THE MARKETING ORGANIZATION'S JOURNEY TO BECOME DATA-DRIVEN

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Abstract

Purpose – This article seeks to improve understanding of data-driven marketing by examining the experiences of managers implementing big data analytics in the marketing function. Through a series of research questions, this exploratory study seeks to define what big data analytics means in marketing practice. It also seeks to uncover the challenges and identifiable stages of big data analytics implementation.

Design/Methodology/Approach – Fifteen open-ended depth interviews were conducted with marketing and analytics executives in a variety of industries in Ireland and the United States. Interview transcripts we subjected to open coding and axial coding to address the research questions.

Findings – The study reveals that managers consider marketing big data analytics to be a series of tools and capabilities used to inform product innovation and marketing strategy-making processes and to defend the brand against emerging risks. Additionally, the study reveals that big data analytics implementation is championed at different organizational levels using different types of dynamic learning capabilities, contingent on the champion's stature within the organization.

Originality/value – From the qualitative analysis it is proposed that marketing departments undergo five stages of big data analytics implementation, which are: *sprouting*, *recognition*, *commitment*, *culture shift* and *data-driven marketing*. Each stage identifies key characteristics and potential pitfalls to be avoided and provides advice to marketing managers on how to implement big data analytics.

Keywords – Data analytics, business intelligence, customer analytics, customer data management, data mining.

Paper type Research paper

Introduction

The term marketing big data analytics (BDA) refers to the technologies and statistical techniques whereby marketers analyze large amounts of data to make useful inferences about customers and competitors. It is evident that becoming data-driven allows firms to better understand their costs, sales potential and the emerging marketplace opportunities. However, managers are challenged (1) to make sense of a rapidly emerging and evolving set of data analytic tools from which to choose and (2) to decide how to integrate analytics with their strategic decision-making process.

A 2016 McKinsey & Company Global Institute Report concluded that many sectors of the US economy had only achieved between 10% and 60% of the value McKinsey had forecasted in 2011 to be achievable from big data analytics within the next five years (Henke et al., 2016). US retail, for example, had only accomplished 30 to 40% of the forecast, citing lack of analytical talent and data silos within companies as the reason for the lag. Other challenges are also symptomatic of a lack of clear understanding of BDA implementation processes. Such challenges include the failure to extend the success of analytics efforts beyond an initial case study, the inability to interpret and translate analytics results into managerial decisions, and a fear that ethical and social implications of analytics will cause unanticipated problems (Fleming et al., 2018). The difficulties of successful BDA implementation have also been attributed to failure to create a data culture that integrates analysis and decision-making (Diaz et al., 2018; Goran et al., 2017).

These challenges in BDM implementation listed above are particularly relevant to marketing departments, which are on the frontline of efforts to become data-driven. The purpose of this article is to provide guidance to marketing managers on how to best implement BDA to support the marketing function. While many chief marketing officers are coping with BDA as a rapidly unfolding area of expertise in which decisions must be made with strong implications for long-term competitiveness, they are grappling with these issues with little guidance in how to do so. In fact, it appears that BDA implementation may be taking more of a "learn-as-we-go" approach rather than a structured deliberate top-down implementation process. Whatever, the case, there is a dearth of information and knowledge as to how to best guide the organization in its journey to become data-driven (e.g., Arthur, 2013; LaValle et al., 2011).

The present exploratory research study addresses this research gap by examining three research questions. First, this paper seeks to define what BDA means in marketing practice and what capabilities are most valuable at different levels in the organization. The second objective is to identify the implementation challenges of BDA in a marketing context. The third goal is to identify the organizational factors that influence the stages by which marketing departments become fully data-driven.

In general, big data refers to data of substantive size that presents challenges to conventional database, software and analysis tools (Manyika et al., 2011). Big data is therefore a subjective concept defined in the moment by the relative growth in digital data flows and information technology innovation as dictated by Moore's Law (Chan, 2013). Gartner Inc. (2011) describes big data as having three characteristics popularly referred to as the three Vs: volume, velocity and variety. According to Gartner Inc. large volumes of data create storage and analysis challenges. In the marketing context, variety refers to the flow of data from different sources and in different formats such as transaction, social media and click stream data that must be integrated and linked to actors and brands. Velocity refers to the speed with which data is produced and must be analyzed to inform decisions.

Together with marketing data, analytics allow marketers to determine the success of marketing initiatives by measuring return on investment (ROI) and marketing attribution (Wedel and Kannan, 2016). The reputation of marketers has suffered from not adequately attributing returns on advertising spend (Homburg et al., 2015). Historically, chief financial officers have been critical of marketing professionals for not adequately demonstrating ROI on marketing expenditures and for using creativity and brand equity nebulously as evidence of adequate performance (e.g., Stewart, 2009). Marketing academicians have also been addressing these concerns for some time with research linking strategy and tactics to market-based assets and shareholder value (Srivastava et al., 1998). In addition, improvements in data integration and analysis that allow precise attribution of marketing spend is increasing marketing accountability. Data analytics are perceived to be the solution to the long-standing problem of justifying marketing actions.

In particular, marketing analytics is generally viewed by top management as bringing efficacy to marketing decision-making and ROI requirements (Maddox, 2006). Research by Feng and colleagues (Feng et al., 2015) supports this assertion by showing a consistent growth in marketing departments' power and influence in the United States based firms during the period 1993 through 2008.

Research Questions and Background

Therefore, the essential question for marketing departments is how to best capture, integrate and analyze data to inform sales and marketing decisions using emerging technologies and techniques. The rapid growth of the three Vs of customer data leaves marketing managers with no room for complacency. In addition, the proliferation of omni-channel experiences and the increase in user generated content means that brand related messages are continuously being created at big data scale by friendly and unfriendly actors. Marketers are negotiating a variety of tools and techniques including building internal software capabilities, transitioning existing capabilities to the cloud and building teams with equal knowledge of analytics, products and customers. It is within this dynamic and disruptive environment that a concept of what BDA means for marketing is becoming crystallized in the mind of the marketing community. In this circumstance, marketers are unlikely to have a uniformed understanding of marketing BDA, yet they are grappling with what BDA means for their organization. Still marketers know that those who are unable to process and react to big data, risk losing control of their brand messaging (Payne et al., 2017) and their market position. Therefore, the first research question asks the following:

> **Research Question One:** What does BDA mean in marketing practice, and what BDA capabilities are most valuable at different levels in the organization?

Marketing departments are particularly challenged because while the marketing function and its relative power and influence within the firm is of increasing importance (e.g., Verhoef and Leeflang, 2009), little systematic research exists to date on marketing capability implementation (White et al., 2003) and more specifically on how marketing departments are accomplishing BDA implementation. This study seeks to uncover a more systematic understanding of marketing BDA implementation experiences, specifically in terms of the organizational factors that facilitate or hamper the marketing organization's goal to become data-driven.

Organizational culture, while important, has not been widely studied in terms of influencing the marketing strategy capabilities of the firm (Deshpande and Webster Jr., 1989). More specifically, the dynamic capabilities literature with emphasis on sensing, learning and filtering (Day, 1994; Day and Schoemaker, 2016) while potentially relevant, has not been used to explain the organizational processes of marketing BDA implementation.

BDA poses a unique challenge for marketing since the same data is often required by multiple departments. For example, logistics, sales and marketing use the same data, so scaling BDA operations often means centralizing data management and analytics as an organization-wide resource. BDA implementation may involve sharing or shifting responsibility between, for example, marketing and IT, making it necessary for managers to figure out how responsibilities for BDA should be shared among functional areas (Berkooz, 2016). Although the marketing department may be an early adopter of BDA, eventually it must make its analytics capabilities available company-wide. BDA is not only creating larger data sets but also adding new variables such as time and location, allowing more analysis and real-time marketing tactics (Bradlow et al., 2017). Hence, data planning becomes a priority for marketing departments and pressure is growing for marketing executives to make their organizations more data-driven. This research seeks to understand how these challenges affect BDA implementation, which leads to the second research question:

> **Research Question Two:** What are the BDA implementation challenges and processes in a marketing context?

As discussed previously, marketing managers are confronted by a barrage of new concepts from Google Analytics to text analytics, machine learning, predictive modeling and advertising optimization. All these concepts, tools and techniques must be understood and implemented, if applicable. Internally, marketing departments attempt to learn quickly by bringing in consultants, recruiting skilled expertise and by updating the skills of current employees. Analytics tools often become trendy and obsolete within months adding to the frenzied pace of leaning required of marketing and analytics employees. Within this context, it is useful for managers to understand if their approach to BDA implementation is consistent with certain stages of development and, consequently, whether certain factors are more essential to success at different stages and if there are pitfalls to be avoided. Against this background, at third research question is asked.

> **Research Question Three:** Are there detectable stages in a firm's implementation of marketing BDA?

Method

The first step in the data analysis process was to review the literature on big data analytics, which is primarily industry focused, including several periodic tracking surveys. The next step was to develop initial research questions, which were continually refined through the process of conducting qualitative interviews. The next step was to select subjects for depth interviews by recruiting participants with a deeper understanding of the subject matter and then by using snowballing techniques when necessary rather than random sampling techniques to recruit participants. (Challagalla et al., 2014; Homburg et al., 2017; Malshe and Sohi, 2009). It was determined that theoretical saturation had been reached when interviews yielded limited additional insights (Strauss and Corbin, 1998). Figure 1 details this methodological process.

This research therefore used a grounded theory approach to study an implementation process that is still ongoing. Grounded theory involves embedding the research in the empirical context and developing and applying concepts from the context and literature to achieve explanatory power (Glaser and Strauss, 1967). A basic assumption of grounded theory is that emerging concepts are shaped and best reported on by those involved in their development

(Glaser and Strauss, 1967; Hollmann et al., 2015; Homburg et al., 2017). A qualitative research method was used for the ability to ask open-ended questions that would help identify emerging concepts is well-suited to the development of grounded theory.

Therefore, fifteen marketing and analytics professionals from the United States (US) and Europe involved in marketing BDA implementation in their respective firms participated in depth interviews for this research. The firms were from a variety of industries including financial services, media and publishing, energy utility, airline, telecommunications and management consulting. Table 1 lists the job titles of study informants that include chief marketing officers, CRM managers, director of analytics and analytics consultants. Informants ranged from middle to senior management and all had over two or more years of experience in marketing analytics and or big data analytics implementation environments.

[Table I here]

An interview protocol ensured the research questions were investigated across all interviews. The first question addressed by the interviews was the meaning of BDA analytics to the organization and its role in marketing strategy. The questions then progressed to organizational priority and challenges to BDA implementation. Finally, the interview questions moved to the role of the marketing staff and the experiences and outcomes of implementation to date. Respondents were then asked about those who championed the BDA effort in their organization and to discuss the learning process involved in the implementation of BDA. This methodology is commonly used in qualitative research (Yin, 1994; 2011) to identify patterns in interview responses. Informants were encouraged to provide examples to illustrate their points to minimize ambiguity of interpretation (Glaser and Strauss, 1967).

The interviews were audiotaped and subsequently transcribed. To analyze the interviews, the researchers undertook iterative reviews of the 43 pages of interview transcript first using open coding to identify zero-order coding categories comprising actual language used by participants. Tables II and III present the coding categories supporting the first and second order categories that ultimately addressed the third order research questions. Researchers then conducted axial coding by creating first-order categories reflecting subdimensions of our research questions (Nog and Gioia, 2012) and categorizing the zero order codes to support each axial code. Zero order codes determined to be irrelevant to our first order codes were abandoned consistent with prior research practice (Homburg et al., 2017; Tuli et al., 2007). Table II illustrates that the first order category of decision-making tools was used to categorize a variety of tools and applications mentioned in discussing marketing related BDA. The emergent themes from this - analyses are discussed in the next section.

[Table II and III here]

Results and Discussion

The Meaning of BDA in Marketing

The research finds that managers regard marketing BDA as decision making tools and capabilities for informing product innovation and marketing strategy and for defending the brand. Managers mentioned several decision-making tools or capabilities such as customer lifetime value analysis, predictive modeling, data visualization and tracking social media among others (see Table II). The purposes for which these tools and capabilities are applied were structured as second order categories consistent with grounded theory research. Informants indicated that marketing BDA's central focus was to inform product innovation and marketing strategy. This was most evident among digital native firms. Digital native firms have a digital infrastructure producing structured data that makes them data driven by default.

According to one consultant interviewed, digital-native firms apply BDA in areas such as prospecting, acquisition, sales cost reduction, advertising optimization, predictive modelling and A/B testing. One of the business-to-consumer digital-native firms interviewed in the telecommunications industry pointed out that the key focus of their use of marketing analytics was predicting customer lifetime value (CLV) and maximizing ROI by minimizing customer acquisition and customer maintenance costs against anticipated CLV. A large business-to-business telecommunications equipment supplier shared that their interest in consumer data analytics is primarily concerned with forecasting consumer needs and trends over a three-year planning horizon by analyzing traction and social media data. The current product development model of the firm is building automated services into products and shifting employees from service delivery to support.

The second purpose of marketing BDA is defensive brand protection. This was primarily observed among brand centric firms, those firms who have primarily focused on brand promotion for their marketing efforts. Attempts by brand-centric firms to develop a digital core can be expensive. According to a consultant interviewed, brand-centric firms initially take a risk management approach to BDA. For these firms, the brand is their biggest asset so their first reaction is “how can we use big data to protect our brand”. Consequently, tracking clickstream and social media to identify and manage risk to the brand takes early priority. This defensive posture may lead to a ‘siloed’ approach to digital transformation in which firms fail to recognize the necessity of fully integrating digital and retail store channels until it’s too late. For example, Sephora Inc., a company not interviewed here, credits its success at digital transformation to avoiding the tendency of legacy firms to initiate digital transformation by building online channels as separate companies resulting in a lack of cross functional integration and customer centricity. Instead, the company fully integrated its channels and loyalty programs and embraced social media as an engagement channel. (Bornstein and McGinn, 2014).

The Role of Champions in the Implementation of BDA in Marketing

Another theme that emerged from the interviews was the important role of champions in BDA implementation and how they functioned using dynamic sensing capabilities. To compete effectively in rapidly changing environments, in addition to having a strong resource base such as protected technology, firms need certain capabilities that allow them to integrate, build, and configure internal and external competencies to address rapidly changing environments (Teece et al., 1997). Dynamic capabilities are clusters of sensing, filtering and learning processes that allow firms to react and seize opportunities as the environment evolves.

An observation from the interviews was that the speed and degree of marketing BDA implementation is a function of the type of dynamic capabilities involved and that these capabilities are a function of the level at which marketing BDA is championed within the firm. These observations are presented in Figure 1. Day and Schoemaker (2016) identify six sub-dynamic capabilities of firms coping with change in dynamic environments, namely peripheral vision, vigilant learning, probe and learn, flexible investing, organizational redesign and external shaping.

The Use of Different Capabilities Depending on Organizational Level

This study found that three sub-capabilities are especially influential in building marketing BDA capabilities. These sub-capabilities are vigilant learning, probe and learn and organizational redesign. *Vigilant learning* involves remaining alert to often weak signals in the environment and interpreting the meaning of these signals before acting on them. When BDA is championed by lower level operatives, vigilant learning becomes critically important. Lower level champions with limited resources are hard pressed to detect emerging techniques and software applications likely to achieve traction in market. Rapid growth and emergence of multiple competing software and analytics services create uncertainty. Lower level champions engage in vigilant learning by sifting through emerging techniques, analytics services and software applications before placing bets on those most likely to match the needs of the firm. Because delivering early ROI on marketing analytics investments is essential for convincing top management to increase resources, lower level champions often feel pressure to select proven and established turnkey solutions instead of custom innovations.

[Place Figure 2 here]

The *probe and learn* capability was suggested by Day and Schoemaker (2016) as a means of reducing the likelihood of placing early bets on new technology or opportunities that end in failure. Before fully committing to an investment, a real options approach is taken by pursuing multiple, small designed experiments to assess payoff before explicitly committing to the most fitting option (Dixit and Pindyck, 1995). Middle managers with resources and market knowledge are effective in building marketing BDA capabilities. Unlike lower level staff, middle managers have specific knowledge of customer trends and market planning requirements. As a learning approach, probe and learn can facilitate a gradual shift in the decision-making culture to becoming more evidence-based. Middle-managers can ease this transition by becoming more tolerant of mistakes or at least not resist senior management's encouragement of experimentation as in, for example, Facebook's mantra of *move fast and break things* (Taplan, 2017).

Another dynamic capability, *organizational redesign,* is required by firms to execute new strategies (Day and Schoemaker, 2016). Marketing BDA implementation involves substantial investments such as integrated data warehousing and cloud-based services that increase centralization of BDA initiatives often away from the marketing department and greater co-ordination between marketing and IT is required. Change on this scale must be championed by senior management. Organizational redesign should be the preferred approach of enlightened senior managers in well-resourced firms. Consequently, senior managers indicate greater use of outside consultants and creation of centralized BDA capabilities in high performing firms seeking transformative change. The underlying themes and results of this research are summarized in Table IV.

[Table IV here]

The Stages of Developing BDA in Marketing

Discussions with managers involved in implementation reveal that the journey of marketing departments in implementing BDA analytics can be structured into five stages. These stages are *sprouting*, *recognition*, *commitment*, *culture shift* and eventually *data-driven marketing*. Figure 3 presents the essential characteristics of each stage and identifies some pitfalls that may impede implementation at each stage.

[Figure 3 here]

Stage 1: Sprouting

The first stage of BDA implementation and the one that is most applicable to small and medium-size firms often starts with a turnkey application such as Google Analytics, initiated by a recent graduate joining the firm. This is the first entry into analytics for many departments.

These are the *sprouts* that will attract the attention of top management internally. Marketing analytics tools are run by staff who report to middle management. They often have limited support and budget to create the dashboards necessary for adequate periodic or real-time reporting.

A UK and Ireland based BDA consultant explained that in his experience, when firms lack C-suite BDA expertise, interest in analytics usually comes from junior management, especially recent recruits. The consultant further explained that despite the enthusiasm of lower-level champions, their efforts are not likely to deliver key performance indicators necessary for strategic decision-making because they don't fully understand the scope of the business. These champions often pursue objectives like increasing web traffic independently of the business strategy. One lower level recent recruit shared that progress at the early stages of analytics implementation involved having his team members aggressively seek out free online training opportunities to build and improve their skills.

Although these early efforts at marketing analytics may be somewhat amateur, they illustrate to senior management the need for a more comprehensive dashboard of performance indicators. Often these early dashboards are only geared towards management and fail to capture the interest of many project teams. It is important that early analytics efforts reach out to these teams to understand their requirements and provide tools and data that address their needs. For example, an in-house media production team may be interested in real-time feedback. These efforts sprout new shoots beyond the organizational core and increase support for resource commitments to BDA. Success of early analytics initiators requires that they quickly determine the differing interests of their internal customers (marketing sales, public relations, advertising, finance etc.) and emphasize different aspects of often the same data to address their needs (Stone and Woodcock, 2014).

A likely pitfall at the sprouting stage is the tendency of some managers to become flustered by the pace of change and take the position that ‘analytics is changing so fast’ that it is impossible to keep pace’ and consequently go into stasis. This may lead to the outsourcing of marketing analytics to advertising agencies, which undermines the probe and learn process and the experimentation and customization necessary for marketing BDA progress.

Stage 2: Recognition

Next, in the recognition stage, the efforts of early analytics champions begin to show results, and sections of the organization begin to grasp the importance of BDA investments for growth. This stage is usually influenced by discussions with outside consultants who explain the journey to becoming data-driven and the need for data warehousing as a basic hurdle. This stage is characterized by the marketing department progressing to descriptive analytic methods such as social media tracking, cluster segmentation and customer lifetime value estimation often based extensively on assumptions rather than precise estimates. The marketing organization begins to appreciate the metrics it needs to track to improve agility of marketing, sales and advertising strategy. Some managers react to the challenges of this stage by placing too much reliance on partners, like advertising agencies, logistics partners and sales partners to provide data and analytics. Although genuine collaboration is essential, it can become an avenue to delay and dependence. Reticence to build internal human capital and technology capabilities at this stage can also impede organizational learning.

Stage 3: Commitment

At the next stage, commitment, robust top management support is manifested by investments in data warehouses and the recruitment of analytics professionals and consultants. A publishing industry analytics executive mentioned that as momentum shifted toward BDA, they quickly scaled their capabilities through cloud migration. At this stage there is an effort to transition analytics from a marketing department capability to an organization-wide capability. Filling the analytics skills gap and integrating diverse streams of data on each customer becomes a priority. The organization begins to experiment with new data-driven and digital marketing strategies to evolve its business model within the big data environment. Emphasis on short-term ROI targets is a likely pitfall. As one informant put it "firms that obsess about ROI on digital initiatives and don't take the occasional leap of faith will achieve small results from big data".

Stage 4: Culture Shift

The next stage after hiring analytics professionals and investing in technology involves a shift in how the organization thinks about itself holistically. Organizational culture is "the pattern of shared values and beliefs that help individuals understand organizational functioning and that provide norms of behavior in the organization" (Deshpande and Webster Jr., 1989). Having achieved some measure of appreciation of analytics, becoming a truly data-driven marketing organization requires a change in the culture for all but those digital native firms that were designed from the start with an analytics core (Meer, 2015; Slater et al., 2011). A 2016 survey of managers by McKinsey and Company found the failure to fully embrace a digital culture and invest in digital initiatives to be an important correlate of firm underperformance (Goran et al., 2017).

At this stage, the presence of data scientists in the organization moves BDA efforts beyond the descriptive to the predictive. From the organic learning process of exploration and experimentation, a dominant philosophy begins to emerge. At the core of this philosophy is treating each customer according to their profit potential and A/B testing of marketing initiatives to ensure that new initiatives demonstrate superior ROI compared to the status quo. Integrating customer transaction data across touch points with clickstream, social media and third party data is a defining threshold of becoming data-driven.

A consultant interviewed remarked that “at a certain point marketing BDA involves a bit of magic that is more than the sum of its parts”. The appointment of more BDA personnel such as data analysts and customer insight analysts provides greater voice to analytics within the marketing organization and increases momentum for a data-driven culture. This shift is exemplified by the observation of a consultant who mentioned that statements like “do you have the data to back that up” and “based on my analysis, it seems like we are missing out on customer engagement with our touch points” are become increasingly frequent within departmental discussions. A/B testing and its influence in decision-making is another telling indicator of the culture shift. The scientific methodology of A/B testing makes it an effective means for junior analysts to get their ideas implemented. It may flatten the decision-making process as junior analysts are able to demonstrate the efficacy of their ideas with an A/B test, reducing the likelihood that their proposals are flatly ignored by middle managers (Ries, 2011).

However, this culture shift is fraught with *ethical dilemmas* that need to be resolved in the interest of clarity on the role of analytics in marketing and sales decisions. Among these is the integration of customer data from third party suppliers. Particularly in the United States, third party data is collected without the direct consent of consumers and while the metadata is innocuous, customer specific data can provide uncomfortable insights into an individual’s private life and risk profile.

European managers were especially concerned about the risk associated with integrating third-party data with their proprietary data but appeared equally enthusiastic about the early benefits of their efforts. Ethical dilemmas may also arise from the use of transaction data that can, for example, predict a customer's stage of pregnancy, which when used for targeting purpose could prove disruptive to the customer's personal life (Duhigg, 2012). Marketers who follow the data may find themselves uncomfortable with its implications. For example, retail banks are highly regulated and are often concerned about how marketing tactics suggested by analytics may be interpreted by regulators and employees are sensitive to how analytics may lead to certain socioeconomic groups being treated differently. As the culture shift unfolds, ethical issues need to be resolved in the interest of team cohesiveness.

A potential pitfall of the culture shift is the failure to prioritize branding over analytics. As the data-driven culture begins to dominate, firms need to make sure that their brand philosophy and values are not sacrificed in the interest of short-term ROI targets. Managers must, for example, ask themselves if the marketing tactics demonstrated to be effective are consistent with the positioning and goals of the brand. One manager in the long-distance calling industry at a firm with a strong culture of A/B testing shared that his firm no longer does brand advertising. The firm markets primarily by placing product advertising on Google search and Facebook. A year-long study by the firm tested product advertising versus brand advertising and found that brand advertising failed to elicit positive ROI in terms of increased sales. However, this approach may be short-sighted.

While it is true that consumers have little trust in long distance calling cards as they often do not deliver the minutes promised on face value (Torres, 2008) and often switch telecommunications firms frequently. Consequently, in this industry, advertising that seeks to establish brand credibility should improve ROI. The benefits of brand advertising are often cumulative over several years and not demonstrable in the short term. While consumers may not initially find brand advertising in the product category believable, it is worthwhile to consider if the opportunity to build a strong expendable brand over time is being missed when decisions are based only on short-term ROI considerations.

The second pitfall as an analytics culture takes shape is that the marketing function fails to coordinate the relationship between *creativity and analytics.* The survey questions probed managers on their opinions of the role of creativity within a BDA environment. The consensus is that marketing needs analytics and creativity, perhaps, in equal proportions to realize its full potential. Traditionally, the advertising creative process would be informed by periodic usage and attitude studies involving focus groups and surveys. Now the creative process must consider big data sources such as click stream and social media as sources of insight and evaluation.

Programmatic advertising also influences the types of advertisements most likely to be impactful. Advertising across media such as billboard, search and television must be even more coordinated or optimized at present to trigger the desired customer response (Nichols, 2013). Although the managers interviewed were firmly convinced that creativity remains a core aspect of marketing going forward, they seem uncertain about how to systematically achieve a balance of creativity, analytics and ROI to advance the practice of marketing.

The third pitfall managers need to guard against as a data-driven culture takes hold is biasing their marketing strategy by focusing disproportionally on strategies and tactics for which data is available while avoiding areas in which data are limited. One manager interviewed shared his frustration with not being able to integrate certain qualitative factors capable of having short-term impact into their mathematical models even though he was convinced that these factors were impacting customer decisions. A possible implication of this is the *streetlight effect* decision-making bias, often explained by the parable of an intoxicated individual who loses his/her keys in the dark but searches for it under a light across the street. Researchers are often criticized for the streetlight effect (Rai, 2016). Frequently, it is the case that researchers conduct large numbers of studies on topics for which data is available while more worthy research questions go unaddressed because data acquisition is difficult. Similarly, managers need to guard against this mistake by not disproportionally focusing on decisions for which data is readily available while ignoring issues with deep implications for the firm's strategic direction.

Stage 5: Data-Driven Marketing

Finally, the organization researches the mature stage of a data-driven marketing. In this stage, customer equity faithfulness or treating each customer according to their profit potential is a core principle of data-driven marketing (Johnson et al., 2012). A mature data-driven consumer marketing organization identifies hundreds of micro-segments in its customer data-base using integrated transactions, click stream and third-party data. Consumers are exposed to advertising of products created for each microsegment using programmatic advertising optimized across channels for target effectiveness. Consumers are selected and offers are refined using predictive AI algorithms as more is learned while the consumer interacts with the products or retailer. To minimize incidents of under or over investment in customers, customer acquisition and maintenance costs for each microsegment is determined by precise estimates of CLV. Advanced BDA firms apply BDA cross-functionally for marketing, accounting, logistics, production, sales and channel partnerships (Spiegel, 2014). This scale of operation means real time analysis of data as it flows and moving access to results beyond IT and marketing into functional areas where middle managers and lower level employees make operational decisions (Davenport et al., 2012).

Conclusions and Future Research

This exploratory study of BDA implementation identifies five clear stages to BDA implementation within marketing departments. The study highlights the change in organizational culture involved in transitioning marketing philosophy from unqualified commitment to customer centricity to customer equity or treating each customer according to their profit potential. This research identifies some implementation pitfalls such as over reliance on external partners for BDA learning that can slow marketing BDA progress. This knowledge is relevant to both managers in the field as well as academics teaching BDA topics, especially from a strategy implementation point of view.

The present study clarifies the role of the marketing department in BDA implementation. Specifically, it suggests that external trends such as programmatic marketing and social media tracking generate flows of big data that forces the marketing function within the firm to become more data-driven regardless of their initial commitment to change. The marketing department plays the role of initiator of BDA within the firm. As these trends gather momentum, marketing is well placed to lead customer data integration and ensure cross functional access to data. Ultimately, BDA will lift marketing's credibility and influence within the firm by improving its ability to assess return on marketing investments. However, it is critical that marketing managers not losing sight of their mission in favor short term ROI considerations. Marketing managers must strengthen the firm's commitment to creativity and to the values of its brands.

Within the firm, BDA implementation is championed at different levels from junior recent recruits to senior management. BDA champions rely on different types of dynamic learning capabilities, namely *vigilant learning*, *probe and learn* and *organizational redesign*, contingent on the champion's stature within the organization. This study identifies a reliance on vigilant learning capabilities by lower level champions of BDA implementation before having the benefit of well-resourced organizational transformation championed by top management

This research is an initial step in understanding the processes by which an organization becomes data-driven. Generalizability was not the objective of the study given the grounded theory research methodology employed. However, as BDA implementation matures, a variety of generalizable research questions can be pursued including further substantiation of issues unearth by this study. A specific exploration of the five-stage model to becoming data-driven through a quantitative study across industries would be the next logical extension of this research. The findings of this study along with further research will be instrumental in improving managers' understanding how to accelerate progress and avoid the pitfalls in becoming a fully data-driven marketing organization. In addition, knowledge of the specific stages by which firms become data-driven can help ease implementation challenges and frustrations.

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Table I. Study Informants

Firm	Job Title	Location
Telecom Equipment Manufacturing	VP of Product Development	USA/China
Telecommunications	Global Head Healthcare Vertical	USA
Advertising	Chief Marketing Officer	USA
Energy Utility	Manager of Data and Business Intelligence	USA
Telecommunications	CRM Manager	USA
Management Consulting	Analytics Consultant	Ireland & UK
Retail Banking	Chief Marketing Officer	Ireland
Management Consulting	Analytics Consultant	Ireland & UK
Media Company	Analytics Manager	Ireland
Telecommunication	Head of Online Marketing	Ireland
Management Consulting	Analytics Consultant	Ireland & UK
Audit/ Consulting	Audit Manager	Ireland
Financial Services	Marketing Consultant	Ireland & UK
Airline Analytics Service Provider	Management Consultant	Ireland & UK
Publishing	Director of Analytics	USA

Table II. Exemplary Coding Results for Meaning of Big Data Analytics

Zero Order Categories	**First Order Categories**	**Second Order Categories: Purpose**	**Third Order Categories** (research question)
Customer lifetime value A/B testing Predictive modelling Managing customer churn Moving beyond historical data Data visualization A single integrated record of the customer Real-time profiling of customer Tracking social media Tracking click stream Predicting customer risk Forecasting consumer needs Analyze traction/click data Analyze social media data Data makes product smarter Using 3rd party data for product development Customer service support Improve customer experience Minimizing customer acquisition cost Selling/service cost reduction Integrating data	Decision-making tools and capabilities	Informing product innovation and marketing strategy by all firms but especially digital natives Defensive brand protection (primarily brand-centric firms)	**The Meaning of BDA in Marketing Practice**

Table III. Sample Coding Results for the Five Stages in BDA Implementation

Zero Order Categories	**First Order Categories**	**Second Order Categories**	**Third Order Categories** (research question)
Tools like Google Analytics Recent recruits Tactical performance indicators Not integrated with firm strategy Seek free online skills training Seek analytics application opportunities with internal customers Tactical objectives: increase page visits Bottom-up decision-making	Sprouting	1st stage BDA implementation	Data-driven marketing
Descriptive analytics Imprecise assumption-based estimates Senior management discussions with external consultants Exploring relevant metrics Finding external sources of data What are we doing about big data?	Recognition	2nd stage BDA implementation	
Data warehouse investment Recruiting analytics expertise Scaling of BDA capabilities ROI on BDA investments Micro-segmentation/customer profiles	Commitment	3rd stage BDA implementation	
Do you have data to back that up Prove new is superior to present Flattening the decision-making process Integrating third-party data Data ethics dilemmas Branding priorities verses analytics	Culture Shift	4th stage BDA implementation	
AI/ deep learning algorithms Precise CLV Programmatic advertising Data scientists Balance creativity with data driven	Mastery: Data driven	5th stage BDA implementation	

Table IV. Summary of Themes and Results

Themes	Summary of Results
Marketing BDA as tools and capabilities for innovation, strategy and risk management (Research Question 1)	*Analytics Tools and Capabilities* Acquisition, churn, advertising optimization, predictive modelling, A/B testing, CLV management, social media tracking and data integration – especially digital native firms *Purpose: Informing Product Innovation and Marketing Strategy* – especially technology firms *Purpose: Defensive Marketing* Clickstream and social media tracking to manage risk – especially brand centric firms
Implementation of BDA in marketing means the organization must sense and interpret the environment and have a devoted champion (Research Question 2)	Implementation is a function of dynamic capabilities (sensing, learning, filtering) relating to the degree to which marketing BDA is championed in the firm.
BDA Champions use different dynamic capabilities depending on their organizational level (Research Question 2)	Recent recruits use vigilant learning to develop turnkey tools and focus on customer churn and acquisition, whereas senior management uses organizational redesign capabilities to invest in warehousing and predictive analytics.
BDA capabilities in marketing develop in stages (Research Question 2)	Five stages of marketing analytics identified: Sprouting, recognition, culture shift and data-driven marketing. There are pitfalls and progress points associated in each stage
Organizational culture shift most pronounced in brand-centric firms (Research Question 3)	In becoming data-driven, all but digital native firms need to work to embrace a digital culture, focus on customer profit, A/B testing and ROI.
Becoming Data-Driven Marketing involves the entire organization (Research Question 3)	Integrating customer transaction data, such as clickstream and social media data and integrating third party data means becoming data-driven and requires capabilities other than those of marketing. Organizational goals take precedence over marketing's desires.

Figure 1. Research Procedure

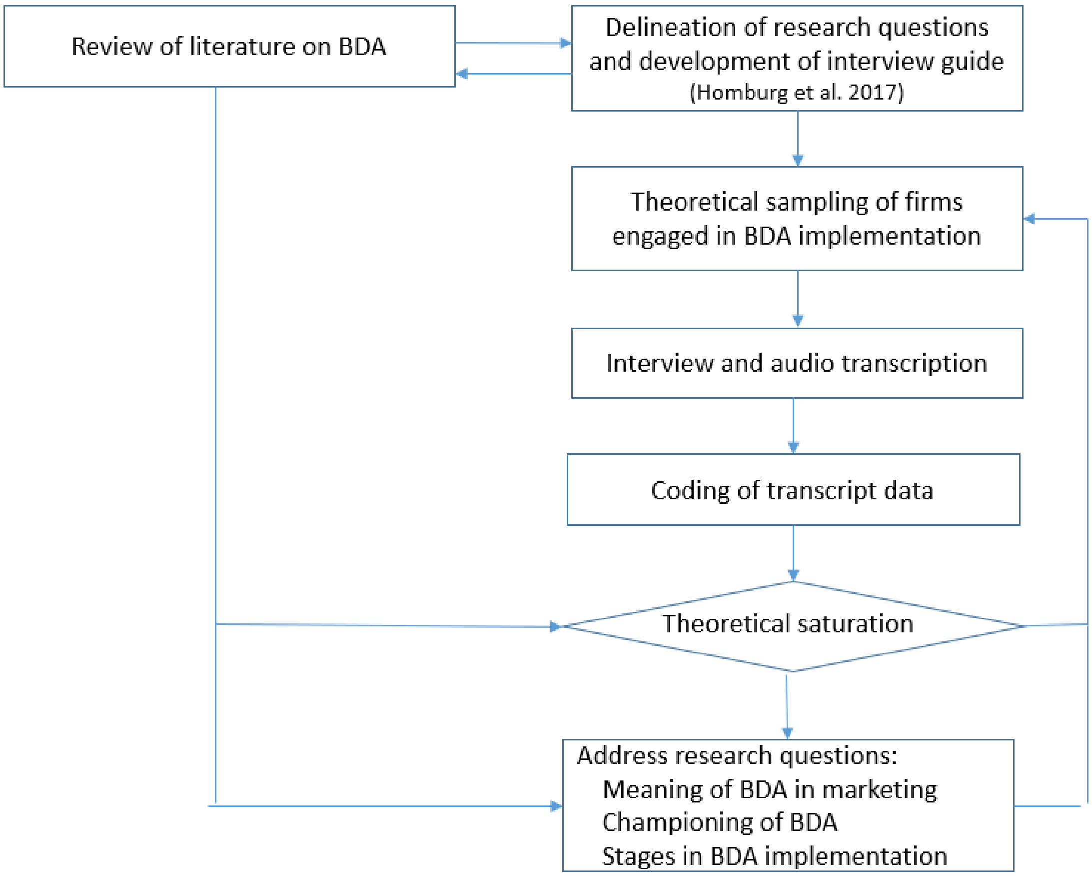

Figure 2. Marketing Big Data Analytics Implementation and Dynamic Capabilities

Championing source		**Dynamic Sub-capabilities** (Day and Schoemaker 2016)		**Impact**
Recent recruit	→	Vigilant learning	→	Turnkey tools, tracking customer churn and acquisition
Middle management	→	Probe and learn	→	Predictive analytics, Social sentiment analysis, A/B testing
Senior management	→	Organizational redesign	→	External consultant, investments: data warehousing, cloud-based, predictive analytics, AI, deep learning

Figure 3. The five Stages of Marketing Big Data Analytics Implemetaion