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MARKETING THEORY AND BIG DATA

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ABSTRACT

During the last half century, the theory-in-isolation (TiI) approach—within which scholars develop theories by first formulating quantitative models meant to approximate stakeholders' behavior and then testing those models with data acquired for that purpose—has remained the gold standard for publishable marketing scholarship. Unfortunately, the almost universal adoption of this approach has blinded marketing scholars to a viable alternative: the empirical-then-theoretical (EtT) approach, which suggests theories based on observed empirical regularities. However, increasingly pervasive data collection efforts, powerful computer hardware, and sophisticated software-implemented algorithms are fostering a 'big data' (i.e., data sets that are massive, complex, yet quickly replenished from various sources) era far more amenable to the EtT approach. Traditionally, marketing theories emerged from managerial experience and/or scholarly activity in marketing and related disciplines (e.g., economics). Big data represents a complementary source. Nonetheless, revelatory big-data-derived scholarship requires multi-disciplinary research teams, knowledgeable industry experts, and specialized computing capabilities. In addition, big data is prone to biases that multi-disciplinary specialists can mitigate substantially. Thus, marketing scholars contemplating a contemporary EtT approach—which relies on big-data-related analytical tools such as data mining, cognitive computing, neural networks, and artificial intelligence—must have access to skills that extend beyond traditional graduate training in businessm .Essentially, we argue big data is more compatible with an empirical-then-theoretical (EtT) approach than a theoretical-in-isolation (TiI) approach to marketing theory development. Our exposition proceeds as follows. First, we introduce both approaches and big data. Then, we discuss three well-established sources of marketing theory and suggest big data as a fourth source. After presenting an abridged set of published marketing-related big data studies, we close with issues posed by using big data to develop marketing theory and a brief look forward.

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INTRODUCTION

At marketing science's inception in the early 1960s, data for testing quantifiable theories and estimating model parameters were 'at a premium'. As a result, many initially published tests and parameter estimates relied on data about single brands (e.g., testing distributed lag models with data for a 'woman's tonic' or a 'dietary weight loss' brand (Bass & Clarke, 1972; Weiss, Houston, & Windal, 1978)) or product categories (e.g., testing brand switching models with soft drink data or the advertising-sales relationship with cigarette data (Bass, 1969, 1974)). Given the then-prohibitive burden of collecting, structuring, and analyzing sufficient data to ensure acceptable generalizability, researchers relied on face validity arguments to allay colleagues' external validity concerns. Concurrently, data

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mining and shotgun research endeavors were discouraged because marketing scholars could not ignore the possible serendipitous nature of findings (i.e., seemingly meaningful results produced by chance). Regardless of data quality and/or sample size, academicians heavily discounted or dismissed apparent patterns teased from datasets unless predicted by extant theory.

This theory-first weltanschauung has shaped scholarly marketing research practice and output for more than a half century. However, exponential data growth—attributable to electronic collection and aggregation (ffoulkes, 2017)—and increasingly sophisticated 'scouting' algorithms have shrunk the data acquisition premium and created an impetus for revisiting this received wisdom. In a business environment increasingly accepting of solutions identified by inscrutable artificial intelligence (i.e., humanly indecipherable reasoning) (Wodecki 2019), will marketing scholars embrace a more inclusive approach to marketing science?

The two main philosophical approaches for developing marketing theory are theoretical-in-isolation (TiI) and empirical-then-theoretical (EtT). The TiI approach creates theories by first formulating quantitative models meant to approximate stakeholders' behavior and then testing those models with data acquired for that purpose. It assumes stochastic data and uses traditional analytical approaches (e.g., regression, factor analysis) and validation techniques (e.g., goodness-of-fit, residuals, percent-of-variance-explained). In contrast, the EtT approach creates theories based on observed empirical regularities. "All that is necessary is to isolate simple regularities in marketing processes by observing and analyzing the extent to which they do or do not occur under all the different conditions of observation" (Ehrenberg, 1966, p. 261). The EtT approach assumes complex data and uses advanced modeling (e.g., neural nets) and validation techniques (e.g., predictive accuracy).

Although the TiI approach prevails among marketing theoreticians, largely due to its affinity with the scientific method, both approaches are valid. Theoretical deficiency is the main reason reviewers offer for rejecting a manuscript (Laczniak, 2015; Perdue, Meng, & Courtney, 2009; Thomas, Cuervo-Cazurra, & Brannen, 2011). However, holding theory supreme does not mandate it precede empirical analyses. The emergence of big data portends a reinvigorated interest in the EtT approach to marketing theory development.

WHAT IS BIG DATA?

Big data is an "imprecise description of a rich and complicated set of characteristics, practices, techniques, ethical issues, and outcomes all associated with data" (Japec et al., 2015, p. 839). A more technical and complementary definition is "datasets that could not be perceived, acquired, managed, and processed by traditional [information technology] and software/hard-ware tools within a tolerable time" (M. Chen, Mao, & Liu, 2014, p. 173). For companies, big data is a cornucopia of digitalized content about consumers' cognitions, emotions, behaviors, and reactions critical to the ongoing data-driven industrial revolution (Lohr, 2015).

Analogous to Thomas Kuhn's paradigm shift, in which normal science is punctuated by periods of revolutionary science, business thinking and innovation tied to big data are shifting radically (Kuhn, 1996). "Leading organizations are transforming their thinking on data, transitioning from treating data as an operational cost to be minimized to

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a mentality that nurtures data as a strategic asset that needs to be acquired, cleansed, transformed, enriched, and analyzed to yield actionable insights" (Schmarzo, 2013, p. 7). Big data analytics are "technologies (e.g., database and data mining tools) and techniques (e.g., analytical methods) employed to analyze large scale, complex data for various applications intended to augment firm performance in various dimensions" (Kwon, Lee, & Shin, 2014, p. 387). Such analytics are reshaping academic research and marketing practice (e.g., Anderson & Semmelroth, 2015; Berman, 2013; Dasgupta, 2018; Foreman, 2013; Huang et al., 2015; Jackson, 2015). Although some academicians dismiss big data as "typically non-experimental in nature and includes many irrelevant variables" (Armstrong & Green, 2017, p. 14), their rejection is caused by misunderstandings attributable to the relative novelty of big data analysis, which is rooted in computational science.

MARKETING THEORY SOURCES

Historically, marketing theoreticians have relied on three inspirational sources: (1) extant marketing scholarship, (2) other disciplines, and (3) managerial intuitions (Wierenga, 2002; Zaltman, LeMasters, & Heffring, 1982). Although seemingly sound, drawing from each of these sources is risky. Only trustworthy marketing scholarship can ground useful marketing theories. Yet, the lack of a broadly recognized 'general theory', a scholarly community poorly trained in theory creation, and generally non-replicable studies suggest much extant marketing scholarship is problematic (Burton, 2005; Hubbard & Armstrong, 1994).

Marketing theories are derivable from content (e.g., observations), techniques, and concepts borrowed from the social sciences and related business domains (Halbert, 1965). Lamentably, this approach, at least among consumer behaviorists, encourages a theory-of-the-month-club mentality in which newly borrowed theories are quickly forgotten and supplanted by subsequently borrowed theories (Jacoby, 1976). In addition, marketing scholars often are unapt interdisciplinary borrowers due to ignorance of 'baggage' associated with non-marketing theories (Hyman, 1990).

Scholars and practitioners have made complementary efforts to understand and address marketing-related phenomena (Jones & Shaw, 2002). Hence, marketing theoreticians may rely on a more inductive and practitioner-centric theory-in-use approach to theory development. For example, "*if you want a good theory of, say, selling, you should understand what a successful salesperson thinks and does*" (Zaltman et al., 1982, p. 114). Some definitions of marketing knowledge, such as "*the insights and convictions about marketing phenomena that marketing managers use or can use for making marketing decisions*" (Wierenga, 2002, p. 356), dovetail with this theory-building strategy. However, theory-in-use is subject to GIGO (i.e., garbage in, garbage out). In transforming anecdotes based on practice into 'rigorous' theory, intuitive approaches often attach an obscuring scholarly veneer onto unscientific folklore.

Rather than these traditional sources, big data offers a new source for theory creation. Analyses of huge consumer or producer datasets can reveal interrelationships, trends, and patterns suggestive of new theories. Big data provides a valuable alternative source for two reasons (Boyd & Crawford, 2012; Huberty, 2015):

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1. Small samples—even those collected ‘scientifically’—are unreliable (i.e., high variance across repeated samples), non-representative (of the population), statistically underpowered (i.e., reasonable inferences are limited), and often non-normally distributed (i.e., problematic for parametric statistical analyses). Big data can overcome these limitations and provide ready tests of population parameters because it is relatively inexpensive, relatively representative, continually replenished, and easily replicated (Mayer-Schönberger & Cukier, 2014).
2. Historically, marketing modelers assumed consumer-related data are non-deterministic; for example, stochastic brand switching and double jeopardy models indicate the probability of buying a brand on the next purchase occasion depends solely on relative market shares rather than consumer learning (Bass, 1974; Ehrenberg, Goodhardt, & Barwise, 1990). However, big data’s finer granularity and depth allow models that consider detailed psychological profiles and behavioral histories. For example, content-based recommendation systems, such as those formulated by online retailers, run on marketing-agnostic models that can operate with minimal user profile data (Aggarwal, Tomar, & Kathuria, 2017). Established data alternatives, such as self-report surveys or panels, can supplement but not match big data’s richness.

MARKETING THEORY AND BIG DATA ARE MUTUALLY SUPPORTIVE

Rather than a ‘silver bullet’, big data represents a complementary source for theory development. The EtT approach is especially compatible with big data, which lends itself to continual revalidation of empirical generalizations (Uncles & Wright, 2004). During the last decade, practitioners who collected and accessed big data acted as gatekeepers protecting ‘the mine’. Recently, academicians began conceptualizing big data integration with existing enterprise marketing systems (e.g., Bradlow, Gangwar, Kopalle, & Voleti, 2017). Although complex, such integration can encourage marketing theory development.

Big data and marketing theory are mutually supportive. When applied to big data, marketing theory can suggest meaningful causal relationships and new trends. Big data analysis without theoretical grounding conduces patternicity (i.e., making type I errors; reifying spurious correlations). Conversely, big data can help refine and extend extant marketing theories by suggesting new yet previously unexplored variables. For example, geo-locational and consumer sentiment data can extend consumer behavior theories, such as finding non-sequential patterns in AIDA models (Van Bommel, Edelman, & Ungerman, 2014). Marketing theory can discourage endogeneity (i.e., making type II error; treating non-random observations as random) when identifying and evaluating models built with big data (Chung, Seo, & Song, 2017).

TESTING MARKETING (AND RELATED) THEORIES WITH BIG DATA

The Table 1 presents examples of marketing-related big data research. (Note: See Ducange, Pecori, and Mezzina (2018) for a more comprehensive review.) Although non-exhaustive, it suggests three tendencies. First, tests of marketing theories often are multi-disciplinary and generally published in more technically oriented outlets. Second, conducting research with big data requires hardware and software expertise beyond the traditional marketing

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scholar's skill set. For example, coping with the three elemental V's of big data—volume, velocity, and variety—has challenged researchers across disciplines (H. Chen, Chiang, & Storey, 2012). Third, industry experts often co-author such research because they understand its intricacies and can access proprietary cloud services hosting big data. These tendencies conform to one response to the aforementioned interdisciplinary borrowing problem: include at least one 'other discipline' expert on the research team (Hyman, 1990).

The EtT approach for discovering and testing marketing theories requires big data tools (methods and algorithms) that can encapsulate big data's complexity. Cognitive computing and artificial intelligence (AI) are the most promising of these tools. Initially developed to eliminate routine white-collar tasks (e.g., automate logistics and procurement decisions), these tools gained broad acceptance and application by suggesting superior decisions beyond human comprehension (Forrest & Hoanca, 2015). Cognitive computing systems rely on contextual insights, hypothesis-generating ability, and continuous learning processes. Such systems collate data from diverse sources—such as big data analytics, machine learning, Natural Language Processing (NLP), and data visualization (Hurwitz, Kaufman, & Bowles, 2015)—that contain image, audio, geo-location, voice, and other content. Based on accumulated knowledge, they yield hypotheses and answers relevant to solving business problems. The aggregate models they produce ultimately are adjusted based on inputs from system users and new data. For marketers, cognitive computing can speed adoption of IoT (internet-of-things) device capabilities (Sheth, 2016).

AI (a.k.a. computational intelligence, synthetic intelligence, or computational rationality) research—the study and design of intelligent agents—is needed in marketing (André et al., 2017) because the "*full effects [of AI] won't be realized until waves of complementary innovations are developed and implemented*" (Brynjolfsson, Rock, & Syverson, 2017, p. 1). AI and big data are complementary because AI can cope with the behavior and properties of big data (i.e., manage unstructured data; bypass traditional analytical processes; handle analysis, decision, and action temporality) (Iafrate, 2018). Practically, AI business applications can address issues such as assessing customer experiences and engagement (Lukosius & Hyman, 2018), detecting outliers and anomalies, increasing revenues, reducing costs, finding patterns, and increasing forecast reliability (Corea, 2019).

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TABLE 1: ACADEMIC PAPERS TESTING MARKETING THEORIES WITH BIG DATA

Article	Publication Outlet	Relationship(s) / EGs Tested	Big Data Analysis Method(s)	Authors' Domain
Bradlow et al. (2017)	Journal of Retailing	Economic theory; demand estimates for given SKU in given store for given period, using several input variables such as price, feature, and display	Logit-type, aggregate-based SKU-level, attraction model.	Marketing, IT practitioner
Óskarsdóttir et al. (2017)	Expert Systems with Applications	Using network analytics to predict customer churn	Social network analytics.	Decision Sciences, Information Management, Decision Analytics and Risk, Economics, IT practitioner
Chong, Li, Ngai, Ch'ng, and Lee (2016)	International Journal of Operations & Production Management	Advertising response model (Bass, Bruce, & Murthi, 2007; Little, 1979); test functional relationship between promotion and demand	Sentiment analysis; neural network analysis.	Information Systems, Digital Economy, Management and Marketing, International Studies, IT practitioner
Kumar, Bezawada, Rishika, Janakiraman, and Kannan (2016)	Journal of Marketing	Effect of firm-generated content on customer spending, cross-buying, and profitability	Social media analytics; Propensity score matching; Difference-in-differences.	Marketing
Sato and Huang (2015)	IEEE International Conference on Data Science and Data Intensive Systems	How retail environments affect purchasing and sale situations	Cognitive (computing) approach	Computer Science
Luo, Andrews, Fang, and Phang (2014)	Management Science	Optimization of mobile advertising and targeting strategies (test of contextual marketing theory (Kenny & Marshall, 2000).	Mobile analytics; Econometric modelling.	Marketing, Information Systems
Tirunillai and Tellis (2014)	Journal of Marketing Research	Relationship between consumer satisfaction and brand quality	Unsupervised latent Dirichlet allocation.	Marketing
Netzer, Feldman, Goldenberg, and Fresko (2012)	Marketing Science	Converting online consumer discussions to market-structure insights	Text mining, network analyses.	Marketing, Information Systems
Ziegler and Skubacz (2006)	IEEE/WIC/ACM International Conference on Web Intelligence	Brand reputation monitoring; companies can assess consumers' attitudes about their brand and competitive positioning	Data mining.	Corporate Technology, IT practitioner

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ISSUES WITH BIG DATA AND THEORY DEVELOPMENT

Big data is a trying source for marketing theory. Scholars must approach data structure, content, measurement, reproducibility, and analysis with tools amenable to uniquely comprised datasets. Although the most common big data project is to distill an enormous dataset down to a germane abridged dataset (e.g., reduce billions of data points to a million data points), the result is not a typical-sized dataset (e.g., $n<10{,}000$).

In addition, big data usage is prone to biases irrelevant to small datasets. For example:

1. Bigness bias: Erroneous belief a predictive model is underperforming due to insufficient data (Berman, 2013). Although marketers generally accept estimates derived from huge samples, dataset size and representativeness are non-equivalent.
2. Complexity bias: During multi-set data reconciliation from multiple sources, no common denominator for data selection, filtering, or transformation to perform triangulation and reliability checks. For example, data from social media platforms may have identifiers not adhering to standard credit card usage data.
3. Overfitting bias: When a formula closely defines one dataset but fails to predict behaviors summarized by comparable datasets. In such cases, researchers are modeling noise and 'overfitting likelihood' increases as dataset size increases.
4. Statistical method bias: Tendency to understand and prefer statistical methods that confirm data analysis prejudices (e.g., Tatsioni, Bonitsis, & Ioannidis, 2007). When statistical methods are ill-suited for analyzing atypical big data, researchers must use and develop better tools.

A 'scoop' from a big data ocean is prone to biases non-attributable to one cause because they manifest from a mélange of data collection, management, and transformation processes. As the Table 1 suggests, teams of multi-disciplinary specialists may mitigate such biases. However, the best way to validate marketing theories induced from a big-data-fueled EtT approach is to find theory-confirming patterns in similar datasets.

CONCLUSIONS AND FUTURE MARKETING THEORY DEVELOPMENT

Although both can offer insights into marketing phenomena, most marketing scholars have embraced the theoretical-in-isolation (TiI) approach and rejected the empirical-then-theoretical (EtT) approach. This preference likely was formed by training that indoctrinated Ph.D. students into TiI thinking (Swan & Martin, 1994) and using research methods requisite to TiI scholarship (Summers, 2001).

The TiI approach that grounds current research practice is yielding slowly to 'big data algorithm modeling', which is more compatible with an EtT approach (Breiman, 2001). Using big data in academic research requires specialized skills few marketing scholars possess because "*big data is the realm of computer science, not social science*" (NinjaMetrics, 2014, p. 12). Acquiring big data skills extends beyond a Ph.D. in marketing. Some universities offer Ph.D.'s in data science (e.g., Indiana University-Purdue University Indianapolis); other institutions manage centers specializing in big data research (e.g., National Center for Supercomputing Applications at University of Illinois) meant to aid

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theoretical pursuits by non-technical faculty. Regardless, an unintended consequence of using big data to develop marketing theory is creating a disparity between resource- and talent-rich universities/research centers with smaller, teaching-oriented institutions.

APPENDIX: TOOLS FOR BIG DATA

The appropriate analytical tool depends on how data were generated, the various data sources and how they were acquired (i.e., collected, transmitted, and pre-processed), how data are stored (e.g., real-time versus offline), and data architecture (i.e. file systems, databases, and programming models). A survey by KDNuggets (2012) provides the top five tools used by professionals and amateurs (with percentages in parentheses indicating usage):

1. R (30.7%): open source-programming language and software environment to mine/analyze big data. https://www.r-project.org
2. Excel (29.8%): commercial spreadsheet package, part of Microsoft Office Suite, with advanced plug-ins such as Analysis ToolPak and Solver Add-in. https://products.office.com/en-us/excel
3. Rapid-I Miner (26.7%): open source software for data mining, machine learning, and predictive analytics. https://rapidminer.com
4. Konstanz Information Miner (21.8%): open-source tool with visualized environment for data integration, processing, analysis and mining. https://www.knime.com
5. Weka/Pentaho (14.8%): open-source machine learning and data mining software with statistical functions such as classification, clustering, and regression. http://www.pentaho.com

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