we used within-case and cross-case analysis. We began by building individual reports that triangulated all of our data. We then proceed with the within-case analysis in which the development and use of Business Analytics by the different business units was the unit of analysis, developing preliminary concepts and a theoretical model on performance.

We then conducted a cross-case analysis using replication logic across the firms, treating each firm as a case. We next moved to general cross-case analysis to probe for alternative theoretical relationships and constructs that might fit the data better than our initial emergent theory. Using replication logic, we developed preliminary theories from some cases and tested them on others to validate and refine the emergent theory (Eisenhard 1989).

Developing High-Performing Business Analytics

Our research asks, how do firms develop high-performing business analytics? Prior to our description of our emergent framework we describe how we measured Business Analytics performance.

We measured BA performance as follows: First, we averaged the informant ratings on BA effectiveness for three informant types: business unit general management, middle management and technical staff. Second, we use qualitative assessments from informants. High performance was indicated by positive comments such as:

> *"The information provided by our existing BA is really useful to determine which contents are the most popular, who access which content and at what time. Media streaming services are quite complex from a technical point of view, many things can go wrong and the customer notices it immediately on their screens, our current BA provides lots of data which allows us to analyse and troubleshoot operations. (GM, Sky)."*

Current gaps in performance were indicated by comments such as:

> *"Overall we get sufficient information to make informed decisions. We believe we are quite good at marketing our firm in conventional channels. We need though to improve our visibility on online marketing. This is a brave new world, we spend a significant amount of money on online advertising and certainly would benefit from more information on the effectiveness of marketing campaigns. (GM, IE Business School)".*

Third, we assessed the impact of BA in terms of actual impact on financial, market and strategic outcomes. For example the Spanish agency for organ donation and transplant became the first in the world to achieve a seamless integration of 124 hospitals for the purposes of matching organ donors with recipients under strict timing constraints (Matesanz et al. 2011). The effectiveness of this near real time matching process relies, among other things, on the ability to each involved stakeholder (e.g. surgeons, logistic operators) to get relevant information (e.g. medical backgrounds, type of transport, people involved, medical evolution of the patient).

Following we describe our inducted framework offering theoretical logic to the development of high performing business analytics.

Building up: Developing information processing capabilities

The argument from information processing theory is that organizational performance is contingent on the equilibrium between information processing needs and information processing capabilities. In this regard it would be expected that firms facing given levels of information processing needs would then need to build up enough information processing capabilities.

Our research finds that firms develop information processing capabilities through four mechanisms: data management, data governance, data quality and data science.

Data management as the ability of the business unit to handle large and heterogeneous data (e.g. images, text, sound, sensors) is a core technical competence to have as it provides the foundations for any subsequent analysis and insights generation.

Data governance, as revealed in our research, is another critical mechanism to ensure that decision making is conducted based on accurate and consistent data.

Data quality as the ability of the business unit to provide data "where it is needed, at the right time and in the right format" is an important aspect of high performing business analytics. Data which is of high quality allows managers to customize the manner in which they consume (or produce) insights as reported by the director of business analytics at IE Business School.

> *"Some of our managers prefer visual information such as dashboards, others however feel more comfortable using conventional spreadsheet others even prefer to gain access to raw data and do their own data crunching and analysis.....Delivering data of high quality entails not only enhanced technical capabilities (rich visualization and dashboarding, data export capabilities) but also a special consideration for the needs of decision-makers"*

Data science, as a competence of increasingly important relevance for firms, emerges as the fourth mechanism to develop information processing capabilities. As reported by our informants, extracting practical value from data increasingly calls for advanced analytical skills. Recommender systems, as deployed at SKY, are clear instances on the strategic importance of being able to acquire deep knowledge on customer-product relationships.

Why is information processing capabilities a prerequisite for high performing business analytics? The key insight is that decision making at the firm level builds on information on customers and operations which is consistent and exhaustive thus the importance of having data properly managed, governed and of sufficient quality to facilitate managers' decision making processes. As a general manager noted:

> *"At the beginning we faced the huge challenge of having all the relevant data we needed to make an optimal donor-recipient matching. Contrary to other units we operated under very strict timing constraints (organs must be harvested and implanted in less than 10 hours, transportation included). In addition to our database and communications infrastructure we developed a call centre operating on a 24*7 basis. This call centre coordinates in real time every donation event happening in our country, its role is critical to ensure that surgeons and supporting teams arrive in time at the donor's hospital, are able to harvest organs and return in time to the recipient's hospital"*

More subtly, data of high quality creates a positive feedback loop reinforcing the role of BA as a strategic asset for the company. Managers who get valuable and relevant information increasingly rely on BA allocating resources and additional funding into it. Finally well performing information processing capabilities (e.g. advanced visualization, real time analytics and artificial intelligence) allows managers to formulate alternative strategies and have them tested using available insights (Anderson-Lehman 2014).

This leads us to suggest:

Proposition 1. *Well-developed information processing capabilities positively moderates high-performing business analytics*

Proposition 1a. *Data management positively moderates high-performing business analytics*

Proposition 1b. *Data governance positively moderates high-performing business analytics*

Proposition 1c. *Data quality positively moderates high-performing business analytics*

Proposition 1d. *Data science positively moderates high-performing business analytics*

Adjustment: Achieving information processing equilibrium.

The argument from extant theory is that matching information processing needs with information processing capabilities is conducive to organizational performance. In this regard during the previous building-up stage firms significantly augmented their information processing capabilities in order to ensure that they are able to process large, heterogeneous, volumes of data in a reliable and consistent manner.

Our results indicate, however, that achieving this equilibrium involves a far more nuanced and convoluted pathway than just developing technical and human resources. On the one hand developing new resources and capabilities takes time and effort, on the other hand information processing needs are oftentimes ill-defined or simply not known ex-ante. So, firms shape and refine this information processing equilibrium through deliberate adjusting activities that occur along the development of business analytics.

These deliberate adjusting activities are, according to our informants, explicit attempts to gain new information from experience that clarifies the value of the newly developed capabilities (e.g. ability to store large datasets on customers' past purchases, learning analytics to enable adaptive learning) as well as whether the level achieved is fit for purpose or needs further expansion. Deliberate adjusting activities include experiments (e.g. pilot tests, technical prototyping), partnership agreements (e.g. data providers) and systematic reflection with other business units to identify new information needs.

All BA development initiatives observed included deliberate adjusting activities. An illustration is the marketing business unit at IE Business School in which, as a result of newly developed data processing capabilities, management upgraded their needs for advanced insights on their operations:

> *"Once we started to gain visibility on our processes (e.g. social media, SEO) we wanted to go further and understand how we could act on these channels to improve our conversion rates and how to optimize our digital marketing spending…. A new world of possibilities opened to us from getting to know more about our current situation of our alumni to designing new machine learning based algorithms to optimize our digital marketing spending on google ads. We decided to establish a strategic partnership with LinkedIn to get a new source of valuable information for us"*

The Spanish agency is also a case in point of deliberate adjusting activities for the purposes of matching information capabilities with information needs:

> *"There is so much potential to increase donation rates in developed healthcare systems. We currently are at 40 donors per million population but we believe we could reach 60 in the future. There are so many drivers of performance from the judiciary system to air traffic controllers to relatives consenting to donate. In the beginnings of our existence it was relatively easy to achieve sustained increases in organ donation rates in Spain, however as our system matured it became increasingly hard to gain even minor improvements"*

The analysis of the cases considered reveal that business units adjust their information processing needs according to their newly developed information processing capabilities through two main mechanisms: business process instrumentation and customer touch point instrumentation. The arrival of new, fine grained data, usually reveals inconsistencies or gaps in current knowledge regarding operations thus prompting for further instrumentation of existing business processes. In a similar manner customer facing business units usually identify opportunities for improving their knowledge on how customers interact with current service offerings.

Why are deliberate adjusting activities likely to lead to high-performing business analytics? The key insight is that information processing needs often emerge as ill-defined ideas that are difficult to judge and more nuanced that initially anticipated, this is specially the case in highly uncertain contexts demanding greater amounts of information to be processed by decision makers during the delivery of the service (Galbraith 1974). These activities are effective because they provide a better understanding on the gap between information needs and information capabilities. As a manager IE Business School responsible for the online learning BU noted:

> *"Initially the main purpose of our Business Analytics was to monitor in real time the student's learning journey so that instructors could provide support when needed. Once our BA was in place and running we realized the potential of using real time data to develop adaptive learning and learning personalization, for us this is quite important as it supports our core value proposition (maximize the time that busy managers spend with us), this led to new initiatives to further instrument our learning processes, redefine our teaching material to make it more modular and interactive and change the way we deliver teaching to adapt to these customized learning paradigm".*

Finally gaining and end-to-end perspective on the performance on processes and customers calls for information exchange as well as mutual adjustment across business units, and increasingly third party providers, involved in the delivery of services to customers (Tushman 1978).

Overall, our findings reveal a contingency-based approach to the process of developing data capabilities. Far from a "best-practice" approach to the building of these data capabilities, firms follow a co-evolutionary approach adapting to unforeseen circumstances and establishing a constant dialogue across involved business units (Sousa and Voss 2001). This suggests:

Proposition 2. *Deliberate adjusting activities positively moderate high-performing business analytics.*

Proposition 2a*. Business process instrumentation positively moderate high-performing business analytics*

Proposition 2b*. Customer touch point instrumentation positively moderate high-performing business analytics*

Discussion

We add to theories of information processing theory and the study of how business analytics, an increasingly relevant organizational function, is developed by large firms. Prior results adopt a resource based view whereby the performance of business analytics is contingent on the availability of some well-known capabilities and organizational resources. Empirical evidence however has been only weakly supportive. Addressing this gap, we explore how business units within firms develop high performing business analytics.

Our research offers insights for theories of information processing and organizational design. Prior theoretical assumptions suggest the importance of top management support and a strong data-oriented culture which, in combination with strong technical and analytical capabilities yield to effective business analytics. Our research suggests that a universalistic, best-practice, approach is limited in power though and that the development of business analytics is appropriately viewed as a co-evolutionary, emergent, process (Hindle and Vidgen 2017).

The present study strongly suggests that BA practices are contingent on the firm's service deliveries as well as on its idiosyncratic cultural and organizational aspects. This finding is in agreement with a contingency approach and in contrast with any universalistic approach of the best practice paradigm (Sousa and Voss 2001). In this regard the concept of best practice for BA should be replaced by the concept of "best in class practice" indicating the need to link best practice to the specifics of service delivery context.

The findings can be used to inform the development of the organizational function of business analytics. The study reveals that the firm's industry (e.g. healthcare, media streaming, education) poses unique challenges to the development of BA: (1) Defining which information processing needs are of strategic value for the firm is inherently specific to the firm's operations and strategic positioning. (2) Valuable analytics increasingly require establishing strong partnerships with third party providers (e.g. Web Analytics, Cloud providers) at the risk of disclosing strategic information, (3) strong coordination across business units for the purposes of data integration and end to end instrumentation of business processes, (4) cultural reorientation towards data quality and fact-based decision making.

These challenges must be clearly differentiated from those eventually arising from the process of development of BA, as they may demand different courses of action.

High-performing business analytics provides managers with extensive and real-time knowledge on customers and service deliveries which allows them to consider multiple alternatives concurrently and rapidly assess the viability of each course of action. In this regard we find that enabling fast decision making (Eisenhardt 1989) is the overarching goal for the development of high-effective business analytics.

References

Anderson-Lehman, R., Watson, H. J., Wixom, B. H., & Hoffer, J. A. (2004). "Continental Airlines flies high with real-time business intelligence". *MIS Quarterly Executive*, *3*(4), 163-176.

Cao, G., Duan, Y., & Li, G. (2015). "Linking business analytics to decision making effectiveness: A path model analysis". *IEEE Transactions on Engineering Management*, 62(3), 384-395.

Chen, H., Chiang, R. H., & Storey, V. C. (2012). "Business intelligence and analytics: From big data to big impact". *MIS quarterly*, 36(4).

DalleMule, L., & Davenport, T. H. (2017). "What's Your Data Strategy?". *Harvard Business Review*, 95(3), 112-121.

Davenport, T. H., & Harris, J. G. (2007). *Competing on analytics: The new science of winning*. Harvard Business Press.

Eisenhardt, K. M., & Graebner, M. E. (2007). "Theory building from cases: Opportunities and challenges". *Academy of management journal*, 50(1), 25-32.

Eisenhardt, K. M. (1989). "Building theories from case study research." *Academy of management review*, 14(4), 532-550.

Galbraith, J. R. (1974). "Organization design: An information processing view". *Interfaces*, 4(3), 28-36.

George, G., Haas, M. R., & Pentland, A. (2014). "Big data and management". *Academy of Management Journal*, 57(2), 321-326.

Hindle, G. A., & Vidgen, R. (2017). Developing a business analytics methodology: a case study in the foodbank sector. *European Journal of Operational Research*.

Iansiti, M., & Lakhani, K. R. (2014). Digital ubiquity:: How connections, sensors, and data are revolutionizing business. *Harvard Business Review*, *92*(11), 19.

Kiron, D., & Shockley, R. (2011). Creating business value with analytics. *MIT Sloan Management Review*, 53(1), 57.

Kiron, D. (2017). Lessons from Becoming a Data-Driven Organization. *MIT Sloan Management Review*, 58(2).

Lycett, M. (2013). 'Datafication': Making sense of (big) data in a complex world. *European Journal of Information Systems*, 22(4).

Matesanz, R., Domínguez-Gil, B., Coll, E., de la Rosa, G., & Marazuela, R. (2011). Spanish experience as a leading country: what kind of measures were taken? *Transplant International*, *24*(4), 333-343.

McAfee, A., Brynjolfsson, E., & Davenport, T. H. (2012). Big data: the management revolution. *Harvard business review*, 90(10), 60-68.
Myers, M. D. (1997). Qualitative research in information systems. *Management Information Systems Quarterly*, 21(2), 241-242.
Ransbotham, S., Kiron, D., & Prentice, P. K. (2016). Beyond the hype: the hard work behind analytics success. *MIT Sloan Management Review*, 57(3).
Rogers, P. R., Miller, A., & Judge, W. Q. (1999). Using information-processing theory to understand planning/performance relationships in the context of strategy. *Strategic Management Journal*, 567-577.
Salvador, F., Rungtusanatham, M., Akpinar, A., Forza, C. (2008). Strategic capabilities for mass customization: Theoretical synthesis and empirical evidence. In *Academy of Management Proceedings* (Vol. 2008, No. 1, pp. 1-6). Academy of Management.
Salvador, F., De Holan, P. M., & Piller, F. T. (2009). Cracking the code of mass customization. *MIT Sloan management review*, *50*(3), 71.
Sousa, R., & Voss, C. A. (2001). Quality management: universal or context dependent?. *Production and Operations Management*, 10(4), 383-404.
Tushman, M. L., & Nadler, D. A. (1978). Information processing as an integrating concept in organizational design. *Academy of management review*, 3(3), 613-624.
Van de Ven, A. H., & Poole, M. S. (1995). Explaining development and change in organizations. *Academy of management review*, 20(3), 510-540.
Voss, C., Tsikriktsis, N., & Frohlich, M. (2002). Case research in operations management. *International journal of operations & production management*, 22(2), 195-219.
Wixom, B. H., Yen, B., & Relich, M. (2013). Maximizing Value from Business Analytics. *MIS Quarterly Executive*, 12(2).
Yin, R. K. (2013). *Case study research: Design and methods*. Sage publications.