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Effects of big data analytics and traditional marketing analytics on new product success: A knowledge fusion perspective☆

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ABSTRACT

This study introduces the knowledge fusion taxonomy to understand the relationships among traditional marketing analytics (TMA), big data analytics (BDA), and new product success (NPS). With high volume and speed of information and knowledge from different stakeholders in the digital economy, the taxonomy aims to help firms build strategy to combine knowledge from both marketing and big data domains. The study suggests that knowledge fusion to improve NPS is not automatic and requires strategic choices to obtain its benefits.

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1. Traditional marketing analytics and big data analytics

The majority of traditional marketing relies on analytics dealing with small data sets (megabytes or gigabytes, or kilobytes) with limited analytic platforms and implementation capacity. These fixed-scale data sets are commonly available from the manager or researcher's computer where the analysis takes place locally, the analysis is not easily replicable, and the central entity organizes decision making. However, recent changes in marketing and information technologies feature high magnitude, mobility, and versatile solutions for strategic activities and new product success (NPS). For instance, Netflix analyzes millions of real-time data points that its viewers create, thus helping the firm determine if a pilot will become a successful new show. The literature refers to these changes as big data analytics.

Big data is a term that primarily describes data sets that are so large (terabytes to exabytes), unstructured, and complex (from genome-analysis, political science, sensor, social media, or smartphone apps, to Internet-based gadgets data) that require advanced and unique technologies to store, manage, analyze, and visualize (Chen et al., 2012). For example, Facebook hosts over 500 terabytes of data everyday—including uploaded photos, likes, and users' posts (Provost & Fawcett, 2013). However, big data is not about MB, TB, PB, or EB. Rather, big data is about insights from data. Forrester (2011, p.4) defines big data as "techniques and technologies that make handling data at extreme scale affordable." According to Sathi (2014), big data analysis (BDA) in marketing differs from traditional marketing analysis (TMA) mainly in the revolution rather than evolution of communication channels. Firms use BDA to follow the flow of information and analyze massive volumes of data in real time, whereas TMA focuses mainly on improving key performance indicators for better insights regarding advertising, pricing, customer relationship management, and new product development (NPD) (Sathi, 2014). Because of the novelty of BDA as a field, research examining BDA's use and effects is still scarce. However, organizations currently use BDA to understand their customers better and to achieve optimal customer engagement (Forrester, 2011). Despite its use, big data is just a raw material, not a solution. The challenge still remains to turn the data into insights that managers can use to solve problems, resulting in better performance. BDA differs from TMA in the four Vs of data: volume, velocity, variety, and veracity (Emrich, 2014), and in that BDA has the potential to improve business decision making for better NPS.

Technology's changing pace requires faster market analyses than traditional market analytics can handle. BDA might provide the real-time speed necessary to meet this challenge. To date, no research compares or combines these two types of analyses to examine the effects of each on NPS. The next section presents a theoretical framework for the study. Section 3 presents several propositions and Section 4 presents the conclusions and implications.

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2. Theoretical foundations

The marriage of digital technologies and psychical technologies, the rise of the global brain of crowdsourcing, and the reshaping of global economic power are bringing about an unprecedented degree of disruption (Annunziata, 2015). In 2000, 25% of the world's stored information was digital. Today, more than 98% of all stored information is digital. The disruption of this increase in data has potential for unanticipated challenges in business, with marketing and NPD being the forefront of the shock wave. In the marketing area, the key challenge for any business is how to turn big data into business insights for better customer relationships (Forrester, 2011). Using big data, companies now make real-time decisions to increase sales and productivity, but that use is just the beginning of BDA (Gustke, 2013). As the disruption moves forward, big data holds the key in many aspects of business functions, and the speed of response in analyzing data can provide a critical edge (Lamb, 2014).

2.1. Marketing analytics, big data analytics, and NPD

In general, TMA positively affects NPS. Cravens and Piercy (2005) suggest that the business-analysis stage for NPD comprises revenue forecasts, cost estimation, profit projections, risks assessment, and finally, the possible cannibalization of sales; not considering cannibalization can be fatal for NPD (Srinivasan et al., 2005). Additionally, a firm needs to consider the rate of technological change, speed of information dissemination, elasticity of demand, and aggregation of forecasts for families of products regarding NPD (Herbig et al., 1994).

In the web 1.0 and 2.0 era, consumers did not use the Internet and NPD analysis complexity is inferior to that of the web 3.0 era. During that time, mapping/multidimensional scaling, regression modeling, choice modeling, stochastic processes, diffusion modeling, and optimization/math programming modeling are particularly useful marketing analytical methods (Lilien et al., 2013). Firms using these market analytic tools boosted profit, revenue, and share performance, while bringing down costs (Lilien et al., 2013). To achieve these results, more than 70% of retailers still use spreadsheets as their primary analysis tool (Cosentino, 2012). Similarly, Bertolucci (2013) argues that small retailers essentially ignore the potential benefits of deploying customer analytics. Intuitively, SWOT analysis, consumer surveys, and NPV models may still provide useful business insights for NPD in some situations (Rusetski, 2014). However, NPD in more rapidly moving industries and markets is a complex activity requiring large amounts of data from many sources to understand customers' demands and markets' future.

A recent report by Polovets indicates that high-performance firms use more advanced BDA technologies (Asay, 2014). In the web 3.0 era, BDA provides firms with methods to develop products consumers are more willing to buy. However, understanding the marketing environment and consumer appetites is challenging because they change rapidly. BDA provides consumer, market, competitor, and new product insights in real-time, which differentiates BDA from the web 1.0 era and web 2.0 eras. Biased samples, and optimistic estimation of sales existing in TMA, may result in biased information for NPD decision making. In comparison to the benefits of TMA, BDA's use of real-time data has the potential to improve decision making for business planning because of its greater power in dealing with real-time uncertainties.

Operational plans benefit from business intelligence. By applying BDA, firms can closely monitor competitors, observe consumers, search the Internet, deliver low-cost surveys, test prototypes, and acquire feedback. Firms may have been doing these repetitive things for decades. However, big data facilitates the performance and reduces the costs of these activities. One of the critical functions of business intelligence is to monitor competitors' new designs and to evaluate how consumers react to those designs. In addition to designs, firms can learn about their competitors' key-product features, pricing strategies, and customer feedback. This information search and analysis allows firms to determine appropriate new product strategies. In addition, product managers can extract real-time information regarding peoples' sentiments regarding product evaluations, recommendations, and product use for faster modifications to new products.

From the consumer's perspective, the prevalence of social media transforms how people obtain information, connect with others, endorse their favorite brands, and purchase products. Social data analysis grows out of these activities and combines disciplines such as social network analysis, multimedia management, social media analytics, trend discovery, and opinion mining. The revolution also has a significant effect on how analytic tools and marketing strategies work together to generate value. For example, in the traditional marketing era, firms might focus on how advertising affects NPS, whereas in the social media era, those firms can move forward to the frontier of peer effects because people are becoming more social consumers in the sense that they follow their peers' purchasing behavior. Thus, text mining, sentiment mining, and data mining, which are important areas of BDA, become tools for today's managers to quickly modify their new product marketing strategies.

2.2. Knowledge fusion taxonomy

To bring the scientific rigor of BDA to marketing practice, this study proposes a knowledge fusion taxonomy of BDA and TMA employing both complexity theory (Anderson, 1999) and knowledge-based view (Nickerson & Zenger, 2004). Complexity comes into play when a phenomenon has interconnected elements that can interact in a variety of ways so that the whole takes on a life of random movement or chaos, or little predictability, while evolving to a state of order. Different elements adapt and evolve in response to changing internal and external conditions (Anderson, 1999). Complexity can be prone to sudden and unpredictable changes. One or more trends can reinforce other trends in a positive feedback loop until things spiral out of control and cross a tipping point, beyond which behavior changes radically (West, 2013).

In the big data era, knowledge evolves quickly due to the availability of data, the significant reduction of cost for analytics, and the sharing of open knowledge insights on the Internet. The knowledge-based view suggests that firms seek to accumulate, protect, or create new knowledge, while complexity governs the process (Nickerson & Zenger, 2004). Prior scholars identify types of knowledge: propositional knowledge refers to more causal relevance and generalization (Tsoukas & Vladimirou), whereas heuristic knowledge is informal and appears in action (Tsoukas & Vladimirou, 2001). Automated knowledge (Fan et al., 2012) and Automated Knowledge Base Construction (AKBC, 2010) deal mainly with natural language processing, information extraction, information integration, databases, search, and machine learning (AKBC, 2010). These elements fill the gap of classifications of knowledge between the pre-Internet era and the post-Internet era. In the big data era, firms need to not only share real-time information and data with different stakeholders (Nickerson & Zenger, 2004), but also tailor their response according to specific, unique, and customized knowledge in a faster fashion to transfer data and information from customers and other firms into valuable insights. Firms are increasingly applying BDA such as web analytics, search analytics, search engine optimization, customer analytics, and pay-per-click management to obtain automated and customized knowledge. Specifically, in terms of NPD, the initial point is to obtain data that are critical such as (1) lists of sites (competitors, blogs, suppliers, retailers, etc.), (2) product and user information from those sites, and (3) analytic data about those sites (Vreeman, 2014). Vreeman also lists some free BDA that may help business with budget constraints to better manage NPD. With the power of synergistically combining expertise in both TMA and BDA, customized knowledge comes into play when firms can create idiosyncratic value for their customers (Jaakkola & Hakanen, 2013). This level of synergistic combination represents the highest level of knowledge extraction and generation.

3. Theory and propositions

With the wide application of sophisticated revolutions in BDA in marketing, only recently do researchers extend knowledge about BDA and TMA, through a combination of theory and practice. In the pre-Internet era, real-time marketing-performance information (Sathi, 2014) and insights regarding competitors, consumers, and new products were nearly impossible. With TMA, the lag between proposed marketing research questions, data collection, and marketing insights is relatively long, and knowledge building and managerial actions delays are more likely to occur. Much marketing activity focuses on cost centers, involving a basket of tools dealing with telephoning, complaining, returning, recalling, and emailing. However, in the current social media era, BDA features real-time analysis for marketing and NPD activities. This revolution transforms marketing from a department of cost centers to value or profit centers. Widely available web-based big data technologies now permit versatile analytics for online marketing activities which involve the four Vs of data characteristics.

3.1. Knowledge fusion strategies

Following recent advances in computing and engineering, this study introduces the term “knowledge fusion” (Jeong, 2012) to represent the combination of knowledge from both marketing and big data domains. Because of the large amount of knowledge inside and outside an organization, engineers fuse different types, domains, features, and positions of knowledge to represent heterogeneous knowledge expertise in decision making (Jeong, 2012). Combining BDA and TMA, together with the degree of complexity and knowledge types in the above discussion, produces four strategic options appearing in Fig. 1. This classification of knowledge according to characteristics of knowledge generation of pre-Internet and post-Internet eras helps classify the strategic choices for different firms. Fig. 1 shows that at one extreme is bystander, a strategy of adopting low levels of TMA and BDA. At the other end of the continuum, the pioneer is a strategy with a synergistic combination of high levels of BDA and TMA, which coordinates IT capabilities with marketing techniques to generate knowledge with a higher degree of customization. In between these polar extremes are companies whose strategies involve either propositional knowledge or automated knowledge with different levels of complexity.

3.2. Pioneer effects

The main argument of knowledge fusion is that collaborative knowledge exploration between applied sciences and other social sciences can contribute to new ideas and innovation. In the big data era, instead of blind-trusting automatic algorithms or models, pioneer firms increasingly build knowledge fusion by combining IT expertise, marketing analytics, and customer knowledge. Contingency theory suggests that the ability to make decisions quickly is more important in dynamic environments. Netflix provides an example in the TV and film industry (Carr, 2013, firm website). Using about 800 developers to generate complex algorithm ecosystems based on millions of users' consuming habits, Netflix moves from DVD rental to a web streaming media model. In parallel with these big data algorithms, Netflix continuously engages in TMA. For instance, Netflix “has been testing new pricing strategies for a long time and its plan to increase prices has been positive in the markets where it has been tested” (Cramer, 2014, web site). Specifically, Netflix designs, performs, and analyzes experiments with both test and control groups to understand consumer perceptions toward new products (Netflix, 2011). Netflix uses customer-lifecycle metrics to derive the optimal customer-acquisition and customer-retention strategy. By synergistically employing both BDA and TMA, Netflix selects movies, creates contents, builds recommendation algorithms, and makes multimillion dollar new product decisions. In sum, Netflix makes a good case of why and how to achieve NPS by using both TMA and BDA. Theoretically, the knowledge-based view suggests that managers must choose valuable problems—those which lead to valuable solutions, knowledge, and capability if managers analyze them successfully (Fidel et al., 2015; Nickerson & Zenger, 2004). To implement this knowledge-based view in dynamic environments, new product managers must use collaborative knowledge generation mechanisms of both TMA and BDA to quickly develop proactive marketing strategies. This discussion suggests the relationships in Fig. 2 and the following propositions.

P1a. Firms adopting both a high level of TMA and BDA have the highest levels of knowledge fusion.

P1b. Firms adopting both a high level of TMA and BDA have the highest levels of NPS.

See Fig. 2

3.3. Explorer and perfectionist effects

The taxonomy defines the perfectionist as firms who rely heavily on TMA while ignoring the revolution in BDA. Conversely, the explorer represents firms who employ BDA while underperforming TMA. Because of TMA's reliability for generating propositional statements, firms can rely on TMA to generate responses to standardized queries such as “for this type of problem, this type of solution is appropriate” (Tsoukas & Vladimirou, 2001). However, because of the underuse of real-time big data, TMA misses the uncertainty that real-world events bring in social media, blogs, and smartphone apps, which may affect knowledge accuracy and customization. On the other hand, the extreme usage of BDA features sophisticated algorithms increasingly common in today's marketing as strong forecasting tools to generate automated knowledge and improve NPS. However, the use of either method while ignoring the other limits knowledge generation in either the short term or the long term. This discussion suggests the following propositions.

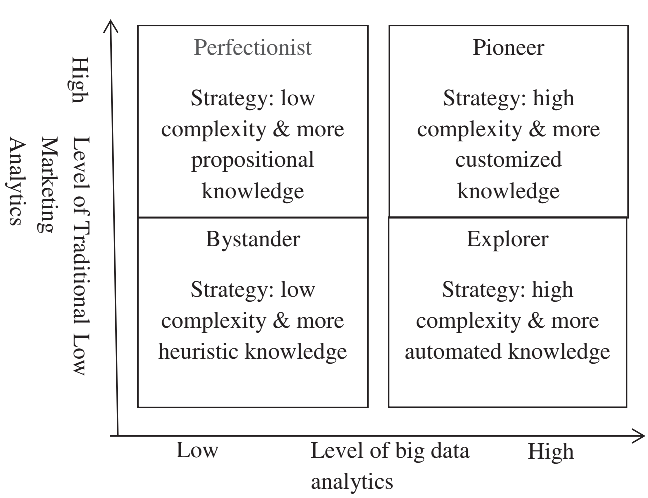

Fig. 1. Knowledge fusion taxonomy.

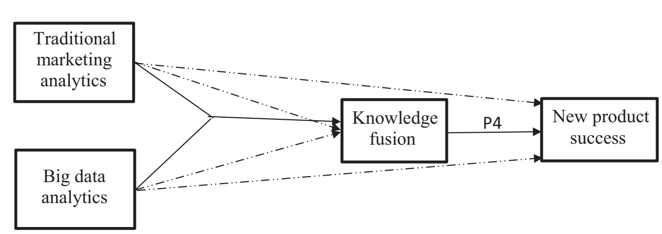

Fig. 2. Main effects.

P2a. Firms adopting either TMA or BDA have medium levels of knowledge fusion.

P2b. Firms adopting either TMA or BDA have medium levels of NPS.

3.4. Bystander effects

Bystanders, as the matrix defines them, represent firms resistant to analytics. With low levels of TMA and BDA, these firms rely on managers' heuristic judgments to make marketing and new product decisions. The complexity of decision making might be low for these firms. In practice, these firms rely on informal knowledge or managers' experience to make decisions (Persson & Ryals, 2014). Individual managers' knowledge storage, mindset, and environment affect the quality of decision making.

According to Tsoukas and Vladimirou (2001), decisions made in this circumstance are subject to individual judgment and the emergence of novelty, which make this style more suitable to social-relation management and less to the management of digital information. From this perspective, the degree of knowledge fusion is likely to be low because of the little collaborative-knowledge exploration between applied science and other social sciences. Most importantly, a typical phenomenon is that knowledge from TMA, NPD practice, and BDA may provide contradictory results. As a result, many managers may rely on heuristic decision making for strategic decisions. With the underuse of both TMA and BDA, low levels of NPS are likely to occur. This discussion suggests the following propositions.

P3a. Firms adopting low levels of both TDA and BDA have low levels of knowledge fusion.

P3b. Firms adopting low levels of both TDA and BDA have low levels of NPS.

3.5. Knowledge fusion

The knowledge-discovery mechanism in social media has implications for today's NPS. In practice, knowledge exists as a text without structure and semantic information with both noise and valuable insights. For firms adopting a pioneer position, the optimal strategy is to combine both BDA and TDA to generate information and knowledge that are important for NPS. In particular, firms can eventually customize new product or service offerings for better NPS. In the case of releasing a new game, movie, or electronic device, extracting critical information relevant to the new product is a key challenge in NPD for most business because of the scale and rapidity of information diffusion. Using BDA, Tuarob and Tucker (2015) demonstrate that for smartphones, firms can mine top features such as waterproof, solar panel, hybrid, tooth pick, and ihome from social media so that the next generation products includes these features, thus creating a buzz > design > new buzz virtuous cycle of NPS by considering social media as a key strategic platform in NPD.

Twitter API allows extracting large numbers of tweets with sentiments embedded in them. This possibility is a significant improvement over the many hours that hand-labeling training data may otherwise take (Go et al., 2009). For instance, managers can search the number of web resources discussing Nokia, Samsung, and Apple to predict popularity of different brands from a social perspective. Mestyán et al. (2013) found that the analysis and measurement of the activity level of editors and viewers of the corresponding entry to a movie in Wikipedia can predict the popularity of that movie much before its release. The ability to fuse the data from TMA and the many social media sites provides firms with a means to make optimal strategic choices and improve NPS. This discussion suggest the mediation of knowledge fusion between TDA, BDA, and NPS as presented in Fig. 3 as stated in proposition four.

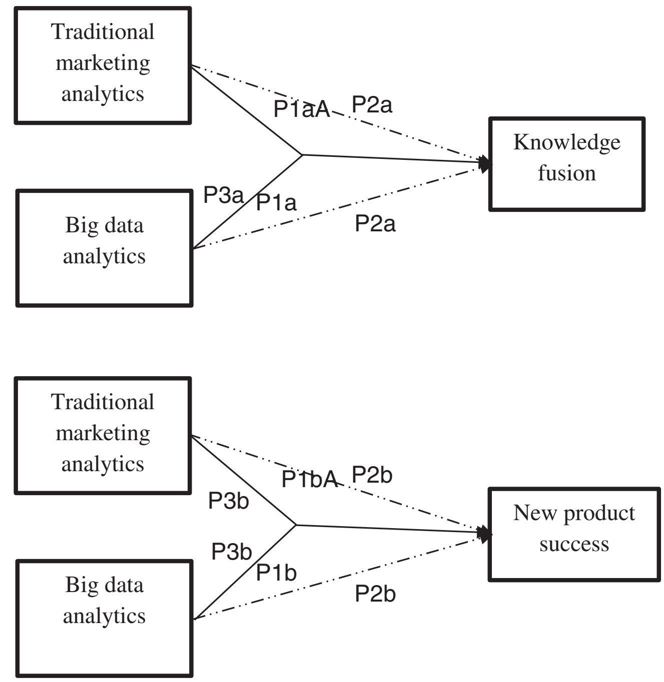

Fig. 3. Mediation effects.

P4. The degree of knowledge fusion has a positive relationship with NPS.

4. Conclusions

New product success requires a great deal of information from many stakeholders. As the speed of markets, technology, regulation, competition, and inputs increases and as more of these elements become critical to a particular product, the complexity and speed with which a firm acquires and analyzes information must also increase. In docile markets, TMA may still work well for NPD. However, some markets may require information from social media, whereas others may require less traditional information, and a higher amount of digital information depending on the speed with which each of the key elements changes. This conceptual study provides a framework to initiate research into this phenomenon.

The taxonomy suggests that all firms will benefit from use of both TMA and BDA. However, perhaps not all situations justify the cost of collecting and analyzing both types of data. The study offers insight for managers to help determine when to use each or both types of data. In addition, the taxonomy and propositions provide a starting point for researchers to investigate the value of each of the types of data analytics relative to the other in terms of firms' strategic needs.

Future research should test the propositions to determine if firms actually fall into each of the four cells in the taxonomy, and if a difference truly exists in NPS for firms following the proposed strategies.

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