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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.

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