THE ROLE OF EMERGENT DIGITAL TECHNOLOGIES IN MARKETING RESEARCH AND STRATEGY

By

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ABSTRACT

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Emergent digital technologies (EDTs), such as artificial intelligence (AI), augmented and virtual reality (AR/VR), and robotic and mechanical automation, are of increasing strategic value to practitioners and marketing academics. Collectively, these technologies are expected to contribute more than $17 trillion to global GDP by 2030, up 760% from 2019 (PwC 2019a; PwC 2019b). This rapid growth presents significant challenges for marketing researchers and practitioners. Specifically, despite the movement towards EDT-oriented topics, marketing scholars assert that academic research has been outpaced by industry in the understanding and implementation of EDT. Additionally, firms face critical challenges such as when and how to integrate EDTs into their product offerings to provide a competitive advantage. Consequently, my two-essay dissertation seeks to: (1) fill a gap in EDT understanding by offering a macro-level perspective of EDT-oriented research in marketing and related business disciplines to advance marketing research (Essay One) and (2) fill a gap in brand-level understanding of EDTs by empirically examining theoretically driven factors that influence a firm's marketing performance (Essay Two). In Essay One, I employ multidimensional scaling (MDS) to examine the intellectual structure of EDT research in marketing (and, for comparison, across six related business disciplines) by evaluating 280,961 citations drawn from 6,099 articles in a sample of 221 journals. To advance EDT-oriented research within marketing, I develop a cross-disciplinary and integrative research framework supported by three distinct theoretical perspectives: the resource-based view (RBV), the technology acceptance model (TAM), and the theory of

reasoned action (TRA). In Essay Two, I draw upon the three theories (i.e., RBV, TAM, and TRA) in conjunction with the economic theory of additive utility to develop a theoretical framework to examine the marketing performance of a firm's digital technology capabilities. Specifically, I address two research questions in Essay Two: 1) *To what extent should a firm establish its digital technology capability?* 2) *Under what conditions does a firm's digital technology capability lead to a competitive advantage?* I compiled a unique and knowledge-rich panel data set comprising 20 automotive brands, 304 vehicle models, and 8,692 observations from 2010 - 2019. The data set integrates variables from nine separate data sources. Broadly, the results show a nuanced picture, which suggests that while digital technology capabilities lead to short-term gains (e.g., brand sales), the long-term effect (e.g., customer satisfaction) may be detrimental for extremely advanced firms. Essay Two captures the full details of these digital technology results and provides actionable, practical implications.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

KEY TO ABBREVIATIONS

ACSI	American Customer Satisfaction Index
AI	Artificial Intelligence
AR	Augmented Reality
CSAT	Customer Satisfaction
EDT	Emergent Digital Technology
FWDIFF	Feature-Weighted Digital Technology Index Difference
FWDTI	Feature-Weighted Digital Technology Index
JDPA	JP Powers & Associates
MDS	Multidimensional Scaling
UDIFF	Unweighted Digital Technology Index Difference
UDTI	Unweighted Digital Technology Index
VR	Virtual Reality

DISSERTATION INTRODUCTION

Emergent digital technologies (EDTs) have revolutionized consumer experiences and enhanced firms' revenue significantly. Global consumer spending on digital technologies such as artificial intelligence (AI), augmented and virtual reality (AR/VR), drones, internet of things (IoT), and robotic and mechanical systems totaled $1.6 trillion in 2018 and is forecasted to reach nearly $2.1 trillion in 2023 (Statista 2021a). Collectively, these technologies are expected to contribute more than $17 trillion to global GDP by 2030, up 760% from 2019 (PwC 2019a; PwC 2019b). In fact, the fusion of digital technologies (i.e., the Fourth Industrial Revolution) is projected to "create more capital and enable humans to accumulate more wealth to drive economic growth" than revolutions of the past (Skilton and Hovsepian 2017, p. 6). Accordingly, researchers have taken an interest in the financial and societal impacts of EDTs on marketing phenomena (e.g., Marinova et al. 2017; Mende et al. 2019; Tellis, Yin, and Niraj 2009) and the application of EDTs as methodological tools in industry and academic research (e.g., Hershfield et al. 2011; Thieme, Song, and Calantone 2000).

However, despite the progressive movement towards understanding the impact of EDTs on marketing phenomena, the rapid proliferation and technological advancements of digital technologies present significant challenges for marketing researchers and practitioners. Specifically, marketing scholars assert that academic research has been outpaced by industry in the understanding and implementation of EDT. Current topics of interest include AI's effect on customer engagement and decision-making, long-term value creation, and marketing capabilities (Marketing Science Institute 2020), "Marketing in the Age of [Technological] Disruption" (*American Marketing Association* Summer Academic Conference 2020 Theme), and "Creating

Customer, Firm, and Social Value through Cutting-Edge Digital Technologies" (*Journal of the Academy of Marketing Science* Special Issues for Publication in 2021). While these topics will advance EDT knowledge in the marketing discipline, there is an opportunity to propel research forward more efficiently through a thorough examination of EDT literature's cross-disciplinary foundations. Therefore, Essay One of my dissertation seeks to fill this gap in EDT understanding by offering a macro-level perspective of EDT-oriented research in marketing and related business disciplines to advance marketing research.

Essay One intends to provide three key contributions to the marketing discipline and EDT domain. First, I conduct a cross-disciplinary quantitative examination of the EDT literature. Using co-citation analysis, I employ multidimensional scaling (MDS) to examine the intellectual structure of EDT research in marketing and, for comparison, across six other related business disciplines, which include marketing, innovation, general management and strategy, organizational behavior and human resource management, operations research and management science, management information systems and knowledge management, and finance and accounting. Second, I investigate and synthesize the interrelationships of EDT-related research topics and methods across the disciplines to develop a cross-disciplinary and integrative research framework supported by three distinct theoretical perspectives: the resource-based view (RBV), the technology acceptance model (TAM), and the theory of reasoned action (TRA). Third, I delineate the most influential recently published and theory-based EDT articles in the marketing literature in the context of the proposed framework. My guiding purpose in this research is to remove the silos between related business disciplines, take inventory of EDT-oriented business literature, and build theoretical and methodological bridges between marketing and related business disciplines to accelerate EDT-oriented research in the marketing discipline.

Additionally, firms face critical challenges such as when and how to integrate EDTs into their product offerings to gain a competitive advantage. EDTs are becoming far more prevalent in every aspect of consumers' lives, enabling more personalized, seamless, and relevant experiences by providing new forms of knowledge, entertainment, and interactions (Hamel and Prahalad 1994; Schmitt 2019; Tellis, Yin, and Niraj 2009). These seamless digital technology experiences are made possible by brands that embrace existing and emerging digital technologies. Prior research suggests that embracing digital technology as a strategic resource enables brands to establish a competitive advantage by offering consumers greater value such as personalized offerings, enhanced consumer delight, and revolutionize customer experiences (Hilken et al. 2017; Hoffman and Novak 2018; Ramaswamy and Ozcan 2018). This competitive advantage may be evidenced by greater sales and high customer satisfaction than a brand's competitive set. However, research on technology adoption and technological learning curves indicate that EDTs may adversely affect critical brand outcomes such as lower adoption of technology products and lower product evaluations (Billeter, Kalra, and Loewenstein 2011; Davis, Bagozzi, and Warshaw 1992; Thompson, Hamilton, and Rust 2005). Given these conflicting findings, the questions pertinent to brand decision-making as it pertains to digital technology are: 1) *To what extent should a brand establish its digital technology capability?* 2) *Under what conditions does a brand's digital technology capability lead to a competitive advantage?*

Essay Two intends to provide four key contributions to the marketing discipline and EDT domain. First, I draw upon the three theories discussed in Essay One (i.e., RBV, TAM, and TRA) in conjunction with the economic theory of additive utility to develop a theoretical framework to examine the marketing performance of a firm's digital technology capabilities.

Specifically, I posit that the relationships between digital technology capability and marketing outcomes are dynamic, divergent, and non-linear. Second, I empirically test the model using a unique and knowledge-rich panel data set comprising 20 automotive brands, 304 vehicle models, and 8,692 observations from 2010 - 2019. The data set integrates variables from nine separate data sources, including US News (Cars), American Customer Satisfaction Index (ACSI), Automotive News, J.D. Power & Associates (JDPA), Wards Intelligence, Compustat, Statista, automotive brand websites, and expert raters. Third, I examine the moderating role of brand status in the purchase of mainstream versus luxury products. Luxury brand products are those that signal the highest level of quality and design, may be purchased for utility, symbolic, and experiential motivations, and promote a plethora of features that may not be functionally necessary (e.g., Berthon et al. 2009; Hagtvedt and Patrick 2009; Silverstein and Fiske 2003). As a result, luxury brand products are often perceived as possessing greater value than mainstream brand products. Subsequently, I postulate that luxury brands have greater exposure to the positive effects and are more insulated from the negative effects of a brand's digital technology capability than mainstream brands. Fourth, I adopt a resource-based view (RBV) theoretical perspective to understanding how a brand's digital technology capability promotes a sustainable competitive advantage (Barney 1991). Specifically, I propose that brands that exceed their competitive set's digital technology capability standard may be uniquely positioned to garner greater sales and greater customer satisfaction than their direct competitors. I refer to the excess capability beyond the competitive set as a brand's digital technology capability surplus. Broadly, the results show a nuanced picture, which suggests that brand managers should consider both the short- and long-term implications of investing in digital technology capabilities.

ESSAY ONE

A Cross-Disciplinary View of Emergent Digital Technology Literature: Opportunities for Future Advancements in Marketing Research

Abstract

The scholarly study of emergent digital technologies (EDTs) in marketing has led to a substantial body of literature and an accelerated need for conceptual research that addresses how EDTs impact our understanding of marketing phenomena. This research aims to conduct a holistic examination of the EDT domain in marketing and across six other related business disciplines and identifies the topics informed by each discipline's most influential works. Using co-citation analysis, we employ multidimensional scaling (MDS) to evaluate 280,961 citations drawn from 6,099 articles in a sample of 221 journals, resulting in an intellectual structure of EDT research for each discipline. To advance EDT-oriented research within the marketing discipline, we develop a cross-disciplinary and integrative research framework based on established literature from each field and recently published influential works in the marketing literature to suggest theoretical and research stream gaps to advance EDT research in marketing.

Keywords: Emergent Digital Technology, Artificial Intelligence, Virtual Reality, Augmented Reality, Automation, Multidimensional Scaling, Social Network Theory

Introduction

Emergent digital technologies (EDTs), such as artificial intelligence (AI), augmented and virtual reality (AR/VR), and robotic and mechanical automation, are of increasing interest to practitioners and marketing academics. Collectively, these technologies are expected to contribute more than $17 trillion to global GDP by 2030, up 760% from 2019 (PwC 2019a; PwC 2019b). The fusion of digital technologies, often referred to as the Fourth Industrial Revolution, is projected to "create more capital and enable humans to accumulate more wealth to drive economic growth" than revolutions of the past (Skilton and Hovsepian 2017, p. 6). Subsequently, this digital revolution has led to a surge of EDT-oriented literature in marketing over the last two years. For example, between 2000-2018, the total number of EDT-oriented articles published in the top 10 marketing journals was 88 compared to 91 articles published between 2019-2020.[1] Thus, this accelerated need to understand the current and future impact of EDTs on marketing phenomena is significant for practitioners and researchers alike.

Researchers have traditionally focused on the effect of individual EDTs (e.g., AI, AR/VR, and robotic and mechanical automation) on marketing outcomes. For example, EDT topics examined in marketing include perceptions of EDTs in the service domain (Hilken et al. 2017; Marinova et al. 2017; Van Doorn et al. 2017), job replacement and supplement (Huang and Rust 2018; Mende et al. 2019), adoption and utilization (Kumar et al. 2016; Leung, Paolacci, and Puntoni 2018), consumer experience enhancement (Hoffman and Novak 2018; Kozinets et

[1] Articles retrieved from Clarivate Analytics (2020) Web of Science Platform published 2010-2020 for the following journals: *Journal of Marketing, Journal of Marketing Research, Marketing Science, Journal of Consumer Research, Journal of the Academy of Marketing Science, Journal of Consumer Psychology, Journal of Advertising, Journal of Interactive Marketing, Journal of Retailing, International Journal of Research in Marketing.*

al. 2002), and notably, EDTs as methodological tools applied to industry and academic research (Hershfield et al. 2011; Little 1979; Thieme, Song, and Calantone 2000). Collectively, these studies indicate that EDTs have a profound and potentially volatile effect on business outcomes. However, despite the progressive movement towards EDT-oriented topics, scholars continue to assert that the academic research to date is outpaced by industry in the study and implementation of technology tools and further guidance for leveraging the benefits of technologies in marketing is needed (Huang and Rust 2021; Wedel and Kannan 2016).

Drawing attention to the accelerated need for EDT-oriented literature, the Marketing Science Institute (MSI) and prominent marketing journals have called for theoretical papers that address how EDTs impact our understanding of critical marketing issues. Recent topics include AI's effect on customer engagement and decision-making, long-term value creation, and marketing capabilities (Marketing Science Institute 2020). Similarly, advances in real-world applications of digital technologies have motivated interest in topics like "Marketing in the Age of [Technological] Disruption" (*American Marketing Association* Summer Academic Conference 2020 Theme), "Leveraging AI to Create Value for Consumers, Organizational Frontlines, and Firms," and "Creating Customer, Firm, and Social Value through Cutting-Edge Digital Technologies" (*Journal of the Academy of Marketing Science* Special Issues for Publication in 2021). Scholarly interest in these topics, among others, will assuredly advance EDT knowledge in the marketing discipline. However, marketing researchers have an opportunity to advance research topics through a thorough examination of EDT literature's cross-disciplinary foundations.

We propose that a thorough examination calls for an aggregated view of EDT literature across marketing and related business disciplines. In practice, marketers who seek to integrate digital technologies into their business successfully are often guided by a broader business strategy that allows for the combinative application of several digital tools (Tabrizi, Lam, Girard, and Irvin 2019). This "best practice" highlights the need for EDTs to be evaluated and applied collectively and impresses upon marketing leaders the importance of viewing digital integration as a cross-disciplinary goal. This view is consistent with the principle that marketing researchers, in the study of marketing phenomena, should "cast their nets wider to consider more disciplines" in pursuit of "intellectual cross-pollination" (Deshpande 1999, p. 166). Thus, we posit that a holistic examination is critical to advancing pertinent marketing research in the EDT domain.

This research provides three key contributions to the marketing discipline and EDT domain. First, we conduct a cross-disciplinary quantitative examination of the EDT literature. Using co-citation analysis, we employ multidimensional scaling (MDS) to provide a cross-disciplinary view of the foundational literature. As an essential step in the scientific process, we present careful identification and synthesis of relevant literature to provide scholars with a "state-of-the-art" view of the EDT domain (Bem 1995; Palmatier, Houston, and Hulland 2018). This approach offers a richer, more in-depth understanding of our collective, scholarly knowledge to date. Guided by Harzing's Journal Quality List (Harzing 2019), this examination includes theoretical and conceptual perspectives from selected publications across seven business disciplines (marketing, innovation, general management and strategy, organizational behavior and human resource management, operations research and management science, management information systems and knowledge management, and finance and accounting). Table 1-1 provides a list of the journals included in this study by discipline.

Second, we investigate and synthesize the interrelationships of EDT-related research topics and methods across the disciplines. We draw from these findings theoretical and methodological research gaps in the EDT literature and propose a multi-disciplinary research framework. Third, to complement the quantitative examination, the qualitative examination introduces the most influential recently published and theory-based EDT articles in the marketing literature and discusses these articles in the context of the proposed framework. This approach is designed to provide a rigorous, usable, and thoughtful guide for future research (Palmatier, Houston, and Hulland 2018).

We structure the rest of this article as follows: We first discuss social network theory as the theoretical lens through which we analyze the intellectual structure for each discipline. Then, we offer a quantitative examination of the literature and introduce MDS as the method employed to analyze co-citation data. Following the method review, we present our results. We then present a multi-disciplinary framework of the EDT literature. Lastly, we conclude by discussing our findings' theoretical and managerial implications and providing suggestions for future research.

Theoretical Foundation: Social Network Theory

Social network theory suggests that members exchange valuable resources through interactions over time (Baumgartner and Pieters 2003; Pieters, Baumgartner, Vermunt, and Bijmolt 1999). In bibliometric studies, the members may consist of journals, articles, or authors. The generation of ideas, knowledge, and influence are the valuable resources exchanged. The interactions are co-citations drawn from influential published works that form an intellectual structure (e.g., Kuhn 1962).). Within this structure, distinct subgroups of ideas and knowledge are identified based on network ties (Tichy, Tushman, and Fombrun 1979). These subgroups can represent scholarly themes, theories, and methodologies within a domain.

Social network theory is often the basis for co-citation research. Co-citation pattern analysis uncovers the exchange or cross-fertilization of influential research within a topical domain (Zinkhan, Roth, and Saxton 1992). Spatially, the nodes represent influential scholarly works and are joined by links (network ties) representing co-creation patterns. The spatial proximity between each node is determined by the strength of the link (Samiee and Chabowski 2021). Nodes that are close in proximity (i.e., strong ties) are similar in nature. Nodes that are farther in proximity from others (i.e., weak ties) often represent novel knowledge generation, institutional voids, or different types of information (e.g., Borgatti and Halgin 2011). Importantly, these intellectual structures bring forth the past and current knowledge of a discipline or domain. From this knowledge or understanding, scholars may infer future research developments (Borgatti, Mehra, Brass, and Labianca 2009).

This study views the seven business disciplines as distinct social networks (e.g., scholarly communities, sets of publication outlets for intellectual exchange). This approach provides a deeper understanding of the themes, theories, and methodologies formed by influential works and highlights recent trends and traditions within each discipline (Carrington, Scott, and Wasserman 2005) that have and will continue to influence future studies within related fields (e.g., Borgatti et al. 2009). By revealing the concentration or dispersion of knowledge (Baumgartner and Pieters 2003) within each unique environment, we are primed for cross-disciplinary comparisons. Insights drawn from the observed similarities and differences between neighboring disciplines should serve as a multi-disciplinary guide to future EDT-oriented research in marketing. Additionally, marketing is inherently a cross-functional discipline that has been cross-functional in both practice and research (Grønholdt and Martensen 2005). As such, there is a tremendous opportunity for marketing to take a multi-disciplinary view to advance EDT-oriented research.

Method

This study of the EDT literature originated with the identification of 221 journals listed in Harzing (2019) as ranked A or higher in the ABDC categorization of research publication outlets (Chabowski and Mena 2017). Since the goal of this evaluation is meant to reflect the multi-disciplinary nature of EDT in the study of business, data were drawn representing the following disciplines: marketing (28 journals), innovation (6 journals), general management and strategy (27 journals), organizational behavior and human resource management (31 journals), operations management and management science (40 journals), management information systems and knowledge management (33 journals), and finance and accounting (56 journals) (Chabowski, Samiee, and Hult 2017; Harzing 2019). The list of journals included in the analysis is found in Table 1-1.

Guided by prior bibliometric mapping techniques used in marketing (Martínez-López, Merigó, Gázquez-Abad, and Ruiz-Real 2020; Ringel and Skiera 2016; Samiee, Chabowski, and Hult 2015) and other business-related subject areas such as general management and strategy (Shafique 2013; Zupic and Čater 2015), innovation (Rossetto, de Carvalho, Bernardes, and Borini 2017; Van Eck, Waltman, Dekker, and van den Berg 2010) and operations research (Colicchia, Creazza, Noè, and Strozzi 2019; de Campos, de Paula, Pagani, and Guarnieri 2017), we employ MDS to analyze the co-citation data from each subject area. MDS is one of the most widely accepted statistical techniques for constructing bibliometric maps (McCain 1991) and has proven more dynamic than factor and cluster analysis in the delineation of past and current research as well as future research opportunities (Chabowski and Mena 2017; Samiee, Chabowski, and Hult 2015).

Research related to the EDT topic was consulted extensively, and keywords emphasizing the theme were included in the syntax were used to draw a meaningful sample from the commonly used Web of Science (WOS) database (Zha, Melewar, Foroudi, and Jin 2020). We followed other bibliometric studies in an attempt to be thorough and included keyword terms such as "artificial intelligence," "augmented reality," "automated technology," "deep learning," "eye-tracking," "machine learning," "neural networks," and "virtual reality" (cf. Samiee, Chabowski, and Hult 2015).[2] As is typical in bibliometric studies, the articles included in the database for analysis were retrieved if a syntax keyword was found in the title, abstract, author-supplied keyword, or reference identifiers (Clarivate Analytics 2020; Foroudi, Kitchen, Marvi, Akarsu, and Uddin 2020; Zha et al. 2020). Publications not considered directly applicable to EDT research- such as book reviews, biographical items, editorials, and other non-central research materials - were not included in the sample (Chabowski, Kekec, Morgan, Hult, Walkowiak, and Runnalls 2018; Foroudi et al. 2020; Zha et al. 2020). In all, 280,961 citations from 6,099 articles were gathered across the seven business disciplines (marketing: 18,693 citations in 309 articles; innovation: 13,575 citations in 263 articles; general management and strategy: 10,087 citations in 221 articles; organizational behavior and human resource

[2] The precise syntax is available from the authors upon request. For review purposes, the syntax is as follows: (“artificial intelligence” OR “augmented reality” OR “automated technology” OR “automation” OR “avatar” OR “bot” OR “chatbot” OR “cognitive technology” OR “conversational agent” OR “deep learning” OR “digital assistant” OR “e-human” OR “emotional technology” OR “eye-tracking” OR “human intelligence” OR “human-computer interaction” OR “information agent” OR “intelligence agent” OR “intelligent agent” OR “machine learning” OR “mechanical intelligence” OR “natural language processing” OR “neural networks” OR “robot” OR “virtual assistant” OR “virtual reality”).

management: 6,484 citations in 104 articles; operations research and management science: 110,676 citations in 2,652 articles; management information systems and knowledge management: 110,899 citations in 2,357 articles; and finance and accounting: 10,547 citations in 193 articles).

Following previous studies, a citation analysis of approximately 25 of the most highly cited publications was conducted for each of the seven EDT disciplines under consideration (Ramos-Rodríguez and Ruíz-Navarro 2004). Then, co-citation matrices were developed for use in MDS. As found in bibliometrics, MDS is a suitable method to use with models possessing fewer than 100 plotted items (van Eck et al. 2010). In fact, based on previous applications, such an approach leads to more interpretable and meaningful results (Hair, Black, Babin, Anderson, and Tatham 1998; Foroudi et al. 2020; Zha et al. 2020). Since the data used were co-occurrences between publications in our seven databases, a proximity-based function of MDS called PROXSCAL was applied. The loss function that is minimized in low-dimensional space by PROXSCAL is shown in Equation 1:

$$\mathrm{f}(\boldsymbol{X}_1, \dots, \boldsymbol{X}_m) \equiv \frac{1}{m}\sum_{k=1}^{m}\sum_{\mathrm{i<j}}^{n} w_{ijk}\,[\delta_{ijk} - d_{ij}(\boldsymbol{X}_\mathrm{k})]^{\mathbf{2}} \tag{1}$$

where the similarities δ_{ijk} between n objects (i, j = 1, ..., n) for m sources (k = 1, ..., m) determine m configurations $\boldsymbol{X}_k$ of order (n x p) such that Euclidean distances $d_{ij}(\boldsymbol{X}_k)$ between the rows of the $\boldsymbol{X}_k$'s (derived as n points in p dimensions) approximate the given similarities δ_{ijk} as well as possible for i, j = 1, ..., n and k = 1, ..., m where w_{ijk} is a given nonnegative weight (Commandeur and Heiser 1993). The stress value from this function is used to measure the goodness of fit of the specified model (Kruskal 1964; Ramos-Rodríguez and Ruíz-Navarro 2004).[3] This model statistic, shown in Equation 2, is calculated as:

$$\text{stress} = \sum_{\text{i<j}} (d_{ij} - \delta_{ij})^2 \tag{2}$$

where d_{ij} is the distance between objects *i* and *j* and δ_{ij} represents the fitted distance between these two objects from the original data (Kruskal 1964; Ramos-Rodríguez and Ruíz-Navarro 2004). The stress values for five of the seven models are marketing at 0.07 (a good fit), organizational behavior and human resource management at 0.06 (a good fit), finance and accounting at 0.10 (a good fit), innovation at 0.10 (a good fit), and management information systems and knowledge management at 0.11 (a fair fit). As sometimes happens in bibliometrics (Chabowski and Samiee 2020), two disciplines failed to converge into a workable model: 1) general management and strategy, and 2) operations research and management science. This result indicates that a viable pattern was not found in each of these two samples; therefore, we could not interpret these two samples confidently and reliably. We subsequently excluded them from the analysis. With five models to evaluate, this process provides the opportunity to present and discuss the EDT literature's social network in a multi-disciplinary fashion (Kuhn 1962; Price 1965). Unlike literature reviews and expert assessments of the field, as implied in this process, bibliometrics can be considered a more objective approach as it indicates past and present research has a considerable influence on future studies (Kuhn 1962; Pritchard 1969; Small 2003).

To allow for presentation, interpretation, and discussion of the results and following precedent in the network and bibliometrics literature (Foroudi et al. 2020; Wasserman and Faust 1994; Zha et al. 2020), a Euclidean distance threshold of 0.25 was applied to form research

[3] To measure the meaningfulness of the goodness of fit data, a stress value of 0.00-0.025 shows a perfect fit, 0.025-0.05 indicates an excellent fit, 0.05-0.10 provides a good fit, 0.10-0.20 shows a fair fit, and 0.20-1.00 indicates a poor fit (Kruskal 1964; Ramos-Rodríguez and Ruíz-Navarro 2004).

groups, cliques (research groups of three or more items), and chains (two or more research groups connected together). The names of the research groups and cliques in the EDT literature were established based on the cited and citing publications related to each network's identified piece (Schrock, Zhao, Hughes, and Richards 2016).

The research groups were evaluated across the five intellectual structures to allow for an integration of concepts into a framework for consideration by researchers. Also, to contribute to current developments in the specific field, the marketing citation data were searched for recently published influential articles over the last ten years. Following previous studies, we sought a manageable list to render insight into our study (Chabowski, Samiee, and Hult 2013; Chabowski et al. 2018). As such, we determined the cutoff for this portion of the analysis as two citations per year for articles published during this time frame, which produced a list of 23 publications to contribute to the analysis and advancement of this study.

Next, the results of our analysis are provided in the following section such that the research groups, cliques, and chains across the five domains in this study can provide insight into EDT research. After that, a presentation is made of possible synthesis and direction for the EDT literature. The presentation is designed to contribute to the growing need to analyze this research base. Though the framework provided is explicitly developed in the Kuhnian tradition for the marketing discipline, parallel research and practitioner applications could be used in other domains (Kuhn 1962).

Results

For this part of the study, we present an analysis of each of the five social networks in this EDT study. The analyses include an evaluation of the top works from each literature base and a presentation of the configurations in their respective MDS maps. Following this detailed overview, we introduce the most influential recently published theory-based EDT articles in the marketing literature. From these aspects of this section, suitable groundwork is established to discuss the EDT literature's multi-disciplinary, marketing-oriented framework in the subsequent section.

As indicated in Figure 1-2, the EDT intellectual structure in the marketing literature is shown. In this first social network illustrated, 27 influential publications and 16 total groups were identified, two research chains were found, and four isolated research groups are shown. One research chain, located on the left side of the MDS map, is centered on advertising attention capture and transfer (Pieters and Wedel 2004) and ranges from themes such as eye movement, information processing, advertising, and memory (Group 10) to eye tracking and point of purchase position (Group 16). Meanwhile, the research chain found on the opposite side is anchored by topics related to sales force automation (Jones, Sundaram, and Chin 2002; Speier and Venkatesh 2002) and varies in topics from user perceptions and technology acceptance (Group 4) to technology attitudes, productivity, and sales force automation (Group 8). Also, three isolated groups are located in the top right and focus on two method-related topics - mediation and regression (Group 1) and structural equation modeling (Group 3) - as well as computer-mediated environments and virtual reality (Group 2). The final lone group is found in the bottom left and emphasizes eye movement, visual attention, and advertising (Group 9).

The EDT intellectual structure in the innovation literature is displayed in Figure 1-3. As noted in the MDS map, 30 influential publications and 16 total groups were identified, five research chains were found, and one isolated research group is shown. Spanning from topics such as citation and morphology analysis (Group 12) to forecasting and rapid technological networks (Group 16), the research chain found at the bottom of the displayed results is centered on work related to the use of patent data for text mining and the discovery of new technologies (Lee, Yoon, and Park 2009; Yoon and Park 2004). Consisting of three interrelated research cliques related to technology belief, attitude, and voluntary acceptance (Group 9), technology belief, attitude, and differential (voluntary and mandatory) acceptance (Group 10), and technology belief, attitude, expectancy, and acceptance (Group 11), the next chain is anchored by work specifically related to technology acceptance (Davis 1989; Davis, Bagozzi, and Warshaw 1989). Also, the chain found at the top right contains research on random forests (Breiman 2001) at its center and extensions related to random forests and support-vector networks (Group 7) and random forests and decision trees (Group 8). Another chain with two groups is found on the left side of the display. It is anchored by research focusing on scientific networks (Price 1965), with branches emphasizing network citation trends and patterns (Group 1) and network document relationships (Group 2). The last research chain is located at the top right of the map, has research on machine learning and scientific output (Group 4) as the middle group, and also includes research related to machine learning and suffix stripping (Group 3) and scientific output classification (Group 5). Then, the only isolated research group is found toward the middle of the graph and focuses on probability distributions and scientific search (Group 6).

The EDT intellectual structure in the organizational behavior and human resource management literature is presented in Figure 1-4. Indicated in the MDS results, 21 influential publications and eight total groups were found, one research chain was identified, and two lone research groups were discovered. The research chain of this domain is found on the right side, is connected by research on strategic human resource management and sustainable competitive advantage (Group 5), and covers topics from strategic human resources, sustainable competitive advantage, and performance (Group 3) to human resource architecture (Group 8). Located on the left side of the map, the works in the first secluded research group form a clique and converge on nearly the same spot to cover workplace automation and the second machine age topics (Group 1). The other isolated group is found above Group 1 and examines work degradation and the smart machine (Group 2).

The EDT intellectual structure in the management information systems and knowledge management literature is located in Figure 1-5. As found in the MDS map, 26 influential publications and seven total groups were discovered, one research chain was uncovered, and six isolated research groups were found. Consisting of two groups, this domain's only research chain centers on topics related to data mining and machine learning (Witten and Frank 2005). Two isolated research groups were, in fact, research cliques. The first of these two is found at the top left of the MDS depiction and focuses on technology design and acceptance (Group 2). Meanwhile, the other research clique emphasizes classification and decision trees and machine learning (Group 3). The research group located most closely to the center of this intellectual structure relates to random forests and statistical comparisons (Group 4). However, three other lone groups are found on the left side and cover themes such as probability distributions and lexicon (Group 1), deep learning and neural networks (Group 7), and opinion mining, sentiment classification, and machine learning (Group 8).

The EDT intellectual structure in the finance and accounting literature is shown in Figure 1-6. Indicated in the MDS graph, 25 influential publications and nine total groups were found, two research chains were discovered, and four lone research groups are displayed. One research chain, located on the right side of the domain and consisting of two cliques, finds its central topic on financial ratios and bankruptcy predictions (Group 6) flanked by themes related to corporate bankruptcy forecasting (Group 5) and bankruptcy prediction methods (Group 7). On the opposite side, the other research chain has a central topic of language quantification (Tetlock, Saar-Tsechansky, and Macskassy 2008) that contributes to two cliques focused on Internet language use and information extraction (Group 8) and language use, textual analysis, and investor sentiment (Group 9). Found scattered across the topic of the MDS results, the four isolated research groups emphasize topics from machine learning and modeling principles (Group 1) and statistical learning and randomness testing (Group 2) to random forests and regression trees (Group 3) and adaptive nonlinear models and recurrent neural networks (Group 4).

To ensure that this study is relevant to the EDT literature, we also examined the most influential recently published theory-based EDT articles in the marketing literature. The citation data used to create Figure 1-2 were applied to articles published over the last ten years (2010-2019) since this was deemed a sufficient window to consider the identified sources as "recent" with the most potential for future impact on the field (Burrell 2002, 2003). To obtain an article list similar in size to Chabowski, Samiee, and Hult (2013) and Foroudi et al. (2020), a minimum citation threshold for articles was an average of two times per year. The result was a list of 23 marketing-specific EDT articles as found in Table 1-2. Combined with the findings from the intellectual structures of the five business disciplines presented above, this information provides considerable evidence for developing a research framework for the EDT literature. In the following section, research opportunities and managerial implications are discussed.

Discussion and Implications

For this section of the study, we reply to calls in the literature to develop more conceptual research in marketing (MacInnis 2011; Moorman, van Heerde, Moreau, and Palmatier 2019; Yadav 2010). The approach taken mirrors the Kuhnian perspective that past and current research in a domain tends to influence future research significantly (Kuhn 1962). As such, we advance a framework synthesizing the EDT intellectual structures presented earlier influential recently published EDT articles in the marketing discipline. In fact, as an integrated, two-level model, the proposed approach is supported by three distinct theoretical perspectives found in this study: the resource-based view (RBV) (Barney 1991), the technology acceptance model (TAM) (Davis 1989; Davis, Bagozzi, and Warshaw 1992), and the theory of reasoned action (TRA) (Fishbein and Ajzen 1975). Found in Figure 1-7, the framework forwarded has elements from each of the disciplines analyzed in this study. Still, it is specifically developed for the marketing field with the intention of becoming more directed in its study and multi-disciplinary in its application of the EDT topic.

EDT Research Framework

The research framework advanced in Figure 1-7 has its foundations in the EDT literature's important facets across the five intellectual structures evaluated. Two distinct processes are incorporated into an approach that assigns, explicitly, critical aspects of the marketing literature found in this study and beyond to facilitate its essential position in advancing the EDT paradigm. Based on the studies found in this analysis, the framework begins by taking a strategic perspective and uses the RBV as an approach to encapsulate the varying components and processes at work in EDT research. Then, to link this framework's strategic aspects with its consumer-related elements, the importance of customer relationship management (CRM) and trust is introduced to impact a TAM-influenced and TRA-related process.

More specifically, the role of the RBV in this framework is based on the fundamental nature of this perspective that, if appropriately deployed, resources (e.g., decision tools) are converted into capabilities (learning), which drive competitive advantage (or output) which may be sustainable (Barney 1991). As applicable to this study, there are five aspects of resources found to support the framework. First, probability distributions are an important facet of developing resources in the EDT phenomenon (Blei, Ng, and Jordan 2003). When used as a decision tool for text-based information, perplexity is found to decrease while accuracy is discovered to increase with higher use of data in classification models. The second decision tool that may be considered a resource would be the combination of decision trees and random forests (Breiman 2001; Breiman, Friedman, Stone, and Olshen 1984; Quinlan 1986). These two interrelated concepts are based on the notion that error in forests tends to converge with the increase of trees. Third, a related resource that could be used is adaptive nonlinear models (Shapiro 2000). Accounting for the randomness that can sometimes occur in capabilities development, this application provides the opportunity to stabilize information interpretation so it may be actionable. The next tool that is a part of the model relates to predictive modeling (Altman 1968; Beaver 1966; Hastie, Tibshirani, and Friedman 2009; Ohlson 1980; Shumway 2001; Tam and Kiang 1992). This decision tool typically has been used to predict the possibility of corporations in financial distress (Altman, Marco, and Varetto 1994; Zmijewski 1984).

Finally, a decision tool that has become much more prevalent recently is neural networks (Altman, Marco, and Varetto 1994; Krizhenvsky, Sutskever, and Hinton 2017; Tam and Kiang 1992). Early in the development of this resource, unidirectional feedforward networks were used (Hornik, Stinchcombe, and White 1989). Later, recurrent networks were applied to enhance EDT learning (Tenti 1996). Taken together, this tool has provided an iterative basis from which AI has emerged.

Learning is essential to a firm's ability to adapt to the competitive environment. As this concept applies to this study, various learning levels occur with the EDT phenomenon. For instance, the general overarching deep learning topic (cf. LeCun, Bengio, and Hinton 2015) encompasses topics related to statistical and machine learning (Fu and Aliferis 2010; Goldberg 1989; James, Witten, Hastie, and Tibshirani 2013; Khandani, Kim, and Lo 2010; Mitchell 1997; Quinlan 1993; Sebastiani 2002; Vapnik 1995). This learning process aims to facilitate the development of capabilities and deliver EDT-based value to customers. One capability deals with morphology and textual analysis (Loughran and McDonald 2011; Yoon and Park 2005). As they apply to EDT, this category evaluates word patterns to enhance the understanding of particular content. Relatedly, the second capability deals with information extraction and opinion mining (Hall, Frank, Holmes, Pfahringer, Reutemann, and Witten 2009; Hastie, Tibshirani, and Friedman 2009; Yoon and Park 2004). Typically, these skills are developed by analyzing Internet postings and other web-based opinion-related information (Antweiler and Frank 2004; Das and Chen 2007; Pang and Lee 2008). The last learning facet of the model involves lexicon and language quantification (Miller 1995; Tetlock, Saar-Tsechansky, and Macskassy 2008). Building on the capability of evaluating text, this component usually involves cultivating the aptitude to learn and apply language in a technological setting.

As the final stage of the strategic process, three EDT-centered competitive advantage components result from the decision tools and learning that occurs earlier. One facet of actionable output relates to sentiment classification (Pang, Lee, and Vaithyanathan 2002). Usually, searching information, such as opinion evaluations, provides the ability to segment markets, so a more detailed understanding of the different consumer groups results. Another aspect of competitive advantage identified focuses on workplace automation (Autor 2015). Sometimes implemented in marketing with the computerization of the sales function (Erffmeyer and Johnson 2001; Jones, Sundaram, and Chin 2002; Keillor, Bashaw, and Pettijohn 1997; Parthasarathy and Sohi 1997; Speier and Venkatesh 2002), this technological transition has been referred to as a form of work degradation (cf. Braverman 1974) brought on by EDT phenomena (Brynjolfsson and McAffe 2014; Ford 2015; Orlikowski 2007; Zuboff 1988). The last competitive advantage component involves forecasting technologies (Daim, Rueda, Martin, and Gerdsri 2006). Forecasting technologies is an essential aspect of the output produced because it allows managers to anticipate marketplace demands and, if able, to preemptively track the diffusion of technology and develop marketing strategies that better position the company (Rogers 1995).

To link the RBV-focused portion of this two-level framework to the TAM-influenced and TRA-based section, we apply the science of design and execution (Hevner, March, Park, and Ram 2004), which indicates this process is required to produce something of value, identify and respond to relevant problems, be well-executed to contribute to the market, and contain an iterative search and communication process for effectiveness. Furthermore, Srivastava, Shervani, and Fahey (1999) propose that marketing scholars must address, explicitly, the postulation of cause-and-effect linkages between marketing and the design and execution of core business processes. This approach is critical in the continual undertaking of interacting with customers and delivering value to the market through the belief-attitude-acceptance relationship. Based on the approach that the EDT perspective involves a considerable number of psychological factors in the interface between people and technology (Card, Moran, and Newell 1983; Hoffman and Novak 1996), we assert that developing customer relationship management (CRM) processes are vital to establishing and maintaining company- and consumer-related trust and commitment in the acceptance of new technology (Grewal and Stephen 2019; Payne and Frow 2005; Morgan and Hunt 1994). Since the focus of this study is on ultimate customers, as defined by Morgan and Hunt (1994), the CRM emphasis relates to "the implementation of an integrated series of customer-oriented technology solutions" (Payne and Frow 2005, p. 168). To combine the strategic- and consumer-based aspects of this study's framework, most EDT research in marketing has related to eye movement (Lohse 1997; Rayner 1998; Russo and Leclerc 1994; Wedel and Pieters 2000, 2008), visual attention (Janiszewski 1998; Pieters and Warlop 1999; Pieters and Wedel 2004; Rosbergen, Pieters, and Wedel 1997), and AR and VR (Javornik 2016; Steuer 1992). Taken together, these are the EDT design elements that are driving research in the marketing domain currently and provide the early components that may be used to design a trust-centered CRM program in the future by gauging and acting upon consumer reactions in these three research conditions.

The final stage of this framework's development is based on two consumer-focused perspectives that have been juxtaposed previously in the literature: the TRA and TAM approaches (Davis 1989; Davis, Bagozzi, and Warshaw 1989; Fishbein and Ajzen 1975; Venkatesh and Davis 2000; Venkatesh, Morris, Davis, and Davis 2003). These original two perspectives have been modified and combined based on the EDT literature's specific conditions and reflect the complex process of technology acceptance. As a result, we propose that a trust-focused CRM approach will mildly influence the impact of belief on attitude. This perspective is advanced as the company-consumer relationship originates, and each side grows accustomed to each other. As this relates to the EDT phenomenon, the consumer's beliefs and evaluations concerning a new technology can influence attitudes toward the technology based on preexisting perceptions. Thus, this study's framework states that an RBV-based CRM approach emphasizing trust will have a moderating influence on the stated TAM-related belief-attitude relationship. Taken to the next stage, the competitive use of resources (or decision tools), capabilities (or learning), and competitive advantage (or output) should have a more substantial influence on the impact of attitude on acceptance as the relationship between firm and customer becomes more intimate. If implemented well, the differential (voluntary versus mandatory) acceptance of a technology will be based on how successfully the firm designs its program and the conditions in which it is offered. Stated differently, a well-timed marketing approach that is informed by user needs and wants for an EDT has the potential to be very effective in the consumer space as a voluntary transition. For instance, such a plan could increase brand attention and evaluation at the point of purchase (Chandon, Hutchinson, Bradlow, and Young 2009). However, suppose the firm cannot apply the RBV well and instead has a less than ideal marketing program that does not generate trust. In that case, the EDT may have its status altered to mandatory acceptance via an intermediate step in the relationship process or a third-party requiring user application of the technology.

Recently Published EDT Articles in Marketing

By far, the most prevalent setting in recent EDT marketing research has been using AR and VR technologies. Acknowledged as critical aspects of EDT applications (Grewal, Roggeveen, and Nordfält 2017), AR and VR applications in the literature have produced considerable recent support for the design and belief-attitude-acceptance relationship aspects of this study's proposed framework. Typically, the setting for AR and VR technologies resides in the retail environment. Whether focusing on shopper eye movement (Meißner, Pfeiffer, Pfeiffer, and Oppewal 2019), its relation to e-commerce (Yim, Chu, and Sauer 2017), or the blending of online and offline facets to construct omnichannel retail opportunities (Beck and Rygl 2015; Hilken, Heller, Chylinski, Keeling, Mahr, and de Ruyter 2018), their application reflects the essential aspect of the virtual setting in the design stage of bringing EDT offerings to market (Bigné, Llinares, and Torrecilla 2016).

In terms of the TAM- and TRA-based belief-attitude-acceptance process of the framework, the TAM approach is applied in online consumer decision-making using AR (Pantano, Rese, and Baier 2017; Rese, Baier, Geyer-Schulz, and Schreiber 2017), which leads to the specific influence of design on the attitude-acceptance relationship. In this facet of the model, recent EDT research has found that AR improves the impact of customer value perceptions (e.g., gratification expectations) on behavioral and purchase intentions (Hilken et al. 2017; Rauschnabel 2018; Van Kerrebroeck, Brengman, and Willems 2017), thus leading to the findings that mobile AR applications can influence acceptance of omni-retailing strategies (Dacko 2017).

The issue of CRM and customer experience has been presented in the recent EDT literature, as well. Specifically, in the customer-firm frontline exchange, there is a considerable level of emotion that relates to the overall technology acceptance process and the establishment of meaningful relationships between consumers and firms (Rafaeli, Altman, Gremler, Huang, Grewal, Iyer, Parasuraman, and de Ruyter 2017; Scholz and Duffy 2018). In fact, while the consumer experience is critical to satisfaction and willingness to buy (Poushneh and Vasquez-Parraga 2017), controlling access to personal data while in the AR environment resounds particularly strongly with users (Poushneh 2018). Taken further, customer experience involves interactions that begin well before technology acceptance and long after purchase (Lemon and Verhoef 2016). This perspective of customer experience makes room for a more comprehensive understanding and application of EDT offerings.

The final integration of the EDT framework in recent influential research focuses on applying its RBV components. Though not extensive in the literature, there are two aspects of the RBV that relate to the model's capabilities aspect, which have been applied. First, acknowledged as a learning process that can detect patterns more readily as it is largely automated, textual analysis has been introduced to advance understanding of sources such as Internet discussions and product reviews (Humphreys and Wang 2018). Additionally, processing tools have been applied to focus specifically on the general essence of language use in content developed by consumers (Melumad, Inman, and Pham 2019). In effect, textual analysis and language quantification capabilities can be developed, leading to a competitive advantage.

Future Research Opportunities

Based on the application of recent influential EDT research, five gaps in the literature are identified for future research opportunities. Below, we discuss the impact of (1) design on the belief-attitude relationship, (2) design on the attitude-acceptance relationship, (3) EDTs on strategic decision-making, (4) EDTs on a sustainable competitive advantage, and (5) trust on CRM and customer experience.

The impact of design on the belief-attitude relationship. The influence of design on the attitude-acceptance relationship in the model has been examined to a significant degree to date.

However, the impact of design on the belief-attitude relationship has yet to receive much attention. As emotion is a critical driver in the exchange between consumers and companies (Melumad, Inman, and Pham 2019; Rafaeli et al. 2017), user beliefs of EDT offerings are firmly embedded in the individual. Consequently, a firm's ability to design marketing programs and products for customers and marketing processes and tools for employees that address these perspectives should be examined.

The impact of design on the attitude-acceptance relationship. Second, though the general phenomenon of EDT acceptance has been examined in recent research (Dacko 2017), there has been little distinction between the voluntary and mandatory aspects in this portion of the TAM-related framework. For example, EDT research in marketing has addressed sales force automation (Jones, Sundaram, and Chin 2002; Speier and Venkatesh 2002), but the emergence of artificial intelligence brings the potential for the unilateral replacement of many current marketing functions (Huang and Rust 2018). As this relates to the relationship between customers and companies, there are opportunities to assess the differential sentiment regarding the influence of design on the attitude-acceptance relationship. In other words, evaluating the different processes involved in designing a marketing program for conditions of voluntary versus mandatory acceptance should be undertaken.

The impact of EDTs on strategic decision-making. Concerning the application of the RBV to date in the marketing-specific EDT literature, two facets must be addressed. While capabilities have been introduced as relevant to the domain (Humphreys and Wang 2018; Melumad, Inman, and Pham 2019), decision tools and output have not been studied significantly. More specifically, identifying and applying such resources as predictive modeling and neural networks in the EDT space has been lacking. Furthermore, without integrating probability distributions, decision trees and random forests, or adaptive nonlinear models, our understanding of decision tools' influence in the RBV portion of the EDT framework will be minimal, thus creating difficulty understanding the development of marketing-specific capabilities.

The impact of EDTs on a sustainable, competitive advantage. In addition, research related to relevant marketing-based aspects of competitive advantage like sentiment classification, workplace automation, and forecasting technologies has been sparse. As the EDT domain should expand and better understand the output that this model's RBV processes produce, greater insight into the development of marketing-specific competitive advantages is required as it leads to the design of market-focused programs to relate to the consumer and internally-focuses processes that lead to greater productivity yet pose a potential threat to jobs traditionally performed by humans (Huang and Rust 2018).

The impact of trust on CRM and customer experience. While EDT research has examined the roles of CRM and customer experience in designing effective interactions with consumers (Lemon and Verhoef 2016; Poushneh 2018; Poushneh and Vasquez-Parraga 2017; Rafaeli et al. 2017; Scholz and Duffy 2018; van Doorn et al. 2017), very few studies have examined the importance of trust in this context. To a certain degree, both CRM and trust develop in tandem with the firm's attention to the customer. Stated differently, an effective long-term CRM program provides the opportunity for consumers to build trust with companies. Through valuable communication, the marketing organization can develop a level of intimacy based on the use of resources (or decision tools), capabilities (or learning), and competitive advantage (or output) that creates a sustainable position in the marketplace.

The scholarly study of EDTs in marketing has led to a substantial body of published works that have significantly advanced our understanding of relevant marketing phenomena.

This research has enriched the field of marketing and has become of increasing importance as prominent journals call for more studies of this domain. As such, we present an aggregated, strategic, and integrated view of digital technology's effect on marketing outcomes to address these calls. Our guiding purpose in this research is to remove the silos between related business disciplines, take inventory of EDT-oriented business literature, and build theoretical and methodological bridges between marketing and other business disciplines to accelerate and perhaps illuminate the study of pertinent marketing phenomena within the EDT domain.

APPENDICES

APPENDIX A: TABLES

Table 1-1 Journals Included in the Study by Discipline

Marketing (28)	*European Journal of Marketing, International Journal of Public Opinion Research, International Journal of Research in Marketing, Industrial Marketing Management, Journal of Advertising, Journal of the Academy of Marketing Science*, Journal of Advertising Research, Journal of Business and Industrial Marketing, Journal of Brand Management, Journal of Business Research, Journal of Consumer Psychology*, Journal of Consumer Research*, Journal of Interactive Marketing, Journal of Marketing*, Journal of Marketing Management, Journal of Marketing Research*, Journal of Public Policy and Marketing, Journal of Retailing, Journal of Retailing and Consumer Services, Journal of Services Marketing, Journal of Service Research*, Journal of Strategic Marketing, Marketing Intelligence and Planning, Marketing Science*, Marketing Letters, Managing Service Quality, Public Opinion Quarterly, Public Relations Review*
Finance and Accounting (56)	*Accounting Auditing & Accountability Journal*, *Advances in Accounting Behavioral Research*, *Annals of Actuarial Science*, *Abacus*, *Accounting and Business Research*, *Accounting and Finance*, *Accounting Horizons*, *Accounting Organizations and Society*, *Accounting Review*, *Auditing*, *British Accounting Review*, *Behavioral Research in Accounting*, *Contemporary Accounting Research*, *Critical Perspectives on Accounting*, *European Accounting Review*, *European Financial Market*, *European Journal of Finance*, *Financial Analysts Journal*, *Finance and Stochastics*, *Financial Management*, *Financial Review*, *Finance Research Letters*, *Global Finance Journal*, *International Journal of Accounting*, *International Journal of Accounting Information Systems*, *International Journal of Auditing*, *International Journal of Managerial Finance*, *Information and Organization*, *International Review of Finance*, *International Review of Financial Analysis*, *Journal of Applied Corporate Finance*, *Journal of Accounting and Economics*, *Journal of Accounting Literature*, *Journal of Accounting Research*, *Journal of Behavioral Finance*, *Journal of Banking and Finance*, *Journal of Business Finance and Accounting*, *Journal of Empirical Finance*, *Journal of Finance*, *Journal of Financial Economics*, *Journal of Financial Markets*, *Journal of Futures Markets*, *Journal of Financial Stability*, *Journal of International Financial Markets Institutions and Money*, *Journal of Information Systems*, *Journal of Portfolio Management*, *Journal of Real Estate Finance and Economics*, *Journal of Risk and Insurance*, *Management Accounting Research*, *Managerial Auditing Journal*, *North American Actuarial Journal*, *Quantitative Finance*, *Quarterly Journal of Finance*, *Qualitative Research in Accounting and Management*, *Review of Accounting Studies*, and *Review of Financial Studies*
General Management and Strategy (27)	*Australian Journal of Management*, *Academy of Management Annals*, *Academy of Management Discoveries*, *Academy of Management Journal*, *Academy of Management Learning & Education*, *Academy of Management Perspectives*, *Academy of Management Review*, *Administrative Science Quarterly*, *British Journal of Management*, *California Management Review*, *Group Decision and Negotiation*, *Harvard Business Review*, *International Journal of Conflict Management*, *International Journal of Management Reviews*, *Journal of Forecasting*, *Journal of Management Inquiry*, *Journal of Management*, *Journal of Management Studies*, *Journal of Sport Management*, *Long Range Planning*, *Management Learning*, *Organizational Research Methods*, *Strategic Entrepreneurship Journal*, *Strategic Management Journal*, *(MIT) Sloan Management Review*, *Strategic Organization*, and *Theory, Culture, & Society*
Innovation (6)	*Journal of Product Innovation Management*, *R&D Management*, *Scientometrics*, *Science Technology and Human Values*, *Technovation*, and *Technological Forecasting and Social Change*

Table 1-1 (cont'd)

Management Information Systems and Knowledge Management (33)	*ACM Transactions on Computer-Human Interaction*, *Communications of the ACM*, *Data and Knowledge Engineering*, *Decision Support Systems*, *Electronic Commerce Research*, *European Journal of Information Systems*, *Electronic Markets*, *Human-Computer Interaction*, *IBM Systems Journal*, *IIE Transactions*, *International Journal of Electronic Commerce*, *International Journal of Information Management*, *Information and Management*, *Insurance Mathematics and Economics*, *Information Society*, *Information Systems Frontiers*, *Information Systems Journal*, *Information Systems Research*, *Information Software Technology*, *Journal of the Association for Information Systems*, *Journal of the American Society for Information Science and Technology*, *Journal of Computer Information Systems*, *Journal of Global Information Management*, *Journal of Information Systems*, *Journal of Information Technology*, *Journal of Knowledge Management*, *Journal of Management Information Systems*, *Journal of Organizational Computing and Electronic Commerce*, *Journal of Quality Technology*, *Journal of Strategic Information Systems*, *Knowledge-Based Systems*, *MIS Quarterly*, and *MIS Quarterly Executive*
Operations Research and Management Science (40)	*Advances in Applied Probability*, *Annals of Operations Research*, *Annals of Probability*, *Annals of Statistics*, *Biometrics*, *Biometrika*, *Computers and Operations Research*, *Decision Sciences*, *European Journal of Operational Research*, *IEEE Transactions on Intelligent Transportation Systems*, *International Journal of Logistics Management*, *International Journal of Operations and Production Management*, *International Journal of Physical Distribution and Logistics Management*, *International Journal of Production Economics*, *International Journal of Project Management*, *International Journal of Production Research*, *Journal of Business Logistics*, *Journal of Multivariate Analysis*, *Journal of Operations Management*, *Journal of the Operational Research Society*, *Journal of Productivity Analysis*, *Journal of Scheduling*, *Journal of Service Management*, *Journal of Transport Geography*, *Management Science*, *Mathematics of Operations Research*, *OMEGA International Journal of Management Science*, *Operations Research*, *Operations Research Letters*, *Production and Operations Management*, *Reliability Engineering and System* Safety, Research Technology Management, Supply Chain Management, Theory and Decision, Technometrics, Transport Reviews, *Transportation*, *Transportation Science*, *Transportation Research Part B*, and *Transportation Research Part C*
Organizational Behavior and Human Resource Management (31)	*British Journal of Industrial Relations*, *Human Performance*, *Human Relations*, *Human Resource Management*, *Human Resource Management Review*, *International Journal of Human Resource Management*, *International Journal of Industrial Organization*, *International Journal of Intercultural Relations*, *International Journal of Manpower*, *International Journal of Selection and Assessment*, *Industrial Relations*, *Journal of Business Ethics*, *Journal of Business and Psychology*, *Journal of Conflict Resolution*, *Journal of Human Resources*, *Journal of Industrial Relations*, *Journal of Organizational Behavior*, *Journal of Vocational Behavior*, *Labor History*, *Leadership Quarterly*, *New Technology Work and Employment*, *Organizational Behavior and Human Decision Processes*, *Organizational Dynamics*, *Organization*, *Organization Science*, *Organization Studies*, *Personnel Psychology*, *Personnel Review*, *Psychology of Women Quarterly*, *Small Group Research*, and *Work and Stress*

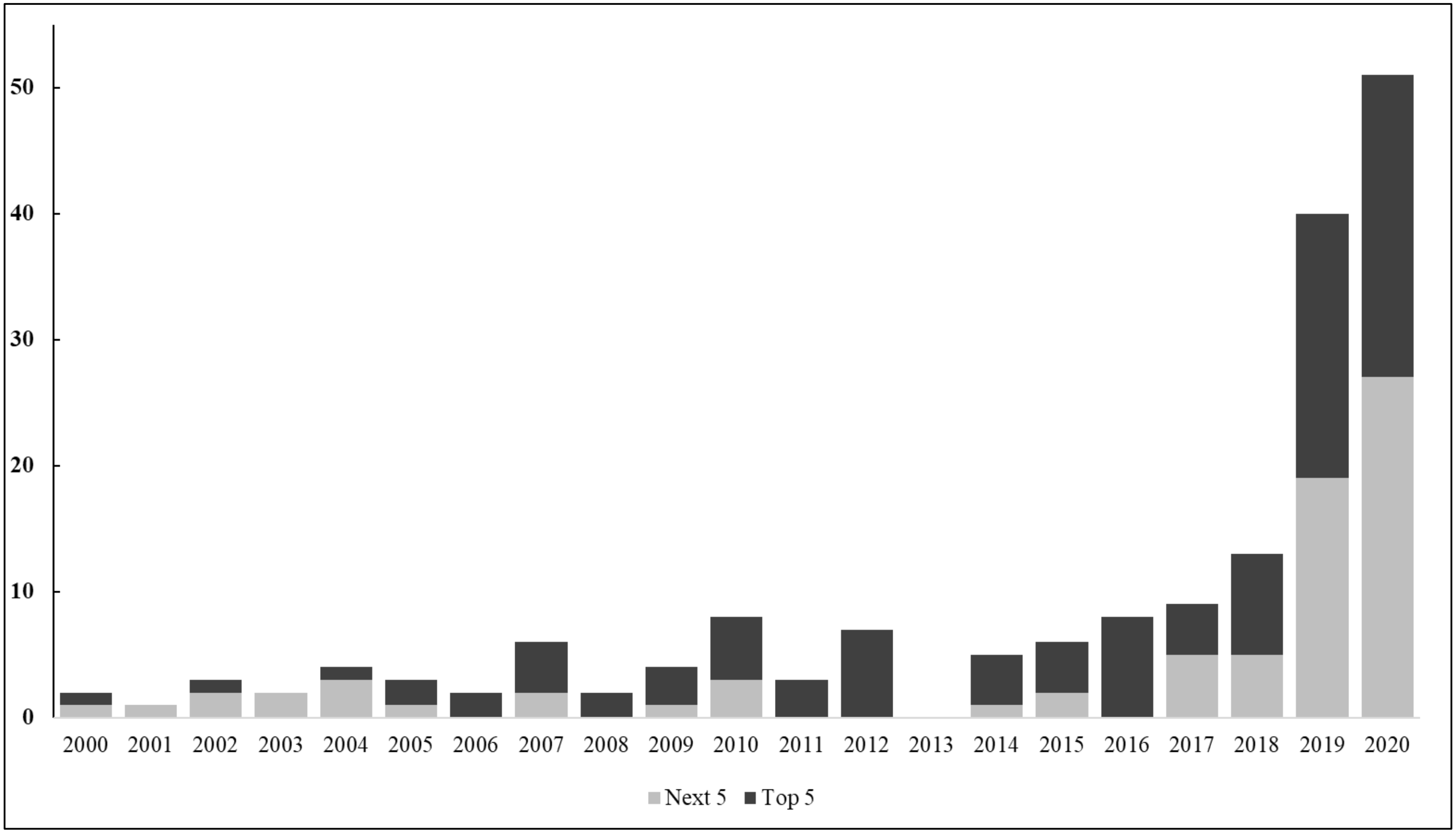
Topic Area and journal quality ratings classified by the Harzing Journal Quality List February 2019

Table 1-2 Most Influential Recently Published Theory-Based EDT Articles in the Marketing Literature

Publication	Outlet	Times Cited per Year
Meißner, Pfeiffer, Pfeiffer, and Oppewal (2019)	*Journal of Business Research*	5.00
Beck and Rygl (2018)	*Journal of Retailing & Consumer Services*	5.00
Yim, Chu, and Sauer (2017)	*Journal of Interactive Marketing*	3.67
Scholz and Duffy (2018)	*Journal of Retailing & Consumer Services*	3.50
Hilken, de Ruyter, Chylinski, Mahr, and Keeling (2017)	*Journal of the Academy of Marketing Science*	3.33
Poushneh (2018)	*Journal of Retailing & Consumer Services*	3.00
Poushneh and Vasquez-Parraga (2017)	*Journal of Retailing & Consumer Services*	3.00
Javornik (2016)	*Journal of Retailing & Consumer Services*	3.00
Dacko (2017)	*Technological Forecasting and Social Change*	2.33
Grewal, Roggeveen, and Nordfält (2017)	*Journal of Retailing*	2.33
Pantano, Rese, and Baier (2017)	*Journal of Retailing & Consumer Services*	2.33
Rafaeli, Altman, Hremler, Huang, Grewal, Iyer, Parasuraman, and de Ruyter (2017)	*Journal of Service Research*	2.33
van Doorn, Mende, Noble, Hulland, Ostrom, Grewal, and Petersen (2017)	*Journal of Service Research*	2.33
Lemon and Verhoef (2016)	*Journal of Marketing*	2.25
Melumad, Inman, and Pham (2019)	*Journal of Marketing Research*	2.00
Bonetti, Warnaby, and Quinn (2018)	book chapter	2.00
Hilken, Heller, Chylinski, Keeling, Mahr, and de Ruyter (2018)	*Journal of Research in Interactive Marketing*	2.00
Huang and Rust (2018)	*Journal of Service Research*	2.00
Humphreys and Wang (2018)	*Journal of Consumer Research*	2.00
Rauschnabel (2018)	*Psychology & Marketing*	2.00
Rese, Baier, Geyer-Schulz, and Schreiber (2017)	*Technological Forecasting and Social Change*	2.00
Van Kerrebroeck, Brengman, and Willems (2017)	*Virtual Reality*	2.00
Bigné, Llinares, and Torrecilla (2016)	*Journal of Business Research*	2.00

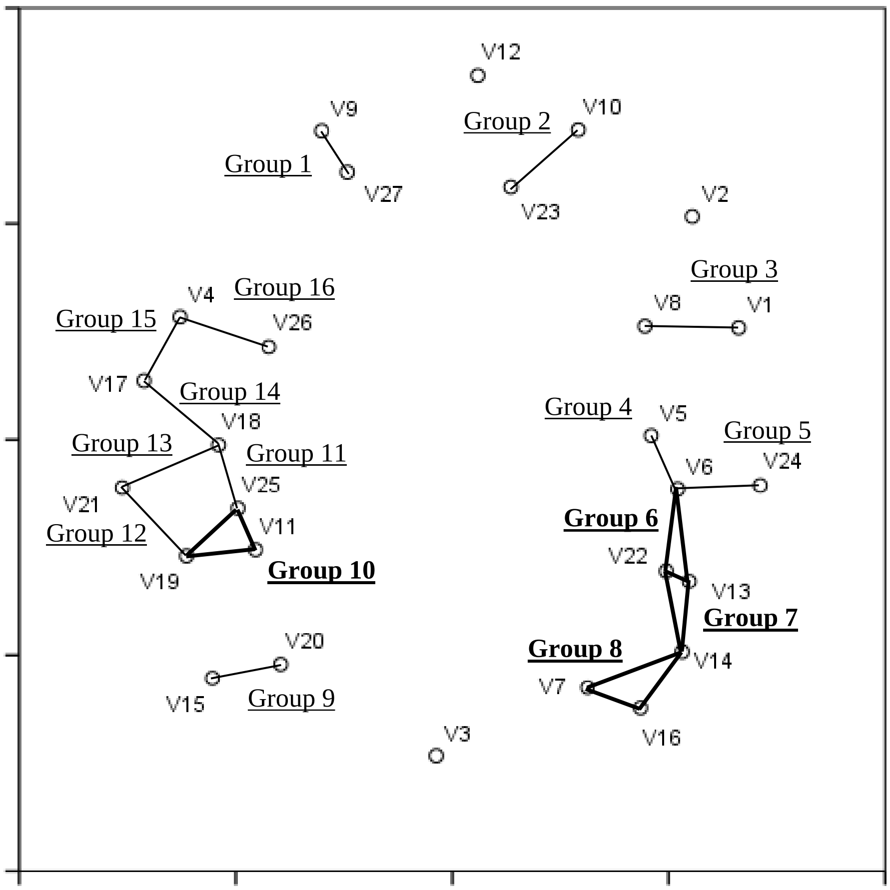
APPENDIX B: FIGURES

Figure 1-1 EDT-Oriented Articles Published in Top 10 Marketing Journals (2010 - 2020)



Articles retrieved from Clarivate Analytics (2020) Web of Science Platform published 2010 - 2020 for the following journals: *Journal of Marketing, Journal of Marketing Research, Marketing Science, Journal of Consumer Research, Journal of the Academy of Marketing Science, Journal of Consumer Psychology, Journal of Advertising, Journal of Interactive Marketing, Journal of Retailing, International Journal of Research in Marketing.*

Figure 1-2 EDT Intellectual Structure in the Marketing Literature

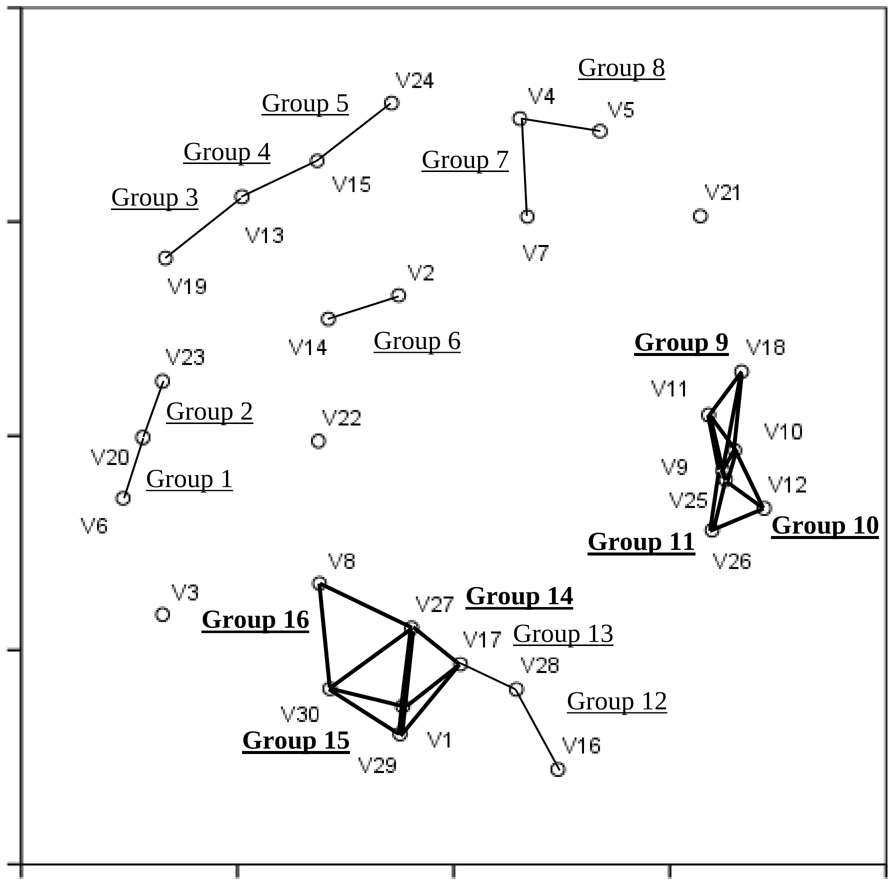


Notes: Stress value = 0.07; standardized Euclidean distance ≤ 0.25; research cliques are **bolded**.

V1 = Anderson and Gerbing (1988); V2 = Bagozzi and Yi (1988); V3 = Baron and Kenny (1986); V4 = Chandon, Hutchinson, Bradlow, and Young (2009); V5 = Davis (1989); V6 = Davis, Bagozzi, and Warshaw (1989); V7 = Erffmeyer and Johnson (2001); V8 = Fornell and Larcker (1981); V9 = Hayes (2013); V10 = Hoffman and Novak (1996); V11 = Janiszewski (1998); V12 = Javornik (2016); V13 = Jones, Sundaram, and Chin (2002); V14 = Keillor, Bashaw, and Pettijohn (1997); V15 = Lohse (1997); V16 = Parthasarathy and Sohi (1997); V17 = Pieters and Warlop (1999); V18 = Pieters and Wedel (2004); V19 = Rayner (1998); V20 = Rosbergen, Pieters, and Wedel (1997); V21 = Russo and Leclerc (1994); V22 = Speier and Venkatesh (2002); V23 = Steuer (1992); V24 = Venkatesh and Davis (2000); V25 = Wedel and Pieters (2000); V26 = Wedel and Pieters (2008); V27 = Zhao, Lynch, and Chen (2010).

Group 1 (V9 & V27): Mediation and Regression; Group 2 (V10 & V23): Computer-Mediated Environments and Virtual Reality; Group 3 (V1 & V8): Structural Equation Modeling; Group 4 (V5 & V6): User Perceptions and Technology Acceptance; Group 5 (V6 & V24): User Perception Antecedents, Intention, and Technology Acceptance; Group 6 (V6, V13, & V22): User Acceptance and Sales Force Automation; Group 7 (V13, V14, & V22): Attitudes, Productivity, and Sales Force Automation; Group 8 (V7, V14, & V16): Technology Attitudes, Productivity, and Sales Force Automation; Group 9 (V15 & V20): Eye Movement, Visual Attention, and Advertising; Group 10 (V11, V19, & V25): Eye Movement, Information Processing, Advertising, and Memory; Group 11 (V18 & V25): Attention Capture and Transfer, Eye Fixation, Advertising, and Memory; Group 12 (V19 & V21): Eye Movement and Information and Choice Processes; Group 13 (V18 & V21): Attention Capture and Transfer, Eye Fixation, Advertising, and Choice Processes; Group 14 (V17 & V18): Visual Attention and Capture and Brand Choice; Group 15 (V4 & V17): Visual Attention, Brand Choice, and Point of Purchase Position; Group 16 (V4 & V26): Eye Tracking and Point of Purchase Position

Figure 1-3 EDT Intellectual Structure in the Innovation Literature

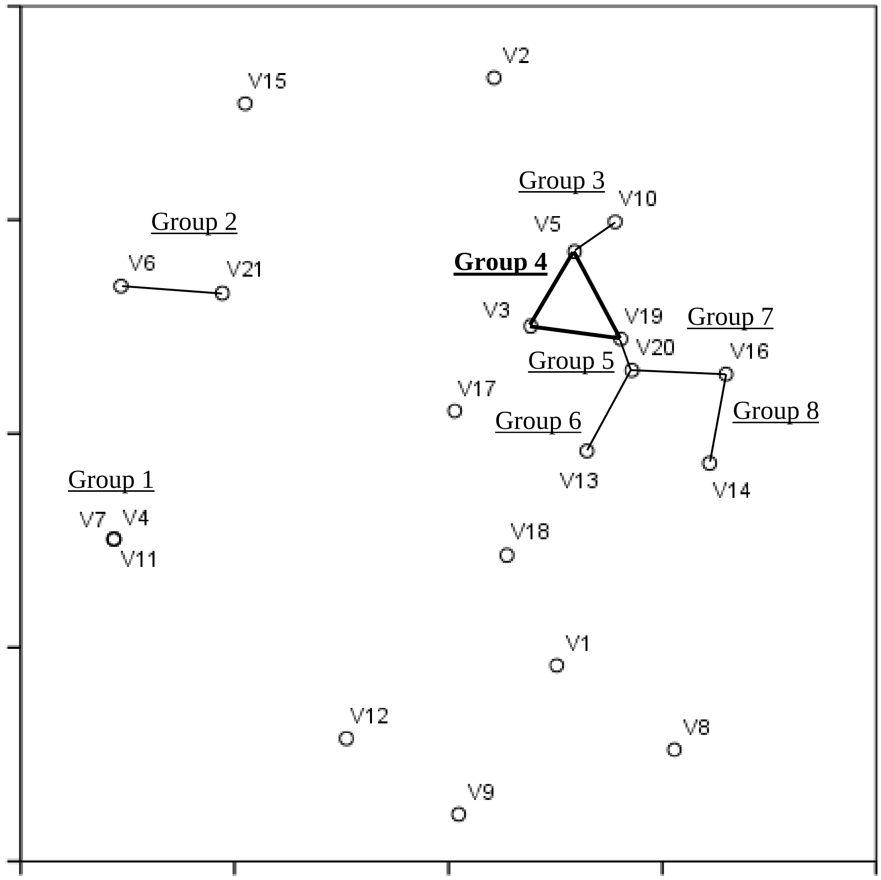


Notes: Stress value = 0.10; standardized Euclidean distance ≤ 0.25; research cliques are **bolded**.

V1 = Bergmann, Butzke, Walter, Fuerste, Moehrle, and Erdmann (2008); V2 = Blei, Ng, Jordan, and Lafferty (2003); V3 = Boyack, Klavans, and Börner (2005); V4 = Breiman (2001); V5 = Breiman, Friedman, Stone, and Olshen (1984); V6 = Chen (2006); V7 = Cortes and Vapnik (1995); V8 = Daim, Rueda, Martin, and Gerdsri (2006); V9 = Davis (1989); V10 = Davis, Bagozzi, and Warshaw (1989); V11 = Fishbein and Ajzen (1975); V12 = Fornell and Larcker (1981); V13 = Fu and Aliferis (2010); V14 = Griffiths and Steyvers (2004); V15 = Hirsch (2005); V16 = Kostoff (1998); V17 = Lee, Yoon, and Park (2009); V18 = Podsakoff, MacKenzie, Lee, and Podsakoff (2003); V19 = Porter (1980); V20 = Price (1965); V21 = Rogers (1995); V22 = Rotolo, Hicks, and Martin (2015); V23 = Small (1973); V24 = Teufel, Siddharthan, and Tidhar (2006); V25 = Venkatesh and Davis (2000); V26 = Venkatesh, Morris, Davis, and Davis (2003); V27 = Yoon and Park (2004); V28 = Yoon and Park (2005); V29 = Yoon, Choi, and Kim (2011); V30 = Yoon and Kim (2011).

Group 1 (V6 & V20): Network Citation Trends and Patterns; Group 2 (V20 & V23): Network Document Relationships; Group 3 (V13 & V19): Machine Learning and Suffix Stripping; Group 4 (V13 & V15): Machine Learning and Scientific Output; Group 5 (V15 & V24): Scientific Output Classification; Group 6 (V2 & V14): Probability Distributions and Scientific Search; Group 7 (V4 & V7): Random Forests and Support-Vector Networks; Group 8 (V4 & V5): Random Forests and Decision Trees; Group 9 (V9, V10, V11, & V18): Technology Belief, Attitude, and Voluntary Acceptance; Group 10 (V9, V10, V11, & V25): Technology Belief, Attitude, and Differential Acceptance; Group 11 (V9, V10, V12, V25, & V26): Technology Belief, Attitude, Expectancy, and Acceptance; Group 12 (V16 & V28): Citation and Morphology Analysis; Group 13 (V17 & V28): Patent Map and Morphology Analysis; Group 14 (V1, V17, V27, & V29): Patent Analysis, Maps, and Networks; Group 15 (V1, V27, V29, & V30): Patent Analysis and Rapid Technological Networks; Group 16 (V8, V27, V30): Forecasting and Rapid Technological Networks.

Figure 1-4 EDT Intellectual Structure in the Organizational Behavior and Human Resource Management Literatures

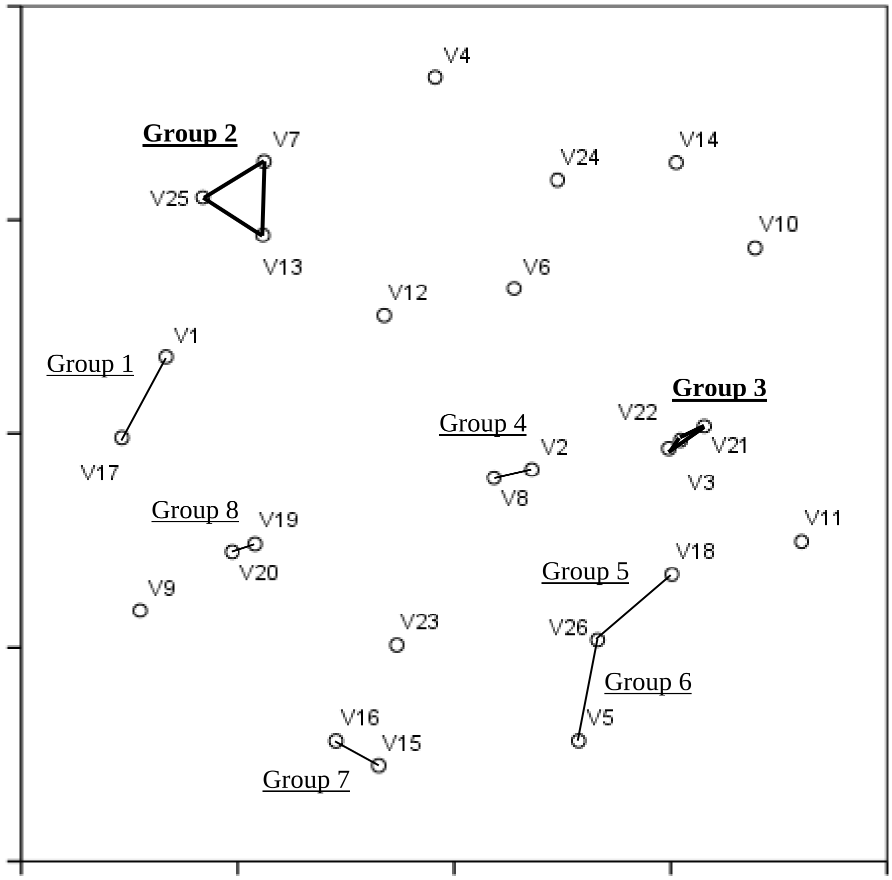


Notes: Stress value = 0.06; standardized Euclidean distance ≤ 0.25; research cliques are **bolded**.

V1 = Adler and Kwon (2002); V2 = Aiken, West, and Reno (1991); V3 = Appelbaum (2000); V4 = Autor (2015); V5 = Barney (1991); V6 = Braverman (1974); V7 = Brynjolfsson and McAfee (2014); V8 = Daft and Lengel (1986); V9 = Davis, Bagozzi, and Warshaw (1989); V10 = Delery and Doty (1996); V11 = Ford (2015); V12 = Hayes (2013); V13 = Huselid (1995); V14 = Lepak and Snell (2002); V15 = Orlikowski (2007); V16 = Podsakoff, MacKenzie, Lee, and Podsakoff (2003); V17 = Podsakoff and Organ (1986); V18 = Snell and Dean (1992); V19 = Wright, Dunford, and Snell (2001); V20 = Wright and McMahan (1992); V21 = Zuboff (1988).

Group 1 (V4, V7, & V11): Workplace Automation and the Second Machine Age; Group 2 (V6 & V21): Work Degradation and the Smart Machine; Group 3 (V5 & V10): Strategic Human Resources, Sustainable Competitive Advantage, and Performance; Group 4 (V3, V5, & V19): Human Resources, Manufacturing Advantage, and Sustainable Competitiveness; Group 5 (V19 & V20): Strategic Human Resource Management and Sustainable Competitive Advantage; Group 6 (V13 & V20): Strategic Human Resource Management, Turnover, Productivity, and Performance; Group 7 (V16 & V20): Strategic Human Resource Management Theory; Group 8 (V14 & V16): Human Resource Architecture.

**Figure 1-5 EDT Intellectual Structure in
the Management Information Systems and Knowledge Management Literatures**

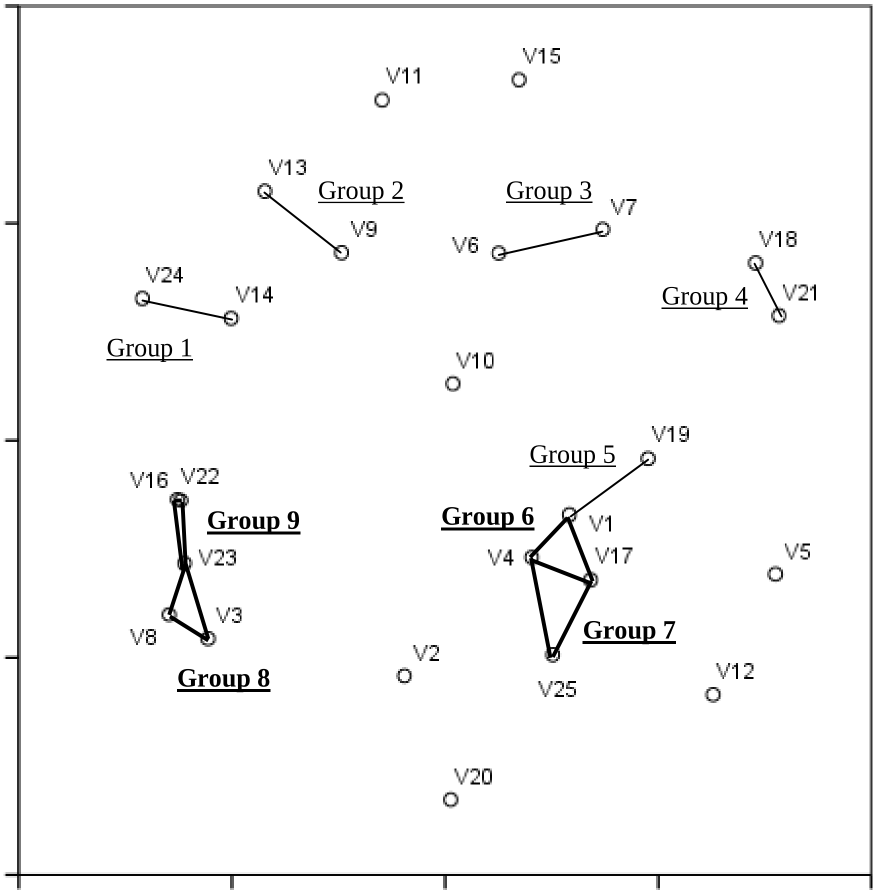


<u>Notes</u>: Stress value = 0.11; standardized Euclidean distance ≤ 0.25; research cliques are **bolded**.

V1 = Blei, Ng, and Jordan (2003); V2 = Breiman (2001); V3 = Breiman, Friedman, Stone, and Olshen (1984); V4 = Card, Moran, and Newell (1983); V5 = Chawla, Bowyer, Hall, and Kegelmeyer (2002); V6 = Cortes and Vapnik (1995); V7 = Davis, Bagozzi, and Warshaw (1989); V8 = Demšar (2006); V9 = Fellbaum (1998); V10 = Goldberg (1989); V11 = Guyon and Elisseeff (2003); V12 = Hall, Frank, Holmes, Pfahringer, Reutemann, and Witten (2009); V13 = Hevner, March, Park, and Ram (2004); V14 = Hornik, Stinchcombe, and White (1989); V15 = Krizhenvsky, Sutskever, and Hinton (2017); V16 = LeCun, Bengio, and Hinton (2015); V17 = Miller (1995); V18 = Mitchell (1997); V19 = Pang and Lee (2008); V20 = Pang, Lee, and Vaithyanathan (2002); V21 = Quinlan (1986); V22 = Quinlan (1993); V23 = Sebastiani (2002); V24 = Vapnik (1995); V25 = Venkatesh, Morris, Davis, and Davis (2003); V26 = Witten and Frank (2005).

<u>Group 1</u> (V1 & V17): Probability Distributions and Lexicon; <u>Group 2</u> (V7, V13, & V25): Technology Design and Acceptance; <u>Group 3</u> (V3, V21, & V22): Classification and Decision Trees and Machine Learning; <u>Group 4</u> (V2 & V8): Random Forests and Statistical Comparisons; <u>Group 5</u> (V18 & V26): Machine Learning and Data Mining; <u>Group 6</u> (V5 & V26): Applied Machine Learning and Imbalanced Classification; <u>Group 7</u> (V15 & V16): Deep Learning and Neural Networks; <u>Group 8</u> (V19 & V20): Opinion Mining, Sentiment Classification, and Machine Learning.

Figure 1-6 EDT Intellectual Structure in the Finance and Accounting Literatures

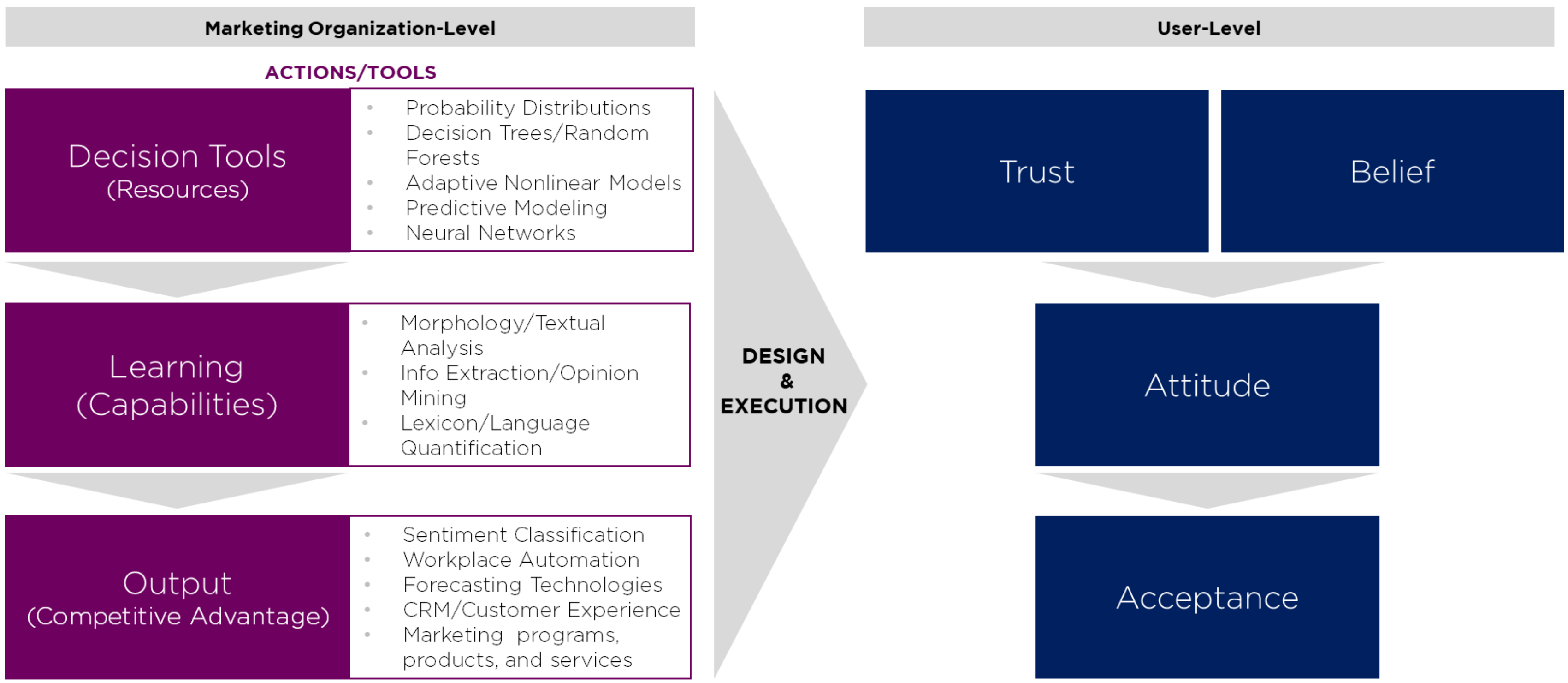


Notes: Stress value = 0.10; standardized Euclidean distance ≤ 0.25; research cliques are **bolded**.

V1 = Altman (1968); V2 = Altman, Marco, and Varetto (1994); V3 = Antweiler and Frank (2004); V4 = Beaver (1966); V5 = Black and Scholes (1973); V6 = Breiman (2001); V7 = Breiman, Friedman, Stone, and Olshen (1984); V8 = Das and Chen (2007); V9 = Efron (1979); V10 = Hastie, Tibshirani, and Friedman (2009); V11 = Hornik, Stinchcombe, and White (1989); V12 = Hutchinson, Lo, and Poggio (1994); V13 = James (2013); V14 = Khandani, Kim, and Lo (2010); V15 = LeCun, Bengio, and Hinton (2015); V16 = Loughran and McDonald (2011); V17 = Ohlson (1980); V18 = Shapiro (2000); V19 = Shumway (2001); V20 = Tam and Kiang (1992); V21 = Tenti (1996); V22 = Tetlock (2007); V23 = Tetlock, Saar-Tsechansky, and Macskassy (2008); V24 = Tibshirani (1996); V25 = Zmijewski (1984).

Group 1 (V14 & V24): Machine Learning and Modeling Principles; Group 2 (V9 & V13): Statistical Learning and Randomness Testing; Group 3 (V6 & V7): Random Forests and Regression Trees; Group 4 (V18 & V21): Adaptive Nonlinear Models and Recurrent Neural Networks; Group 5 (V1 & V19): Corporate Bankruptcy Forecasting; Group 6 (V1, V4, & V17): Financial Ratios and Bankruptcy Prediction; Group 7 (V4, V17, & V25): Bankruptcy Prediction Methods; Group 8 (V3, V8, & V23): Internet Language Use and Information Extraction; Group 9 (V16, V22, & V23): Language Use, Textual Analysis, and Investor Sentiment.

Figure 1-7 A Research Framework for the EDT Literature



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ESSAY TWO

Riding the Digital Technology Wave:

Embracing Emergent Digital Technology Capabilities to Gain a Competitive Advantage

Abstract

Brands are becoming increasingly capable of embedding digital technology features (e.g., those containing artificial intelligence, augmented reality, virtual reality, voice command, and robotics) into product and service offerings to enhance customer and firm value. However, little is known about how a brand’s digital technology capability directly influences critical short- and long-term marketing outcomes such as brand sales and customer satisfaction. The authors show that a brand's digital technology capability exerts a positive, curvilinear effect on brand sales and a negative, curvilinear effect on customer satisfaction. This divergent effect presents a nuanced picture suggesting that while digital technology capabilities lead to short-term gains, the long-term effect may be detrimental for extremely advanced brands. Brand status (e.g., luxury and mainstream brands) moderates the effect on brand sales. There is a greater dispersion of sales for luxury brands, peaking for brands with low and high digital technology capabilities. These findings extend not only theoretical insights into the impact of digital technology capability on critical marketing outcomes but also offer actionable managerial implications.

Keywords: Digital Technology, Artificial Intelligence, Virtual Reality, Augmented Reality, Automation, Resource-Based View, Competitive Advantage, Automotive

Introduction

Global spending on digital technologies is projected to nearly double in the next four years, reaching close to $2.4 trillion by 2024 (Statista 2021b). According to a 2020 global CIO survey, the exponential increase in spending is driven by the need for brands to appeal to customer demand and guard against the competition (Statista 2021c). Digital technologies such as artificial intelligence (AI), augmented and virtual reality (AR/VR), the internet of things (IoT), and robotic and mechanical systems are becoming far more prevalent in every aspect of consumers' lives, enabling more personalized, seamless, and relevant experiences (Schmitt 2019). These benefits are made possible by advances in digital technology capabilities, which have enabled brands to embed these technologies across a multitude of products, providing cross-product, -service, and -environment uses. This wide-scale diffusion of existing and emergent digital technologies is commonly referred to as a "wave" (e.g., Graham and Senge 1980), which consists of the rapid introduction of new high-tech products that provide new forms of knowledge, entertainment, and interactions (Schmitt 2019; Tellis, Yin, and Niraj 2009).

As these new technologies become commonplace, they have the potential to substitute the "old" way with a "new" way of doing things such that people cannot imagine doing things any other way (Hamel and Prahalad 1994; Zhou, Yim, and Tse 2005). In other words, technological waves leave an enduring mark on people's lives. As an illustration, as of mid-2020, there were more than 20 billion connected devices globally, nearly three times the number of humans on the planet (Forbes 2020). These connected devices are equipped with AI-powered virtual assistants like Siri or Alexa, which help us complete daily tasks like checking the weather and scheduling an appointment. They serve as central hubs for music, entertainment, and work.

And they take on expected and unexpected forms such as mobile phones, tablets, vehicles, and refrigerators.

A consumer's ability to transfer experiences seamlessly from one environment to another is made possible by brands that embrace existing and emerging digital technologies. Prior research suggests that embracing digital technology as a strategic resource enables brands to establish a competitive advantage by offering consumers greater value such as personalized offerings, enhanced consumer delight, and revolutionize customer experiences (Hilken et al. 2017; Hoffman and Novak 2018; Ramaswamy and Ozcan 2018). However, the question for brands is more specific than whether "to embrace" or "not to embrace." Brands must decide which digital technologies should be included in their offerings, how many digital technology features should be offered, and what level of technological advancement should these features possess, referred to as a brand's digital technology capability. In other words, the questions more pertinent to brand decision-making as it pertains to digital technology are: 1) *To what extent should a brand establish its digital technology capability*? 2) *Under what conditions does a brand's digital technology capability lead to a competitive advantage?*

The automotive industry lends itself well to examining our central research questions. According to a 2020 Future of Mobility report, automakers are projected to spend over $168 billion in 2025 on digital technologies, up 342% from 2015 (Frost & Sullivan 2020). The substantial increase in spending is unsurprising if one considers the advancements made in automobiles over the last ten years. Today's vehicles are equipped with robotic and mechanical systems that open liftgates when they sense that the driver is nearby and activate windshield wipers at the first drop of rain. IoT features transform vehicles into central connectivity hubs for navigation, infotainment, and smart driving apps. AR- and VR-powered features assist drivers in safe driving by projecting transparent digital displays. Among the most advanced digital technologies, the mass commercialization of AI technology has enabled automakers to equip more vehicles with AI-powered features that autonomously (i.e., without driver intervention) accelerate, steer, stop, and park.

The digital wave also appears to be brand agnostic. Regardless of a brand's positioning and promise, current automotive advertisements often attribute some of the benefits offered by a vehicle or brand to some level of technology. Take Jeep, for example. Jeep's brand promise is to deliver "vehicles enabling life's extraordinary journeys" to "provide vehicles that support a lifestyle of boundless freedom, responsible adventure and are reliable, safe, fun and environmentally friendly" (www.jeep.com). A Jeep ad published in 2019 simply states, "Most technology in its class," implying that the brand promise is delivered through technology. Similarly, Chevrolet "Chevy" pickup trucks are well-known for being among the "most dependable," "longest-lasting," and "rugged" vehicles on the road (www.chevrolet.com). In 2014, Chevy debuted their 2015 Chevy Colorado accompanied by a viral ad campaign called #technologyandstuff featuring the #chevyguy, in which they highlighted the numerous digital technology feature options. As reported by *USA Today*, this ad not only enhanced the association between the Chevy brand and technology, but it earned Chevy $5 million in free media exposure (www.usatoday.com). Additional examples are presented in Figure 2-1. The automotive industry provides a salient example of brands that have embraced digital technology as a resource to a greater (or lesser) degree.

By addressing our central research questions, we make four important theoretical and managerial contributions. First, we develop a conceptual framework that examines the marketing performance implications of a brand's digital technology capabilities (see Figure 2-2). Drawing upon the economic theory of additive utility (Lancaster 1971) and extending the works of Thompson, Hamilton, and Rust (2005), we investigate the direct effects of digital technology capabilities on brand sales and customer satisfaction. Second, we empirically test our model using a unique panel data set comprised of 20 automotive brands, 304 vehicle models, and 8,692 observations from 2010 - 2019, collected from multiple data sources. These data sources include US News (Cars), American Customer Satisfaction Index (ACSI), Automotive News, J.D. Power & Associates (JDPA), Wards Intelligence, Compustat, Statista, automotive brand websites, and expert raters. We operationalize digital technology capabilities as two indices derived from the number of digital technology features (i.e., unweighted digital technology index) and the level of technology possessed by the features (i.e., feature-weighted digital technology index). The branded digital technology features and JDPA awards data were assembled and analyzed using web scraping techniques. Parent firms and brands included in this study are shown in Table 2-1.

Third, prior research has demonstrated differing and more complex consumer perceptions of value associated with purchasing luxury goods (e.g., Lichtenstein, Ridgway, and Netemeyer 1993; Okonkwo 2016). The distinction between luxury and mainstream brands is made strikingly noticeable by the vehicle's brandished badge in the automotive industry. Subsequently, we examine the moderating role of brand status in the context of digital technology capabilities. Fourth, we adopt a resource-based view (RBV) theoretical perspective to understanding how a brand's digital technology capability promotes a sustainable competitive advantage (Barney 1991). Specifically, we calculate the difference between a brand's digital technology capability and the average digital technology capability of the brands within its competitive set (e.g., luxury vs. mainstream brands), referred to as a brand's digital technology surplus, and examine its effect on brand sales and customer satisfaction.

Taken together, these findings extend not only theoretical insights into the impact of digital technology on critical marketing outcomes but also offer actionable managerial implications.

Theory and Hypotheses

Digital Technology Capability and Brand Sales

Previous research on new products has found a strong link between product feature offerings and perceived value, driven by consumer's expectations. Particularly, in selecting durable goods, consumers evaluate product attributes that can be easily verified, such as product features (Narasimhan 1989), and translate information about these features into potential functional benefits (Olson and Reynolds 1983; Winer 1985). Economic theory and in-practice market research techniques, such as conjoint analysis, demonstrate that brands can increase the appeal of new products by offering a greater number of features. From this view, the perceived product value is additive, and this perceived value influences consumers' preference for one product or brand over another (Lancaster 1971). There is an underlying assumption that consumers may need to have prior expertise in using these features or products to assign value, especially when evaluating high-tech features that may be perceived as complex. However, Thompson, Hamilton, and Rust (2005) found that no such expertise is required. Regardless of expertise, consumers displayed a strong preference for products with a higher number of features.

Prominent theories in new product or technology adoption, such as the theory of reasoned action (TRA), the theory of planned behavior (TPB), and the technology acceptance model

(TAM), have all demonstrated efficacy in predicting behavioral intentions and decisions to adopt technology products based on consumer or user expectations. TRA and TPB state that favorable behavioral beliefs and evaluation of outcomes (i.e., expectations) lead to favorable attitudes towards the behavior, leading to actual use behavior (Ajzen 1985; Ajzen and Fishbein 1975; Ajzen and Fishbein 1980). Additionally, according to TAM, when a new product is perceived to be useful, consumers form a favorable attitude towards the new product and are likely to adopt the new product (Bagozzi and Lee 1999; Davis 1989). As brands increase their digital technology capabilities, they become better positioned to offer a greater number and higher level of digital technology features in their products. In turn, this enhanced customer value should be evidenced by increased brand sales.

However, a brand's digital technology offering must meet an established threshold before being perceived as offering enhanced value. This threshold effect occurs once a brand exceeds the standard digital technology offered by all firms in a given market (Liberman and Asaba 2006). Therefore, we do not believe the relationship between digital technology capability and brand sales to be perfectly linear, but rather a gradual increase as the number and level of digital technology increases. Formally stated, we hypothesize that:

H_1: A brand's digital technology capability has a positive, curvilinear effect on brand sales, such that brand sales improve at an increasing rate as its digital technology capability increases.

The moderating role of brand status on the digital technology capability and sales relationship. Luxury brands are those that signal the highest level of quality and design, are often premium-priced, and may be purchased for utility, symbolic, and experiential motivations (e.g., Berthon et al. 2009; Silverstein and Fiske 2003). As a condition of abundance, luxury products often provide features and benefits beyond basic use, even promoting a plethora of features that may not be functionally necessary (Hagtvedt and Patrick 2009). These features, regardless of their necessity, become additive value associated with the branded product.

Beyond the functional utility of the product, luxury brands are also those for which "the simple use of display brings esteem to the owner" (Vigneron and Johnson 2004, p. 202). Compared to mainstream brands, luxury branded products often assume physical and cultural representations of superior value above and beyond what is offered by mainstream brands within the same product category and are designed to evoke desirable emotions and signal status (Loughran Dommer, Swaminathan, and Ahluwalia 2013; Okonkwo 2016). As such, luxury purchase decisions have been strongly attributed to a consumer's ability to express themselves or their ideal selves (Ng and Houston 2006; Swaminathan, Page, and Gürhan-Canli 2007). These luxury brands and products may be conspicuously purchased based on a consumer's desire to signal their superior status, success, and respected position within a culture (Berger and Ward 2010; Han, Nunes, and Drèze 2010).

Luxury brand purchase motivations are considerably salient for products on which the brand badge is highly visible to the public. For example, in the automotive industry, each brand offers a range of models (i.e., products). The opening price-point or entry-level models are often stripped of technology and bonus features, which allow brands to offer vehicles at substantially lower prices. As luxury brands introduce entry-level models, the premium badge becomes more accessible to a larger consumer segment, resulting in the massification or democratization of luxury (Nueno and Quelch 1998). At the high-end, brands offer what is commonly referred to as "fully loaded" models, containing every bell and whistle the brand can capably offer. It is logical for luxury brands to expect a greater sales dispersion across entry-level, lower-equipped and high-end, "fully loaded" models due to varying consumer motivations. Therefore, we should expect the relationship between digital technology capability and sales to reflect a more u-shaped relationship for luxury brands than mainstream brands. Thus, we propose:

$H2_a$: Luxury brands have a higher digital technology capability than mainstream brands.

$H2_b$: The positive, curvilinear effect of a brand's digital technology capability on brand sales is steeper (flatter) for luxury (mainstream) brands.

Digital Technology Capability and Customer Satisfaction

Customer satisfaction is a significant indicator of the strength of a brand's offering. It has been defined as a consumer's evaluation of some object, entity, or experience based on either the confirmation or disconfirmation of their expectations (Yi 1990). Expressly, customer satisfaction evaluations are based on experienced rather than perceived utility. Prior research on product features and design has found that the greater number of features a product possesses, the lower the consumer's ability to use the features, resulting in lower experienced utility (Nielsen 1994; Thompson, Hamilton, and Rust 2005). For example, according to the J.D. Power & Associates 2015 Driver Interactive Vehicle Experience (DrIVE) Report, most unused features in vehicles today are digital technology-powered. The report states, "The five features owners most commonly report that they never use are in-vehicle concierge (43%), mobile routers (38%), automatic parking systems (35%), heads-up displays (33%), and built-in apps (32%)" (J.D. Power & Associates 2015). In this report, consumers indicated that they prefer to use familiar devices (e.g., smartphone or tablet) because it meets their needs.

This finding is consistent with existing new product research, which has found that consumers often experience initial frustration when learning how to use products that require skill. These products may possess a significant number of features, features with a high level of technological advancement, or a combination of the two. At some point, unless this learning curve is addressed, the effect may be so detrimental that it lowers a consumer's product evaluation (Billeter, Kalra, and Loewenstein 2011; Thompson, Hamilton, and Rust 2005). Therefore, we should expect that a brand's digital technology capability should adversely affect customer satisfaction. Formally stated:

H3: A brand's digital technology capability has a negative, curvilinear effect on customer satisfaction, such that customer satisfaction worsens at an increasing rate as its digital technology capability increases.

The moderating role of brand status on the digital technology capability and customer satisfaction relationship. Research has shown that a consumer's sense of status (e.g., felt status) promotes a greater sense of commitment to firms (Lacey, Suh, and Morgan 2007) and increased satisfaction (Vogel, Evanschitzky, and Ramaseshan 2008). In this context, we suggest that luxury brands not only have higher levels of customer satisfaction but are more insulated from the negative effects of a brand's digital technology capability on customer satisfaction. Formally stated:

$H4_a$: Luxury brands have higher customer satisfaction scores than mainstream brands.

$H4_b$: The negative, curvilinear effect of a brand's digital technology capability on customer satisfaction is flatter (steeper) for luxury (mainstream) brands.

Digital Technology Surplus as a Competitive Advantage

Consumers do not make purchase decisions or subsequent evaluations in a vacuum. Rather, in-market consumers may consider the broader market offerings then reduce their comparison, partitioning the market into a set of hierarchical submarkets (Weitz 1985). These submarkets comprise a set of similar or near-identical brands in meeting the consumer's needs, and thus, they are seen to compete against one another directly. For example, luxury brands like BMW, Mercedes-Benz, and Lexus are less likely to directly compete with mainstream brands like Ford, Chevrolet, and Subaru. There is an inherent luxury versus non-luxury partition in the market (Loughran Dommer, Swaminathan, and Ahluwalia 2013).

In the consideration phase, consumers may consider how the brands and branded products differ in their relative superiority or inferiority and identify "leaders" that are superior to their "challengers" within this hierarchy (Li et al. 2021). The relative superiority-inferiority can be assigned based on performance-related attributes such as gas mileage offered by a car (Viswanathan and Childers 1999) or digital technology capability in the case of this investigation. The superior versus inferior classification helps consumers evaluate alternatives and decide which branded product best suits their needs (e.g., Howard and Sheth 1969). In the evaluation phase, a consumer's evaluation of a product is not solely formed by their experience with the product. Brands that belong to a competitive set create a standard of performance for the collective set. In evaluating their satisfaction with a product, consumers also consider their product's performance relative to the standard performance of the competitive set (Hennig-Thurau and Klee 1997).

Drawing on resource-based theory (Barney 1991), digital technology as a resource should lead to a competitive advantage for brands that lead within their competitive set. Specifically, brands that exceed their competitive set's digital technology capability standard may be uniquely positioned to garner greater sales and greater customer satisfaction than their direct competitors. We refer to the excess capability beyond the competitive set as a brand's digital technology capability surplus. Formally, we hypothesize that:

H5: A brand's digital technology capability surplus positively affects brand sales.

H6: A brand's digital technology capability surplus positively affects customer satisfaction.

The moderating role of brand status on the digital technology capability surplus and sales relationship. The premium price attached to a luxury-branded product is comprised of functional, symbolic, and experiential value. The functional value is determined by the physical manifestations of the product (e.g., features, benefits, and aesthetics), which are often of the highest quality and level of technological advancement (Berthon et al. 2009). In essence, luxury brands that lead in digital technology offerings offer superior perceived value compared to their competitive set and the market as a whole, creating the upper limit for digital technology offerings at a point in time. Therefore, we hypothesize:

H7: The positive effect of a brand's digital technology capability surplus on brand sales is stronger (weaker) for luxury (mainstream) brands.

The moderating role of brand status on the digital technology capability and customer satisfaction relationship. Consequently, luxury brands that lead in digital technology offerings provide a greater number and higher level of digital technology features compared to their competitive set and the market as a whole. In other words, luxury brands that possess a digital technology capability surplus offer more complex products. Therefore, we suggest that this surplus leads to lower experience utility and lower customer satisfaction. Unlike luxury brands, mainstream brands offer an acceptable but relatively lower level of quality and number of extraneous features (Lee, Motion, and Conroy 2009). For mainstream brands, a digital technology capability surplus places the brand above their competitive set but not at the high-end of the market. In other words, mainstream brands that lead in digital technology exceed the digital technology capability standard of their competitive set but contain less complexity than the broader market. Therefore, we propose:

H8: The effect of a brand's digital technology capability surplus on customer satisfaction is negative for luxury brands and positive for mainstream brands.

Research Methodology

We manually assembled a panel dataset on brand sales, customer satisfaction, digital technology features, and brand-, parent firm-, and market-level factors that influence the marketing outcome variables of interest to test our conceptual framework. Sources of data include US News (Cars), American Customer Satisfaction Index (ACSI), Automotive News, J.D. Power & Associates (JDPA), Wards Intelligence, Compustat, Statista, automotive brand websites, and expert raters. These variables, their source, and relevant literature are presented in Table 2-2.

Data Collection

The sampling procedure involved several steps. First, we downloaded model-level unit sales data for the US consumer market (2010 - 2019) from Automotive News, resulting in 11,904 observations, 432 models, and 46 brands. To develop a generalizable yet manageable sample for analysis, we identified the top 20 brands, representing more than 94% of automotive units sold in the U.S from 2010 - 2019. After excluding the remaining brands and accounting for missing observations, we obtained a final sample of 8,692 observations, 304 models, and 20 brands. Second, we scraped the U.S. News (Cars) website and assembled a complete list of features and specifications for all models manufactured from 2010 - 2019 by the top 20 brands (example page shown in Figure 2-3). We included the features and specifications for all available trim types (i.e., configurations) to account for all possible standard and optional features at various price points offered by each brand. Third, we use an indicator variable to denote whether a feature contained digital technology or electronics to function. Excluding the non-technology features, we obtained a brand-agnostic list of 29 digital technology features and identified which models contained which features. The features and descriptions are presented in Table 2-3.

Measures

Brand sales. We measure financial performance in the form of the annual sales units sold by each brand. As is customary when examining volatile and dispersed economic data, we take the natural log of sales units. It is important to note that Automotive News provides sales data at the model nameplate level. We aggregated the data to the brand-segment level to meaningfully examine the relationship between digital technology and brand sales (e.g., Ford Trucks) (N = 2,423).

Customer satisfaction. We measure customer satisfaction (CSAT) using the annual scores provided by the American Customer Satisfaction Index (ACSI) database. The ACSI database contains data collected at the consumer level, which captures consumers' experiences with services and products provided by over 200 private and public sector firms in more than 40 industries (Fornell et al. 2006; Gruca and Rego 2005). ACSI specifically captures customer satisfaction measures with auto purchases made between six months and three years prior to the interview. This sampling frame is designed to ensure sufficient experience with the vehicle among the respondents to have formed a cumulative evaluation of the product, its quality and value, their likelihood of remaining loyal, and so forth. Potential respondents are screened prior to interviewing for purchases or leases of new automobiles only (i.e., respondents who purchased used vehicles are excluded from interviewing). The respondent must also still own/lease the vehicle at the time of interviewing. While varying across vehicle brands and nameplates and between years of interviewing, on average, about 1/3 of respondents fall into each of these three categories: purchased/leased the vehicle six months to one year ago, one year to two years ago, or two years to three years ago. In the ACSI sample, the shortest period a customer will have owned a vehicle is six months, suggesting that the effects of brand-level characteristics on brand evaluations should appear at least one year in the future. Thus, we examine the relationship between digital technology and customer satisfaction at the brand level (e.g., Ford) and lag customer satisfaction by one year (N = 174).

Unweighted digital technology index. We developed two proxies to measure a brand's digital technology capability to test our hypotheses. A common method for measuring firm innovativeness and technology capabilities is to take a simple count of the number of patent applications, technology features, and breakthrough products generated by a firm (e.g., Dotzel and Shankar 2019; Sorescu and Spanjol 2008). In theory, the greater the number of technology features offered by a brand, the more technologically advanced the brand. Therefore, we use the number of technology features offered by the brand each year as a proxy for a brand's unweighted digital technology index (UDTI).

Feature-weighted digital technology index. When evaluating a product, consumers consider the number of technology features offered by the brand and the level of technology offered by each feature. For example, features that use artificial technology to deliver a benefit to the user without user intervention may be viewed as more technologically advanced than features that use robotic technology and require the user to activate or actively manage the feature in some way.

To establish a more comprehensive measure of a brand's feature-weighted digital technology index (FWDTI), we asked twenty-one expert raters to carefully consider the 29 digital technology features used in this study. Screening questions for the expert raters required they were (1) employed in the automotive field at the time of this study, (2) rated themselves as an 8 or above on a scale of 1 to 10 in terms of knowledge of automotive features, and (3) rated themselves as an 8 or above on a scale of 1 to 10 in terms of confidence in their ability to rate technology features.[4] Furthermore, the expert raters possessed at least three years of work experience in the automotive industry, with seven respondents having more than 15 years of experience. Companies represented in the sample include Audi, Ford, General Motors, Lear Corporation, and BMW. In the survey, expert raters were shown a single feature along with its description and asked, "In your opinion, how technologically advanced is adaptive cruise control?" The expert rater then rated the feature on a scale of 1 to 5 (1 = Not at all advanced and 5 = Extremely advanced). The features were randomized for each respondent to eliminate order bias. Overall, the expert raters had a high agreement in their classifications of the 29 digital technology features (average SD = 0.57). Feature weights are presented in Table 2-3.

Unweighted digital technology difference. We developed two proxies to measure a brand's digital technology capability surplus as well. We calculate the unweighted digital technology difference (UDIFF) by subtracting the mean unweighted digital technology index for brands in the same status category (i.e., mainstream and luxury) from the brand's unweighted digital technology index, shown in Equations 1 and 2:

[4] Expert raters were asked the following questions to assess their knowledge of technology features and their confidence in evaluating technology features. Specifically, they were asked "On a scale of 1 to 10, how knowledgeable are you about technology features found in consumer vehicles?" and "On a scale of 1 to 10, **how confident do you feel evaluating** technology features found in consumer vehicles?"

$$\text{Luxury UDIFF}_{it} = \text{UDTI}_{it} - \frac{\sum_{k=1}^{N} \text{UDTI}_{ikt}}{N_{kt}} \tag{1}$$

$$\text{Mainstream UDIFF}_{it} = \text{UDTI}_{it} - \frac{\sum_{k=0}^{N} \text{UDTI}_{ikt}}{N_{kt}} \tag{2}$$

where $UDTI_{it}$ is the unweighted digital technology index for brand i in year t, the sum of $UDTI_{ikt}$ is the sum of the unweighted digital technology index scores for all brands in brand status category k (k = 1 for luxury brands and k = 0 for mainstream brands) in year t, and N_{kt} is the total number brands represented in the brand status category k in year t.

Feature-weighted digital technology difference. We calculate the feature-weighted digital technology difference (FWDIFF) by subtracting the mean feature-weighted digital technology index for brands in the same status category from the brand's feature-weighted digital technology index, shown in Equations 3 and 4:

$$\text{Luxury FWDIFF}_{it} = \text{FWDTI}_{it} - \frac{\sum_{k=1}^{N} \text{FWDTI}_{ikt}}{N_{kt}} \tag{3}$$

$$\text{Mainstream FWDIFF}_{it} = \text{FWDTI}_{it} - \frac{\sum_{k=0}^{N} \text{FWDTI}_{ikt}}{N_{kt}} \tag{4}$$

where $FWDTI_{it}$ is the feature-weighted digital technology index for brand i in year t, the sum of $FWDTI_{ikt}$ is the sum of the feature-weighted digital technology index scores for all brands in brand status category k (k = 1 for luxury brands and k = 0 for mainstream brands) in year t, and N_{kt} is the total number brands represented in the brand status category k in year t.

Brand status. J.D. Power & Associates provides publicly available brand-level automotive data, such as brand and vehicle statuses, ratings, and awards. JDPA assigns the term "premium" to all luxury brands and vehicles to distinguish between brand statuses. Therefore, we assigned a status to each brand (1 = luxury and 0 = mainstream) based on JDPA's classification.

Control variables. We controlled for market-, parent firm-, and brand-level characteristics that may contribute to brand sales and customer satisfaction. Consistent with traditional new product and innovation research, we control for year-over-year market growth in automotive industry units reported by Wards Intelligence. Parent firm-level variables include market share, R&D, and advertising spend. Market share is calculated as a percentage of firm-level reported unit sales compared to reported industry unit sales in the U.S. R&D spend is calculated as the firm's reported spending on research and development (in millions USD) as reported by Compustat. Advertising spend is reported as the firm's reported spend on total advertising (in millions USD). Given the substantive nature of the data, we sought to account for missing data at the firm level. We impute missing values of R&D and advertising spend to 0 and include no R&D and no Ad Spend dummy variables (1 = value is missing and 0 = value is present) to maintain the integrity of the data and include more of the collected sample in our analysis (Hirschey, Richardson, and Scholz 2001; Josephson et al. 2019).

Brand-level control variables include brand age, vehicle segment, house status, average MSRP, and two J.D. Power award categories. Brand age is measured as the number of years since the brand was founded (e.g., Luffarelli, Mukesh, and Mahmood 2019). Various factors beyond technology may influence sales and customer satisfaction. Therefore, we include the number of vehicle segments (i.e., sports car, car, SUV, truck, minivan, and passenger van) offered by a brand. Furthermore, prior research demonstrates that branding strategies (e.g., corporate branding, house of brands, or mixed branding) directly affect firm financial performance. We consider that the U.S. automotive industry is mostly comprised of brands that either take on a mixed branding strategy in which the "firm typically employs a set of house or family brands, such as subsidiary names, in their brand portfolio, in addition to using the corporate name" (e.g., General Motors) or a corporate branding strategy in which "the corporate name is dominant in endorsing all or part of the firm's product and service brand" (e.g., Ford) (Rao, Agarwal, and Dahlhoff 2004, p. 127). Therefore, we include a dummy variable to indicate whether the brand belongs to a house of brands (1 = brand within a group of brands under one firm and 0 = single brand as the firm). We also include the natural log of the model-level original average MSRP aggregated to the brand level.

Lastly, we consider the impact public awards and ratings have on brand sales and perceptions. We scraped the J.D. Power & Associates (JDPA) website and assembled a complete list of awards earned by each brand from 2010 - 2019. From this data, we created two award control variables. The first is the number of J.D. Power Awards evaluating vehicle quality, dependability, and performance earned by a brand annually (JDPV). The second is the number of J.D. Power Awards evaluating dealership sales and service earned by a brand annually (JDPD).

Model Specification

Unobserved time-varying factors associated with brand outcomes can produce a correlation between the predictor variables and the error term. To control for unobserved heterogeneity, we used ordinary least squares (OLS) with a lagged dependent variable (Germann, Ebbes, and Grewal 2015). We estimate the relationships between digital technology capability and brand sales in Equations 5 through 8:

$$\begin{aligned}\ln(\mathrm{Sales})_{it} = \; & \beta_0 + \beta_1 \ln(\mathrm{Sales})_{it-1} + \beta_2 \mathrm{UDTI}_{it} + \beta_3 \mathrm{UDTI}_{it}^2 + \beta_4 \mathrm{Status}_{it} + \\ & \beta_5 \mathrm{UDTI}_{it} \text{ x } \mathrm{Status}_{it} + \beta_6 \mathrm{UDTI}_{it}^2 \text{ x } \mathrm{Status}_{it} + \beta_7 \mathrm{X}_{it} + \beta_8 \mathrm{Z}_{jt} + \\ & \beta_9 \mathrm{Market\ Growth}_t + \varepsilon_{it}\end{aligned} \tag{5}$$

$$= \beta_0 + \beta_1 \ln(\text{Sales})_{it-1} + \beta_2 \text{FWDTI}_{it} + \beta_3 \text{FWDTI}_{it}^2 + \beta_4 \text{Status}_{it} + \beta_5 \text{FWDTI}_{it} \text{ x } \text{Status}_{it} + \beta_6 \text{FWDTI}_{it}^2 \text{ x } \text{Status}_{it} + \beta_7 X_{it} + \beta_8 Z_{jt} + \beta_9 \text{Market Growth}_t + \varepsilon_{it} \tag{6}$$

$$= \beta_0 + \beta_1 \ln(\text{Sales})_{it-1} + \beta_2 \text{UDIFF}_{it} + \beta_3 \text{Status}_{it} + \beta_4 \text{UDIFF}_{it} \text{ x } \text{Status}_{it} + \beta_5 X_{it} + \beta_6 Z_{jt} + \beta_7 \text{Market Growth}_t + \varepsilon_{it} \tag{7}$$

$$= \beta_0 + \beta_1 \ln(\text{Sales})_{it-1} + \beta_2 \text{FWDIFF}_{it} + \beta_3 \text{Status}_{it} + \beta_4 \text{FWDIFF}_{it} \text{ x } \text{Status}_{it} + \beta_5 X_{it} + \beta_6 Z_{jt} + \beta_7 \text{Market Growth}_t + \varepsilon_{it} \tag{8}$$

where Sales_{it} is the unit sales for brand i in year t. The inclusion of the lagged dependent variable, Sales_{it-1}, captures the effect of prior brand unit sales and unobserved factors in the model for brand i. UDTI_{it} and FWDTI_{it} are the unweighted and feature-weighted digital technology indices for brand i in year t, UDIFF_{it} and FWDIFF_{it} are the unweighted and feature-weighted digital technology difference scores for brand i in year t, and Status_{it} is the brand status category of the brand in year t. We express the brand-level control variables (brand age, vehicle segment, HOB, JDPV, and JDPD) as X_{it}, representing brand i in year t. We express the parent firm-level control variables (market share, R&D, no R&D dummy, Ad spend, and no Ad spend dummy) as Z_{jt}, representing parent firm j in year t. Lastly, we control for market growth in year t. These control variables are common to all equations.

As described, customer satisfaction measures a consumer's experience with the brand's product or service after a period of use. Therefore, we examine the relationship between digital technology and customer satisfaction experienced one year later. We estimate the relationships between digital technology capability and customer satisfaction in Equations 9 through 12:

$$\mathrm{CSAT}_{it+1} = \beta_0 + \beta_1\mathrm{CSAT}_{it} + \beta_2\mathrm{UDTI}_{it} + \beta_3\mathrm{UDTI}_{it}^2 + \beta_4\mathrm{Status}_{it} + \beta_5\mathrm{UDTI}_{it} \text{ x } \mathrm{Status}_{it} + \beta_6\mathrm{UDTI}_{it}^2 \text{ x } \mathrm{Status}_{it} + \beta_7\mathrm{X}_{it} + \beta_8\mathrm{Z}_{jt} + \beta_9\text{Market Growth}_t + \varepsilon_{it} \tag{9}$$

$$= \beta_0 + \beta_1\mathrm{CSAT}_{it} + \beta_2\mathrm{FWDTI}_{it} + \beta_3\mathrm{FWDTI}_{it}^2 + \beta_4\mathrm{Status}_{it} + \beta_5\mathrm{FWDTI}_{it} \text{ x } \mathrm{Status}_{it} + \beta_6\mathrm{FWDTI}_{it}^2 \text{ x } \mathrm{Status}_{it} + \beta_7 X_{it} + \beta_8 Z_{jt} + \beta_9\text{Market Growth}_t + \varepsilon_{it} \tag{10}$$

$$= \beta_0 + \beta_1\mathrm{CSAT}_{it} + \beta_2\mathrm{UDIFF}_{it} + \beta_3\mathrm{Status}_{it} + \beta_4\mathrm{UDIFF}_{it} \text{ x } \mathrm{Status}_{it} + \beta_5 X_{it} + \beta_6 Z_{jt} + \beta_7\text{Market Growth}_t + \varepsilon_{it} \tag{11}$$

$$= \beta_0 + \beta_1\mathrm{CSAT}_{it} + \beta_2\mathrm{FWDIFF}_{it} + \beta_3\mathrm{Status}_{it} + \beta_4\mathrm{FWDIFF}_{it} \text{ x } \mathrm{Status}_{it} + \beta_5 X_{it} + \beta_6 Z_{jt} + \beta_7\text{Market Growth}_t + \varepsilon_{it} \tag{12}$$

where CSAT_{it+1} is the customer satisfaction score for brand i in year t+1. The inclusion of the lagged dependent variable, CSAT_{it}, captures the effect of prior brand customer satisfaction scores and unobserved factors in the model for brand i.

Estimation Results

Sample Description

Tables 2-4 and 2-5 provide descriptive statistics and correlations, respectively. We first examine the relationship between the digital technology capability measures. As expected, the mean feature-weighted digital technology index is greater than the mean unweighted digital technology index (M = 46.82, SD = 13.40 and M = 20.54, SD = 4.98, respectively; p = .000). Of particular note, the digital technology indices are positively correlated with sales (r = .20 for the unweighted digital technology index and r = .17 for the feature-weighted digital technology index, $p < .01$). However, we see inverse relationships between the digital indices and customer satisfaction (r = -.19 for the unweighted digital technology index and r = -.17 for the feature-weighted digital technology index, $p < .01$). Model-free evidence presented in Figure 2-4 provides context for these relationships. Over ten years, advances in the number and technological level of digital technology features have increased. Yet, customer satisfaction has been far more volatile over time, peaking significantly in 2012, dipping significantly in 2015, and declining 3 points from 2010 - 2019. We find a consistent pattern when evaluating the correlations between the digital technology differences and the outcome measures. The unweighted digital technology difference and feature-weighted digital technology difference are positively correlated with the sales (r = .40 and r = .37, respectively, $p < .01$). We see inverse relationships between the difference measures and customer satisfaction (r = -.12 and r = -.15, respectively, $p < .01$).

Hypotheses Testing

The effect of digital technology capability on brand sales. Table 2-6 reports OLS with lagged and random effect results for brand sales. Because brand sales are aggregated to the brand segment level (e.g., Ford Trucks), we first determined if there were any significant differences in digital technology indices across vehicle segments for brands. We found no difference whatsoever, indicating that once a brand offers a digital technology feature, that feature becomes available across all vehicle segments. Models 1 and 2 support the proposed relationship between digital technology indices and sales. In Model 1, we find a positive linear ($\beta = .05$, $p < .001$) and positive quadratic term ($\beta = .01$, $p < .01$), suggesting the positive, curvilinear effect of the number digital technology features on sales. In Model 2, we find a positive linear ($\beta = .05$, $p < .001$) and positive quadratic term ($\beta = .01$, $p < .05$), suggesting a positive, curvilinear effect of the technological level of digital technology features on sales. The changes in R^2 from the linear regression to the polynomial regression without moderators and from the polynomial regression without moderators to the polynomial regression with moderators are significant for Models 1 and 2 ($p < .001$), indicating that the polynomial technique is appropriate for these models. Collectively, these findings support H_1.

The moderating role of brand status on the digital technology capability and brand sales relationship. We first examine the mean differences between mainstream and luxury brands for each of the digital technology indices. As shown in Figures 2-5A and 2-5B, the mean unweighted digital technology index is greater for luxury brands than for mainstream brands (M = 22.94, SD = 4.38 for luxury brands and M = 19.86, SD = 4.93 for mainstream brands; t = -13.77, p = .000), and the mean feature-weighted digital technology index is greater for luxury brands than for mainstream brands (M = 54.02, SD = 12.19 for luxury brands and M = 44.76, SD = 13.01 for mainstream brands; t = -15.52, p = .000)., supporting H_{2a}. Furthermore, the interactions of brand status and the digital technology indices squared are positive and significant ($\beta = .02$, $p < .001$ and $\beta = .02$, $p < .001$, respectively), shown in Table 2-6 Models 1 and 2. These findings suggest that the curvilinear effect of digital technology on sales is steeper for luxury brands than for mainstream brands, supporting H_{2b}. See Figure 2-6 for visual illustration.

The effect of digital technology capability on customer satisfaction. Table 2-7 reports OLS with lagged and random effect results for customer satisfaction. Models 5 and 6 support the proposed relationship between digital technology indices and customer satisfaction. In Model 5, we find a negative linear ($\beta = -.14$, $p < .05$) and negative quadratic term ($\beta = -.08$, $p < .01$), suggesting a negative, curvilinear effect of the number digital technology features on customer satisfaction. In Model 6, we find a negative linear ($\beta = -.14$, $p < .001$) and negative quadratic term (β = -.07, p < .01), suggesting a negative, curvilinear effect of the technological level of digital technology features on customer satisfaction. The changes in R^2 from the linear regression to the polynomial regression without moderators and from the polynomial regression without moderators to the polynomial regression with moderators are significant for Models 5 and 6 (p < .001), indicating that the polynomial technique is appropriate for these models. Collectively, these findings support H_3.

The moderating role of brand status on the digital technology capability and customer satisfaction relationship. We examine the mean differences between mainstream and luxury brands for customer satisfaction. As shown in Figure 2-5C, the mean customer satisfaction is greater for luxury brands than for mainstream brands (M = 83.58, SD = 2.52 for luxury brands and M = 80.99, SD = 3.01 for mainstream brands; t = -18.50, p = .000), supporting H_{4a}. However, the interactions of brand status and the digital technology indices squared are positive and not significant (β = .07, p = .21 and β = .07, p = .09, respectively). Therefore, we cannot confirm H_{4b}. These findings suggest that, regardless of brand status, customer satisfaction worsens at an increasing rate as the digital technology index increases. See Figure 2-6 for visual illustration.

The effect of digital technology capability surplus on brand sales and customer satisfaction. Table 2-8 reports OLS with lagged and random effect results for brand sales, and Table 2-9 reports OLS with lagged and random effect results for customer satisfaction. Contrary to our hypotheses, we find the inverse of the proposed relationship between digital technology differences and brand sales. In Models 9 and 10, we find a negative linear relationship (β = -.01 and β = -.01, respectively, p < .05). While not hypothesized, we tested for curvilinear relationships for Models 9 and 10. The changes in R^2 from the linear to the polynomial regression without moderators are not significant for these models ($p = .33$ and $p = .57$, respectively). Therefore, these models do not contain the polynomial term.

Consistent with our hypotheses, we find a positive linear relationship ($\beta = .24$ for the unweighted digital technology difference and $\beta = .23$ for the feature-weighted digital technology difference, $p < .001$), supporting H_6. While not hypothesized, we tested for curvilinear relationships for Models 13 and 14. The changes in R^2 from the linear to the polynomial regression without moderators are not significant for these models ($p = .15$ and $p = .14$, respectively). Therefore, these models do not contain the polynomial term.

The moderating role of brand status on the digital technology capability surplus and brand sales relationship. The interaction effect of brand status and the digital technology difference measures are related positively to brand sales ($\beta = .02$, $p < .001$ for both measures). A simple slopes analysis revealed that digital technology differences negatively affect brand sales for mainstream brands ($b = -.005$ for the unweighted digital technology difference and $b = -.002$ for the feature-weighted digital technology difference, $p < .05$), which is consistent with the directionality of the main effect. However, consistent with the proposed directionality for H_5, we find that the unweighted and feature-weighted digital technology differences positively affect brand sales for luxury brands ($b = .019$ and $b = .005$, respectively, $p < .001$), supporting $H_{7.}$ See Figure 2-7 for visual illustration.

The moderating role of brand status on the digital technology surplus and customer satisfaction relationship. The interaction effect of brand status and the digital technology difference measures are related negatively related to customer satisfaction ($\beta = -.13$ for the unweighted digital technology difference and $\beta = -.14$ for the feature-weighted digital technology difference, $p < .001$). A simple slopes analysis revealed that digital technology differences positively affect customer satisfaction for mainstream brands (b = .407 for the unweighted digital technology difference and b = .137 for the feature-weighted digital technology difference, $p < .001$). Inversely, unweighted and feature-weighted digital technology differences negatively affect customer satisfaction for luxury brands (b = -.223 and b = -.081, respectively, $p < .05$), supporting H_8. See Figure 2-7 for visual illustration.

Robustness Checks and Generalizability Assessment

Including the lagged dependent variable as a predictor may lead to dynamic panel bias (Nickell 1981). Therefore, as a robustness check, we examined our hypotheses using two additional models. First, we include time-invariant and time-variant control variables, which collectively reduces the probability of omitting a control variable that correlates strongly with the digital technology, sales, and customer satisfaction measures. This rich data model approach makes use of OLS to estimate our model appropriately (Wooldridge 2002). Second, albeit including a large set of controls, we cannot claim that we have included all potentially critical controls. As such, we used random effect regression to test the hypotheses. Random effect models are efficient in making full use of within and between variance. As reported in Tables 2-6, 2-7, 2-8, and 2-9, the results were consistent across all methods. Therefore, we report estimates using OLS with the lagged dependent variable[5].

[5] Dynamic panel data models, which contain both time-varying exogenous variables, are subject to dynamic panel bias. As such, we considered using a generalized method of moments (GMM) model to test our hypotheses. However, the extensive use of time-invariant and time-variant control variables help minimize the likelihood of biased results. Therefore, we report both the OLS with a lagged DV and random effect estimates as a robust way of analyzing the data.

Discussion and Implications

The application of digital technologies such as AI, AR/VR, IoT, and robotic and mechanical systems has attracted significant attention from researchers and practitioners alike. A considerable number of studies have been conducted to examine the individual effects of technology-oriented product offerings and feature utility on marketing performance outcomes (e.g., Billeter, Kalra, and Loewenstein 2011; Davis, Bagozzi, and Warshaw 1989; Thompson, Hamilton, and Rust 2005). We contribute to the literature by examining these phenomena collectively and demonstrating that digital technology capabilities are theoretically and empirically linked to critical marketing outcomes. Our findings address the aforementioned research questions: (1) *To what extent should a brand establish its digital technology capability*? and (2) *Under what conditions does a brand's digital technology capability lead to a competitive advantage?*

Theoretical Contributions

Our theoretical framework is derived from four distinct theoretical perspectives. In particular, we draw upon the theory of economic theory of additive utility (Lancaster 1971), which suggests that increasing the number of product features leads to increased perceived utility. As demonstrated by prominent theories such as the technology acceptance model (TAM) (Davis 1989; Davis, Bagozzi, and Warshaw 1992) and the theory of reasoned action (TRA) (Fishbein and Ajzen 1975), perceived utility or usefulness leads to greater new product and technology adoption. We theorize that as brands advance their digital technology capability, they become more capable of offering a greater number and higher technological level of digital technology features, and subsequently, generate greater sales.

Consistent with Thompson, Hamilton, and Rust (2005) and Billeter, Kalra, and Loewenstein (2011), we demonstrate the downside of offering “fully loaded” products. Specifically, we theorize that increasing the number and technological level of product features leads to decreased experienced utility (i.e., feature fatigue). These products subject consumers to a learning curve that inhibits the use and subsequent enjoyment of a product feature. Therefore, we posit that as brands advance their digital technology capability, they become more capable of offering a greater number and higher technological level of digital technology features, subsequently eliciting lower customer satisfaction. Broadly, the results show a nuanced picture, which suggests that while digital technology capabilities lead to short-term gains (e.g., brand sales), the long-term effect (e.g., customer satisfaction) may be detrimental for extremely advanced brands.

Furthermore, we draw upon resource-based theory (Barney 1991), suggesting that a brand’s digital technology capability is inherently a resource that should lead to a competitive advantage for brands that lead within their competitive set. Specifically, we examine a brand’s digital technology capability compared to its competitive set's digital technology capability standard, referred to as a brand’s digital technology capability surplus. We postulate that as a brand’s digital technology capability surplus increases, they become better positioned to generate greater sales and elicit greater customer satisfaction than their direct competitors.

We empirically investigate the direct effects of digital technology capabilities on brand sales and customer satisfaction in the automotive industry context. The automotive industry serves as a highly visible example of the digital technology wave, presenting an ideal setting to examine the effects of this phenomenon on marketing performance outcomes. As such, we compiled a unique and knowledge-rich panel data set comprising 20 automotive brands, 304 vehicle models, and 8,692 observations from 2010 - 2019. The data set integrates variables from nine separate data sources. Furthermore, we operationalize digital technology capabilities as two indices derived from the number of digital technology features (i.e., unweighted digital technology index) and the level of technology possessed by the features (i.e., feature-weighted digital technology index). The results support the effect of digital technology capability on perceived and experienced utility, thus positively affecting brand sales and negatively affecting customer satisfaction. However, our findings pertaining to a brand's digital technology capability surplus were surprisingly mixed. For luxury brands, a digital technology capability surplus increases sales but decreases customer satisfaction. Inversely, for mainstream brands, a digital technology capability surplus decreases sales but increases customer satisfaction. These findings suggest that brand status plays a critical role in the target consumer's perception of and experience with branded digital technology products.

Managerial Contributions

A brand's digital technology capability increases brand sales. Our results reveal that a brand's digital technology directly increases brand sales. To put these findings in context, a one-unit increase in a brand's digital technology capability would lead to a 5.1% increase in sales units, beating the average year-over-year growth from 2010 - 2019 of 4.59%. Furthermore, we find that this effect is not linear. A brand's digital technology offering becomes increasingly beneficial to its bottom line.

A brand's digital technology capability affects brand sales differently for mainstream and luxury brands. Our results show a considerably steeper sales curve for luxury brands than mainstream brands. We attribute this finding to the unique drivers behind luxury brand purchases. Consumers are more willing to purchase entry-level, lower-equipped luxury products for the sole purpose of obtaining the brand badge. Therefore, it is unsurprising to observe greater sales at very low- and high-ends of the digital technology spectrum. This finding is critically important for luxury brand managers as it pertains to “up-selling” consumers to encourage increased purchases of mid-level models, should they be more profitable than the lower-level models. Both mainstream and luxury brand managers would benefit from expressly communicating the value of each digital technology feature to enhance the additive perception of utility. In other words, by focusing on the unique benefits of each digital technology feature, managers can demonstrate increased value to the consumer.

A brand’s digital technology capability decreases brand sales. Regardless of brand status, our results revealed that a brand’s digital technology offering becomes increasingly detrimental to customer satisfaction. Consumers may purchase products with greater digital technology features based on the product's perceived value. Yet, once experienced (or not), consumers may find that these products do not deliver their promised value. This finding is consistent with well-established research that demonstrates that people tend to overpredict their ability to use innovative product features (Meyer, Zhao, and Han 2008; Thompson, Hamilton, and Rust 2005). Despite the digital technology advancements that have led to cheaper costs and savings gained through economies of scale, applying digital technology requires significant R&D and purchasing investments. As an illustration, the J.D. Power & Associates 2015 Driver Interactive Vehicle Experience (DrIVE) Report places special emphasis on the fact that “In-vehicle connectivity technology that's not used results in millions of dollars of lost value for both consumers and the manufacturers." Our results suggest that managers should think twice about how their digital technology offerings affect customer service evaluations 1-2 years after purchase. Strategic plans may include educating consumers on using digital technology features or increasing the accessibility/ease of use of certain features to enhance consumers' experienced utility.

A brand's digital technology capability surplus affects marketing outcomes differently for mainstream and luxury brands. Managers often create competitive benchmarks to establish their relative position on price, quality, and performance dimensions (Claycomb, Germain, and Dröge 2000; Kumar et al. 1998; Slater 1993). The question that may be most germane to managers is: *how does my brand compare to those within the competitive domain?* Our findings suggest that the answer to this question is invaluable to assessing whether a brand's digital technology capability provides a competitive advantage. Luxury brands often lead the market in technology advancements. Unsurprisingly, luxury brands that lead within their competitive set are considered to offer the best-of-the-best in perceived value and are rewarded for it in the form of sales. However, as expected, the best-of-the-best in perceived value represents the most complex-of-the-complex in experienced utility. It is advantageous for luxury brands that lead in digital technology to develop strategic plans to educate consumers on using digital features and making these features more accessible to enhance experienced utility. Inversely, for mainstream brands, focusing efforts on communicating the additive value of digital technology features would be more instrumental in gaining an advantage over their direct competitors. Our paper illustrates the methods and calculations for brands to determine their digital technology capability and position relative to the market and direct competition.

Limitations and Future Research Directions

There are inherent limitations to this study that may motivate future research. First, we intentionally sampled our data from one industry to control for industry effects and reduce noise. Future studies may look across durable goods and service industries to determine how these effects may differ. Second, we collapsed various digital technologies (i.e., artificial intelligence, augmented reality, virtual reality, voice command, and robotics) into one category in our analysis. While we account for differences in the level of technological advancement offered by developing a feature-weighted index, future research may examine the individual effects of each digital technology type. This type of study may be particularly interesting as AI technologies become more sophisticated and mass commercialized over time. Lastly, our study includes digital technologies that may be new to the automotive industry but not new to the consumer experience. In fact, these technologies are embedded in a way that promotes a seamless transition in use from one device or environment to another. Prior research on network externalities suggests that large networks of brands that support a technology serve as a signal to the industry and consumers that the technology may become a future standard and subsequently influence adoption (e.g., Robertson, Swan, and Newell 1996; Shurmer 1993; Wang and Xie 2011). Future research may examine the impact of new-to-the-world or new applications of existing digital technologies on marketing outcomes. Collectively, our findings present a nuanced picture suggesting that future scholarship should jointly examine the (1) asymmetry of sales and customer satisfaction in the context of digital technology product purchases, (2) intervening mechanisms to accelerating the digital technology learning curve to maximize the consumers perceived and experienced value, and (3) examine potential contextual effects associated with other durable goods and service industries.

APPENDICES

APPENDIX A: TABLES

Table 2-1 Parent Firms and Brands Included in this Study

	Parent Firm	Brand
1	BMW	BMW*
2	Daimler AG	Mercedes-Benz*
3	Fiat Chrysler	Chrysler
4	Fiat Chrysler	Dodge/Ram
5	Fiat Chrysler	Jeep
6	Ford	Ford
7	GM	Buick
8	GM	Cadillac*
9	GM	Chevrolet
10	GM	GMC
11	Honda	Honda
12	Hyundai	Hyundai
13	Kia	Kia
14	Mazda	Mazda
15	Nissan	Nissan
16	Subaru	Subaru
17	Toyota	Lexus*
18	Toyota	Toyota
19	Volkswagen	Audi*
20	Volkswagen	Volkswagen

*****Brands classified as *Premium* by J.D. Powers & Associates from 2010 - 2009

Table 2-2 Variables, Measures, and Sources

Main Variables	Notation	Source/Literature
Unweighted Digital Technology Index: Total number of digital technology features offered by a brand each year.	UDTI	US News (Cars)
Unweighted Digital Technology Index Difference: The difference between the brand's unweighted digital technology index and the average unweighted technology index for brands within each status category (luxury vs. mainstream).	UDIFF	US News (Cars)
Feature-Weighted Digital Technology Index: Measure capturing a brand's digital technology index weighted by expert raters' technology rating (level of technology in the feature offered by the brand: 1 - very low to 7 - very high) computed as: *Expert Rating for DT Feature (low- vs. high-tech) x DT Index*	FWDTI	US News (Cars) and Expert Raters Expert Raters (insert source)
Feature-Weighted Digital Technology Index Difference: The difference between the brand's weighted feature digital technology index and the average weighted feature technology index for brands within each status category (luxury vs. mainstream).	FWDIFF	US News (Cars) and Expert Raters Expert Raters (insert source)
Customer Satisfaction: Brand-level variable capturing customers' cumulative satisfaction with their experience with automotive brands on a 1 to 100-point scale from an annual national representative sample of more than 65,000 customers reported by the American Customer Satisfaction Index (ACSI).	CSAT	ACSI *Fornell et al. (1996)* *Fornell et al. (2016)*
Unit Sales: The natural log of the model-level reported unit sales aggregated to the brand segment level.	Ln(Sales)	Automotive News
Brand Status: Status category assigned by JDPA brands and classified as either premium - 1 or non-premium - 0.	Status	J.D. Power & Associates (JDPA) *Srinivasan et al. (2009)*

Table 2-2 (cont'd)

Market-Level Controls	**Notation**	**Source/Literature**
Market Growth YoY: Reported YoY growth rate of the U.S. automotive industry units.	MGrowth	Wards Intelligence
Parent Firm-Level Controls	**Notation**	**Source/Literature**
Market Share: Percentage of firm-level reported unit sales compared to reported industry unit sales in the U.S.	MShare	Wards Intelligence
R&D Spend: The firm's reported spend on research and development (millions USD).	R&D	Compustat
Advertising Spend: The firm's reported spend on total advertising (millions USD).	AdSpend	Statista
Brand-Level Controls	**Notation**	**Source/Literature**
Brand Age: The number of years since the brand was founded.	Brand Age	Branded Websites *Luffarelli et al. (2019)*
Vehicle Segment: The vehicle segment (sports car, car, SUV, truck, minivan, and passenger van) assigned to each model.	Segment	J.D. Power & Associates (JDPA)
House Status: Status category classified as either belonging to a house of brands - 1 (brand within a group of brands under one firm) or branded house - 0 (single brand as the firm).	HOB	Branded Websites *Rao et al. (2004)*
Average MSRP: The natural log of the model-level original average MSRP aggregated to the brand level.	Ln(MSRP)	US News (Cars)
J.D. Power Vehicle Awards: The number of J.D. Power Awards for quality, dependability, and performance earned by a brand annually.	JDPV	J.D. Power & Associates (JDPA) *Srinivasan et al. (2009)*
J.D. Power Dealership Awards: The number of J.D. Power Awards for dealership sales and service earned by a brand annually.	JDPD	J.D. Power & Associates (JDPA) *Srinivasan et al. (2009)*

Table 2-3 Digital Technology Features Included in the Study

	DT Feature	Tech Rating	DT Type	Definition
1	Adaptive Cruise Control	3.20	AI	Automatically accelerates or brakes to keep your vehicle at a preset speed and/or distance between you and the car ahead of you. Some systems may bring the car to a full stop, then re-accelerate.
2	Android Auto/ Apple CarPlay	2.40	IoT	Apple CarPlay and Android Auto are in-car assistant systems that let you access certain features of your phone, either through your infotainment system or through your phone interface.
3	Adaptive/Auto-Leveling Headlights	3.50	AI	Adaptive and auto-leveling headlights use electric servomotors to react to the level sensor and keep the headlights aimed down at the road, no matter the position of the car. In some models, the lights turn their beams around each bend in the road, giving you a better view of what's ahead.
4	Auto-On/Off Headlights	1.80	Robotic Automation	Auto Headlights is a system for turning lights on and off based on the environment around the vehicle.
5	Automatic Parking	4.29	AI	Automatic parking is an autonomous car-maneuvering system that moves a vehicle from a traffic lane into a parking spot to perform parallel, perpendicular, or angle parking.
6	Back-Up Camera	3.00	IoT	Back-up camera uses a camera, below the rear window or trunk level, to expand the driver's field of vision.
7	Blind Spot Monitor	2.75	IoT	Blind-spot monitors use a set of sensors mounted on the side mirrors or rear bumper to detect vehicles in the adjacent lanes.
8	Brake Assist	2.43	AI	Brake assist uses electronic sensors to determine if a vehicle is headed toward a collision and applies the brakes, when necessary.
9	Cross-Traffic Alert	2.43	IoT	Side sensors, which can use radar or ultrasonic waves, sense and alert the driver to approaching traffic.
10	Cruise Control	1.50	Robotic Automation	Cruise control is a system that automatically controls the speed of a motor vehicle.

Table 2-3 (cont'd)

11	Electrochromic Rearview Mirror	1.83	AR/VR	Electrochromic mirrors use a front-facing sensor to measure ambient exterior light and a rear-facing sensor to detect glare and adjusts the mirror color to increase visibility.
12	Entertainment System	2.00	IoT	A collection of hardware and software in automobiles that provides audio or video entertainment.
13	Hands-Free Power Liftgate	2.20	Robotic Automation	Hands-Free Power Liftgate uses sensors and levers to automatically open and close the vehicle's rear power liftgate.
14	Heads-Up Display	3.40	AR/VR	Automotive head-up display is a transparent, digital display that presents data in the car (often on the windshield) without requiring users to look away from their usual viewpoints.
15	Keyless Remote Entry	2.17	IoT	Keyless remote entry contains a short-range radio transmitter, and must be within a certain range, usually 5–20 meters, of the car to work. When a button is pushed, it sends a coded signal by radio waves to a receiver unit in the car, which locks or unlocks the door.
16	Keyless Ignition Start	1.57	IoT	Keyless ignition start contains a short-range radio transmitter, which allows the car to be started by simply pressing a button on the dashboard while the key fob is in the vehicle.
17	Lane Departure Warning	2.29	IoT	A lane departure warning (LDW) system uses sensors to alert drivers when they drift out of their lanes without a turn signal.
18	Lane Keeping Assist	3.67	AI	Lane keeping assist system monitors the car's position on the road, detects if the driver is unintentionally leaving their lane, and reacts either through warnings or by actively steering the car back into its lane.
19	Navigation with Telematics	2.50	IoT	Navigation with telematics includes a vehicle tracking device that allows the sending, receiving and storing of telemetry data (e.g., location, speed, idling time, harsh acceleration or braking, fuel consumption, vehicle faults, and more).
20	Navigation System	2.00	IoT	Automotive navigation systems use a satellite navigation device to get its position data which is then correlated to a position on a road. When directions are needed routing can be calculated. On the fly traffic information can be used to adjust the route.

Table 2-3 (cont'd)

21	Night Vision	3.75	AR/VR	An automotive night vision system uses a thermographic camera to increase a driver's perception and seeing distance in darkness or poor weather beyond the reach of the vehicle's headlights.
22	Onboard Hands-Free Communications System	1.83	IoT	Onboard hands-free, voice-activated communication system allows passengers to talk on a Bluetooth^{TM} Hands-Free Profile wireless phone virtually hands-free.
23	Rain Sensing Wipers	2.60	Robotic Automation	Rain sensing wipers tell the system to activate the wipers, as well as adjust wiper speed and frequency based on the intensity of the precipitation combined with the vehicle's speed.
24	Rear Parking Aid	2.86	AR/VR	Parking aid systems use ultrasonic sensors integrated into the front and rear end of the vehicle to monitor the area directly in front of and behind the vehicle, often with visuals and alerts, to assist in parking.
25	Smart Device Integration	2.17	IoT	Smart device integration allows drivers to use mobile apps (often through Android or Apple platforms) to communicate, navigate, and access entertainment.
26	Tire Pressure Monitoring System	2.00	IoT	Tire pressure monitor systems use a sensor mounted in the wheel to measure air pressure in each tire. When air pressure drops 25% below the manufacturer's recommended level, the sensor transmits that information to your car's computer system and triggers the indicator light.
27	Trip Computer	2.20	IoT	A trip computer collects and displays vehicle data such as mileage, fuel consumption, speed and the outside air temperature.
28	WiFi Hotspot	1.67	IoT	In-car WiFi uses the car as a personal hotspot for passengers to connect to with their phones, laptops and all sorts of gadgets.
29	Wireless Cell Phone Hookup	2.33	IoT	Wireless cell phone hookup allows passengers to connect their phone to the car's system, providing wireless access to the phone's function through the car via a control screen, voice commands, steering wheel buttons or the dash.

Note: The self-driving feature was not offered by the Top 20 brands in the U.S. from 2010 - 2019, and therefore, was not included in this study. However, the expert raters were asked to rate this feature for reference and future studies. The average technology rating for the self-driving feature was 4.86.

Table 2-4 Descriptive Statistics

	Mean	SD	Min	Max	N
$CSAT_{t-1}$	81.58	3.14	71.00	89.00	194
$CSAT_{t}$	81.90	2.95	74.00	89.00	174
$CSAT_{t+1}$	82.07	2.96	74.00	89.00	154
$Sales_{t-1}$	53,835.31	59,826.18	0.00	311,451	2,683
$Sales_{t}$	53,433.79	59,304.95	0.00	311,451	2,423
$Sales_{t+1}$	52,749.41	58,491.86	0.00	311,451	2,159
$Ln(Sales)_{t-1}$	9.97	1.95	0.00	12.65	2,683
$Ln(Sales)_{t}$	10.01	1.87	0.00	12.65	2,423
$Ln(Sales)_{t+1}$	10.03	1.84	0.00	12.65	2,159
UDTI	20.54	4.98	9.00	28.00	2,683
UDIFF	.00	2.10	-5.25	5.09	2,159
FWDTI	46.82	13.40	18.90	68.65	2,683
FWDIFF	-.00	5.66	-13.00	14.30	2,683
Status	.22	.42	0.00	1.00	2,683
HOB	.74	.44	0.00	1.00	2,683
Age	91.78	22.68	31.00	121.00	2,683
Ln(MSRP)	10.55	.41	9.77	12.83	2,184
Segment	2.94	1.44	1.00	6.00	2,683
JPDV	3.21	2.64	0.00	13.00	2,683
JPDD	.08	.31	0.00	2.00	2,683
MGrowth	4.59	5.87	-1.76	17.43	2,683
MShare	9.75	5.69	1.29	19.19	2,683
R&D	6,937	2,895	1,344.15	14,811.69	2,099
AdSpend	2,119	1,276	100.00	6,700.00	1,871

Table 2-5 Correlations Table

	1	2	3	4	5	6	7	8	9	10	11	13	14	15	16	17	18	19	20	21
1. $CSAT_{t-1}$	1.00																			
2. $CSAT_{t}$	.67**	1.00																		
3. $CSAT_{t+1}$	.53**	.63**	1.00																	
4. $Ln(Sales)_{t-1}$	-.10**	-.08**	-.05**	1.00																
5. $Ln(Sales)_{t}$	-.10**	-.10**	-.07**	.99**	1.00															
6. $Ln(Sales)_{t+1}$	-.13**	-.10**	-.09**	.98**	.99**	1.00														
7. UDTI	-.28**	-.19**	-.06**	.18**	.20**	.21**	1.00													
8. UDIFF	-.01	-.12**	.05*	.40**	.40**	.40**	.42**	1.00												
9. FWDTI	-.26**	-.17**	-.04	.15**	.17**	.17**	.99**	.42**	1.00											
10. FWDIFF	-.01	-.15**	.05*	.38**	.37**	.37**	.41**	.96**	.42**	1.00										
11. Status	.34**	.34**	.34**	-.51**	-.50**	-.50**	.26**	.00	.29**	.00	1.00									
12. HOB	-.19**	-.18**	-.20**	-.07**	-.07**	-.07**	.05**	.12**	.04*	.10**	.03	1.00								
13. Age	-.37**	-.39**	-.36**	.16**	.6**	.16**	.14**	.43**	.14*	.42**	-.13**	.02	1.00							
14. Ln(MSRP)	.15**	.14*	.13**	-.26**	-.26**	-.25**	.24**	.04*	.26**	.05*	.74**	.09**	.02	1.00						
15. Segment	-.08**	-.08**	-.08**	.14**	.14**	.15**	-.04*	.08**	-.05**	.06**	-.17**	.10**	.16**	-.23**	1.00					
16. JDPV	.06**	.06**	-.03	.56**	.56**	.58**	.16**	.31**	.14**	.28**	-.09**	.07**	.02	.01	.03	1.00				
17. JDPD	.21**	.13**	.11**	-.24**	-.24**	-.24**	.08**	.04*	.08**	.03	.27**	.07**	-.16**	.21**	-.08**	.02	1.00			
18. MShare	-.03	-.03	-.02	.45**	.45**	.46**	.15**	.54**	.11**	.46**	-.19**	.28**	.36**	-.12**	.18**	.32**	.14**	1.00		
19. MGrowth	.29**	.23**	.20**	-.12**	-.14**	-.15**	-.67**	.00	-.65**	.00	-.01	.01	.10	-.03	.03	-.06**	.00	.03	1.00	
21. R&D	.37**	.38**	.34**	-.09**	-.10**	-.11**	.21**	-.01	.23**	.03	.35**	.11**	-.35**	.21**	-.19**	.10**	.14**	-.12**	-.13**	1.00
22. AdSpend	-.09**	-.19**	-.18**	.00	.01	.02	.10**	.19**	.08**	.16**	-.05*	.34**	.27**	-.01	.03	-.01	.08**	.41**	.03	.41**

* $p < .05$, ** $p < .01$ two-tailed.

Table 2-6 The Effect of Digital Technology Indices on Brand Sales

	OLS with Lagged DV		Random Effect	
	(1)	**(2)**	**(3)**	**(4)**
	IV = UDTI	**IV = FWDTI**	**IV = UDTI**	**IV = FWDTI**
DT Index	.05***	.05***	.03***	.01***
DT Index^2	.01**	.01*	.01*	.01**
Status	-.05***	-.05***	-1.40**	-1.51**
DT Index x Status	-.01***	-.02***	-.01**	-.01**
DT Index^2 x Status	.02***	.02***	.01***	.01***
Control Variables				
Lag of DV	.95***	.95***	-----	-----
Brand Age	-.01***	-.01***	-.00	-.00
Segment	.00	.00	.00	.00
HOB	-.01***	-.01***	-.74†	-.81†
JDPV	.03***	.03***	.04**	.01
JDPD	.01*	.00	.00	-.01
MGrowth	-.03***	-.04***	-.01***	-.01***
MShare	-.00	-.00	-.02***	-.01*
R&D	-.01	-.01†	.01†	.01*
No R&D Dummy	-.01***	-.02***	.23	.22
AdSpend	-.00	-.00	.01	.01
No AdSpend Dummy	-.01*	-.01*	-.03***	-.01***
R-Square	**0.99**	**0.99**	**0.96**	**0.98**
Sample Size	**2,423**			

†p< .10, * p < .05, **p< .01, ***p< .001.
Standardized coefficients reported. Two-tailed test were used. Predictor variables are mean-centered.
Note: The changes in R^2 from the linear regression to the polynomial regression without moderators and from the polynomial regression without moderators to the polynomial regression with moderators are significant for models 1-4, indicating that the polynomial technique is appropriate for these models.
MSRP as a control variable is excluded due to high multicollinearity (r = .74) with the moderator variable Brand Status for all models.

Table 2-7 The Effect of Digital Technology Indices on Customer Satisfaction

	OLS with Lagged DV		Random Effect	
	(5)	(6)	(7)	(8)
	IV = UDTI	IV = FWDTI	IV = UDTI	IV = FWDTI
DT Index	-.14*	-.14***	-.21**	-.13***
DT Index^2	-.08**	-.07**	-.03*	-.01**
Status	.25**	.18***	1.70*	1.99*
DT Index x Status	-.07**	-.06*	-.05	.08
DT Index^2 x Status	.07	.07†	.05	.01†
Control Variables				
Lag of DV	.31***	.30***	-----	-----
Brand Age	-.13†	-.10***	-.03**	-.04**
Segment	.07	.02	.34	.63
HOB	-.17*	-.07**	-1.53*	-1.86**
JDPV	.01	.04*	.09*	.06*
JDPD	-.08	.07***	.98*	1.01†
MGrowth	.04	.14***	.08*	.03†
MShare	.35***	.15***	.22***	.23***
R&D	.57***	.37***	.01***	.01***
No R&D Dummy	.49***	.43***	4.08**	3.97***
AdSpend	-.28**	-.32***	-.02***	-.01**
No AdSpend Dummy	-.07	-.01	-.30	-.11
R-Square	**0.57**	**0.59**	**0.37**	**0.40**
Sample Size	**154**			

†*p*< .10, * *p* < .05, ***p*< .01, ****p*< .001.
Standardized coefficients reported. Two-tailed test were used. Predictor variables are mean-centered.
Note: The changes in R^2 from the linear regression to the polynomial regression without moderators and from the polynomial regression without moderators to the polynomial regression with moderators are significant for models 5-8, indicating that the polynomial technique is appropriate for these models.
MSRP as a control variable is excluded due to high multicollinearity (r = .74) with the moderator variable Brand Status.

Table 2-8 The Effect of Digital Technology Differences on Brand Sales

	OLS with Lagged DV		Random Effect	
	(9)	(10)	(11)	(12)
	IV = UDIFF	IV = FWDIFF	IV = UDIFF	IV = FWDIFF
DT Index	-.01*	-.01*	-.02***	-.01***
Status	-.01	-.01	-1.42**	-1.19**
DT Index x Status	.02***	.02***	.03***	.02*
Control Variables				
Lag of DV	.96***	.96***	-----	-----
Brand Age	.00	.00	-.00	-.01
Segment	.00	.00	.00	.14
HOB	-.01***	-.01***	-.77	-.74†
JDPV	.03***	.03***	.01**	.01*
JDPD	-.00	-.00	.05*	.05*
MGrowth	-.05***	-.05***	-.01***	-.00†
MShare	.00	.00	-.02***	-.01†
R&D	.00	.00	.03***	.02*
No R&D Dummy	-.00	.00	.20	.21
AdSpend	-.01†	-.01†	.02*	.02*
No AdSpend Dummy	-.02***	-.02***	-.07***	-.07***
R-Square	**0.99**	**0.99**	**0.98**	**0.95**
Sample Size	**2,423**			

†$p < .10$, * $p < .05$, **$p < .01$, ***$p < .001$.

Standardized coefficients reported. Two-tailed test were used. Predictor variables are mean-centered.

Note: While not hypothesized, we tested for curvilinear relationships for Models 9-12. The changes in R^2 from the linear to the polynomial regression without are not significant for these models.

MSRP as a control variable is excluded due to high multicollinearity (r = .74) with the moderator variable Brand Status for all models.

Table 2-9 The Effect of Digital Technology Differences on Customer Satisfaction

	OLS with Lagged DV		Random Effect	
	(13)	**(14)**	**(15)**	**(16)**
	IV = UDIFF	**IV = FWDIFF**	**IV = UDIFF**	**IV = FWDIFF**
DT Index	.24***	.23***	.28***	.17**
Status	.08**	.09**	1.93*	1.99*
DT Index x Status	-.13***	-.14***	-.73*	-.27**
Control Variables				
Lag of DV	.34***	.35***	-----	-----
Brand Age	-.21***	-.20***	-.04*	-.04*
Segment	.04†	.03†	.81	.86
HOB	-.16***	-.17***	-2.15*	-2.23*
JDPV	.13***	.11***	.07*	.06*
JDPD	.02	.02	.03	.02
MGrowth	.12***	.12***	.14**	.14***
MShare	.16***	.16***	.17*	.17*
R&D	.21***	.19***	.09**	.12**
No R&D Dummy	.50**	.47**	4.41**	4.45**
AdSpend	-.15***	-.15***	-.01†	-.01†
No AdSpend Dummy	-.02	-.00	.19	-.00*
R-Square	**0.55**	**0.58**	**0.19**	**0.20**
Sample Size	**154**			

†*p*< .10, * *p* < .05, ***p*< .01, ****p*< .001.
Standardized coefficients reported. Two-tailed test were used. Predictor variables are mean-centered.
Note: While not hypothesized, we tested for curvilinear relationships for Models 13-16. The changes in R^2 from the linear to the polynomial regression without are not significant for these models.
MSRP as a control variable is excluded due to high multicollinearity (r = .74) with the moderator variable Brand Status for all models.

APPENDIX B: FIGURES

Figure 2-1 Examples of Technology-Focused Automotive Advertisements

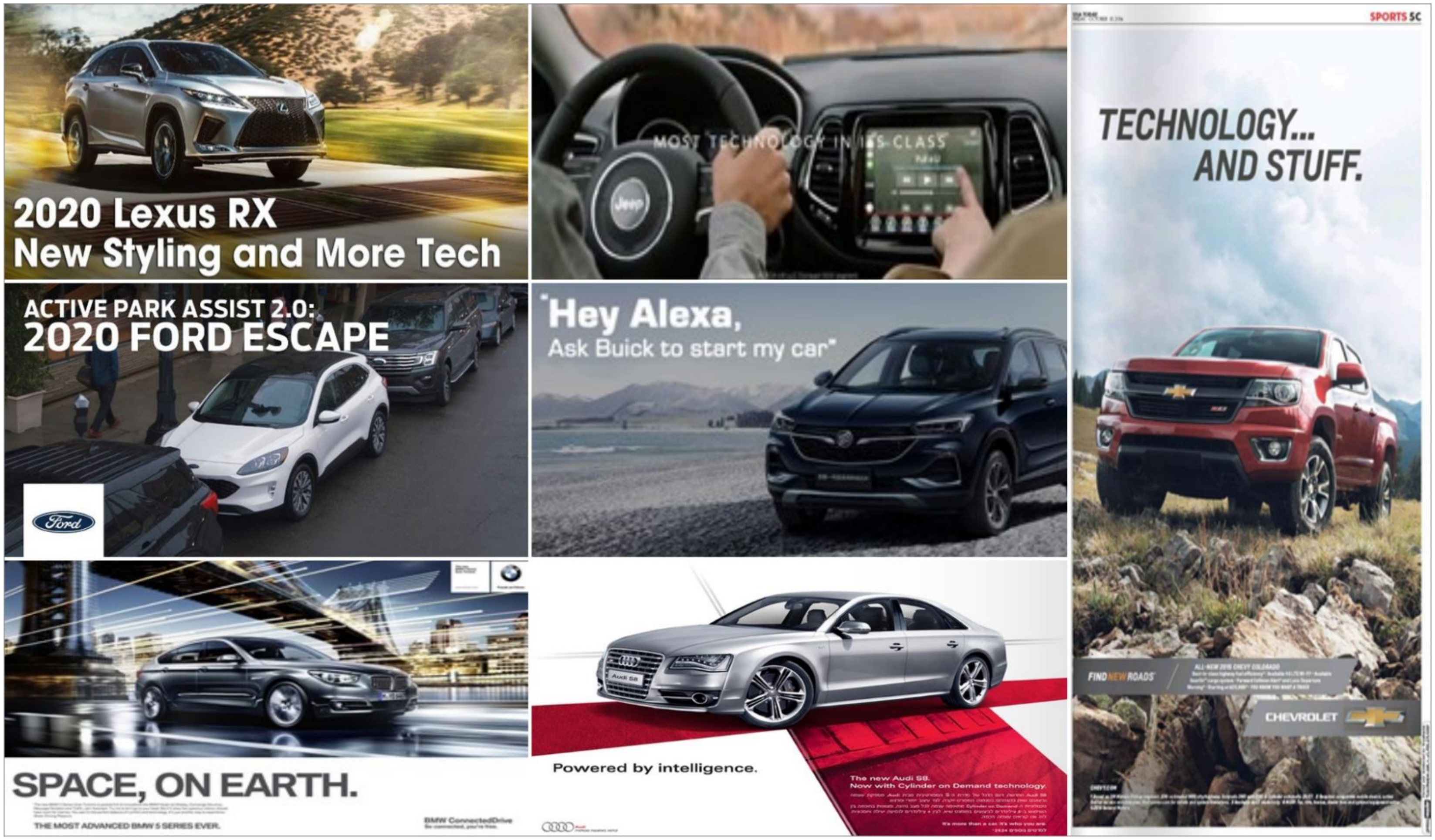
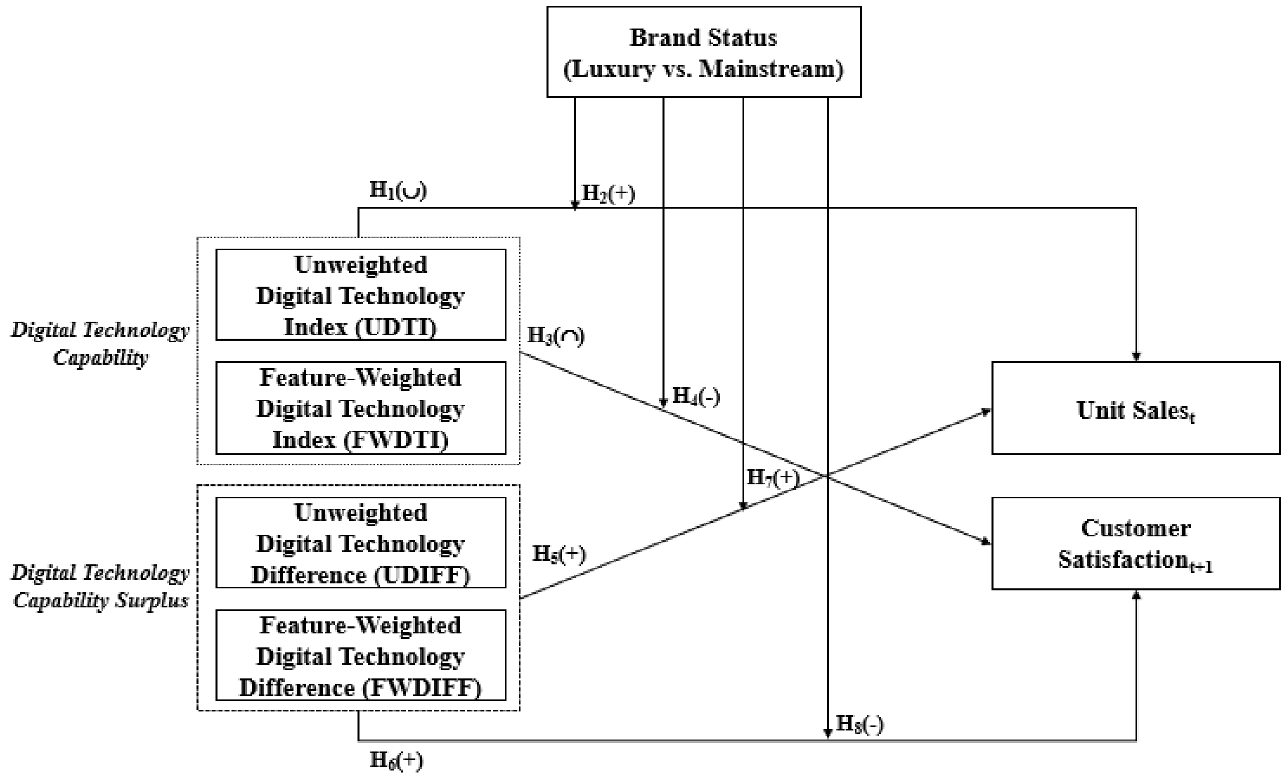


Figure 2-2 Conceptual Model



Control Variables		
Industry-Level	**Firm-Level**	**Brand-Level**
Market Growth YoY	Market Share R&D Spend Advertising Spend	Brand Age Vehicle Segment House Status Average MSRP JD Power Vehicle Awards JD Power Dealership Awards

Figure 2-3 Example of U.S. News (Cars) Webpage with Vehicle Features

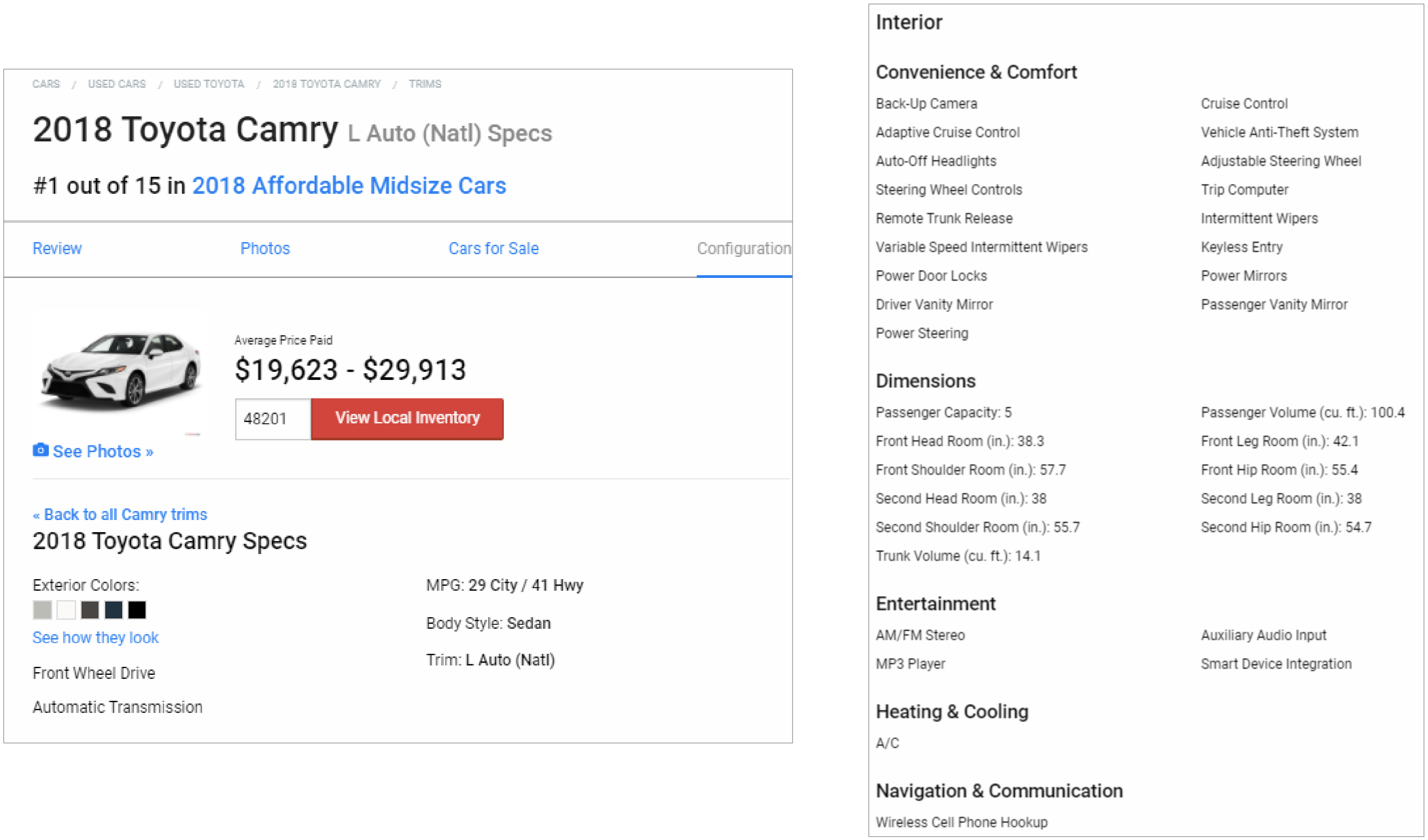


Figure 2-4 Model-Free Changes in Key Measures from 2010 - 2019

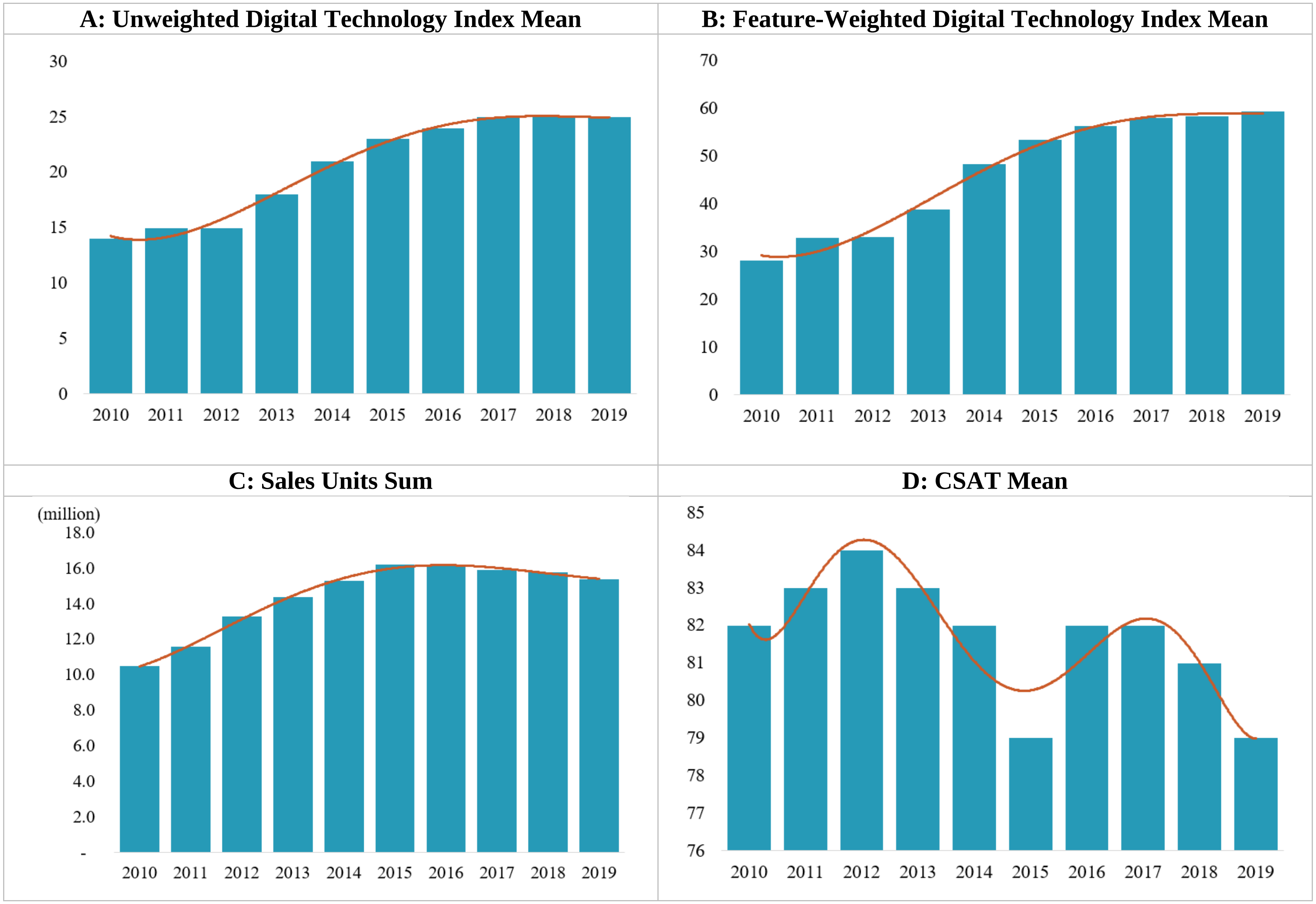


Figure 2-5 Mean Differences Between Mainstream and Luxury Brands

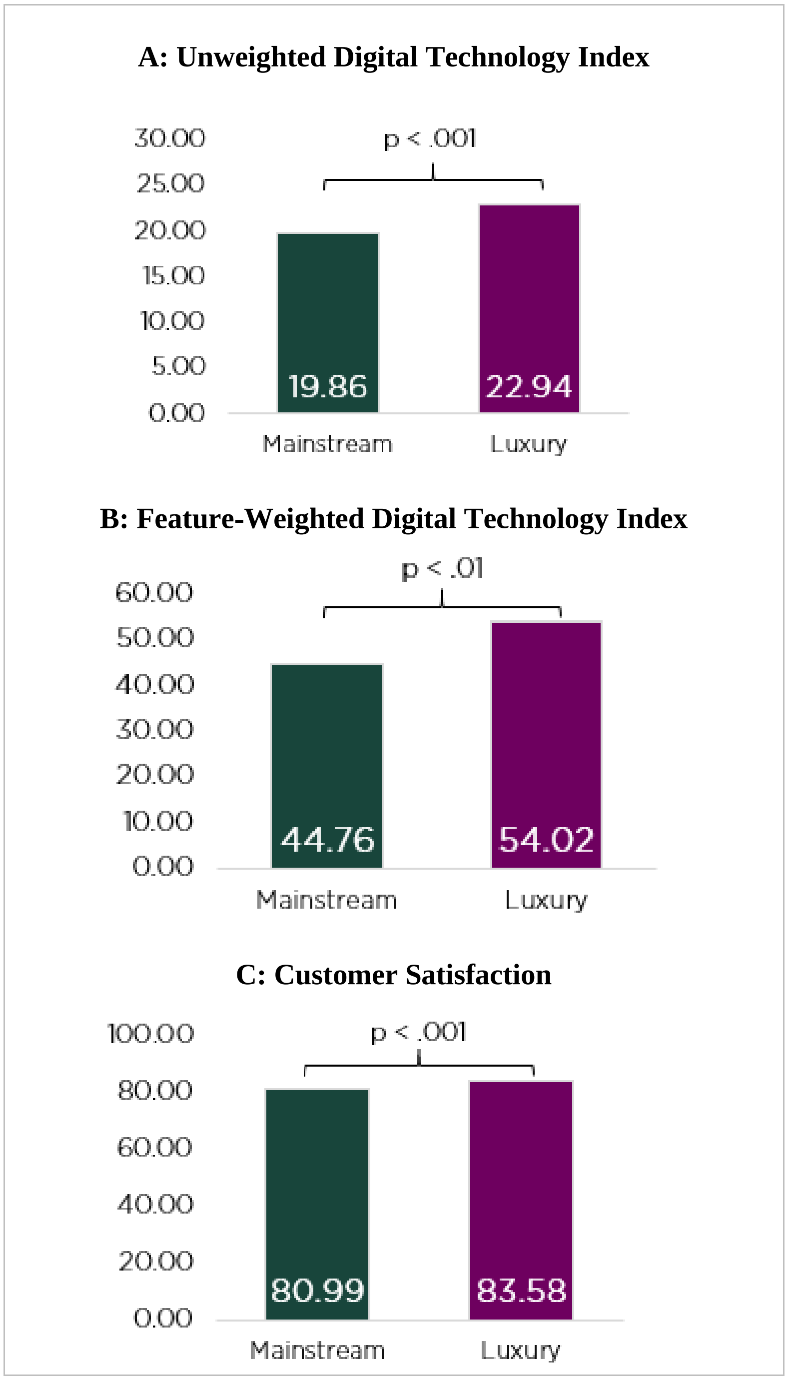
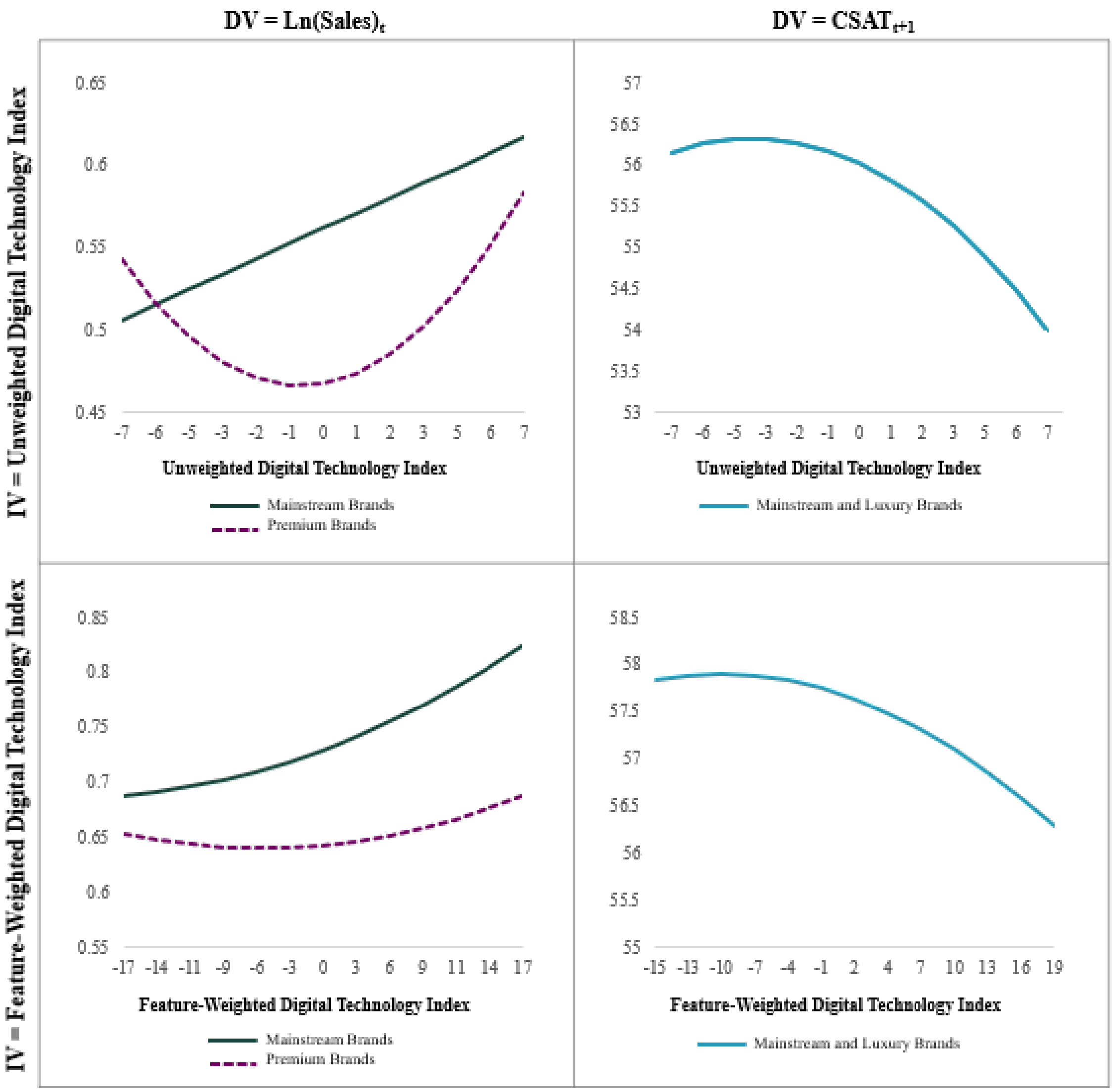
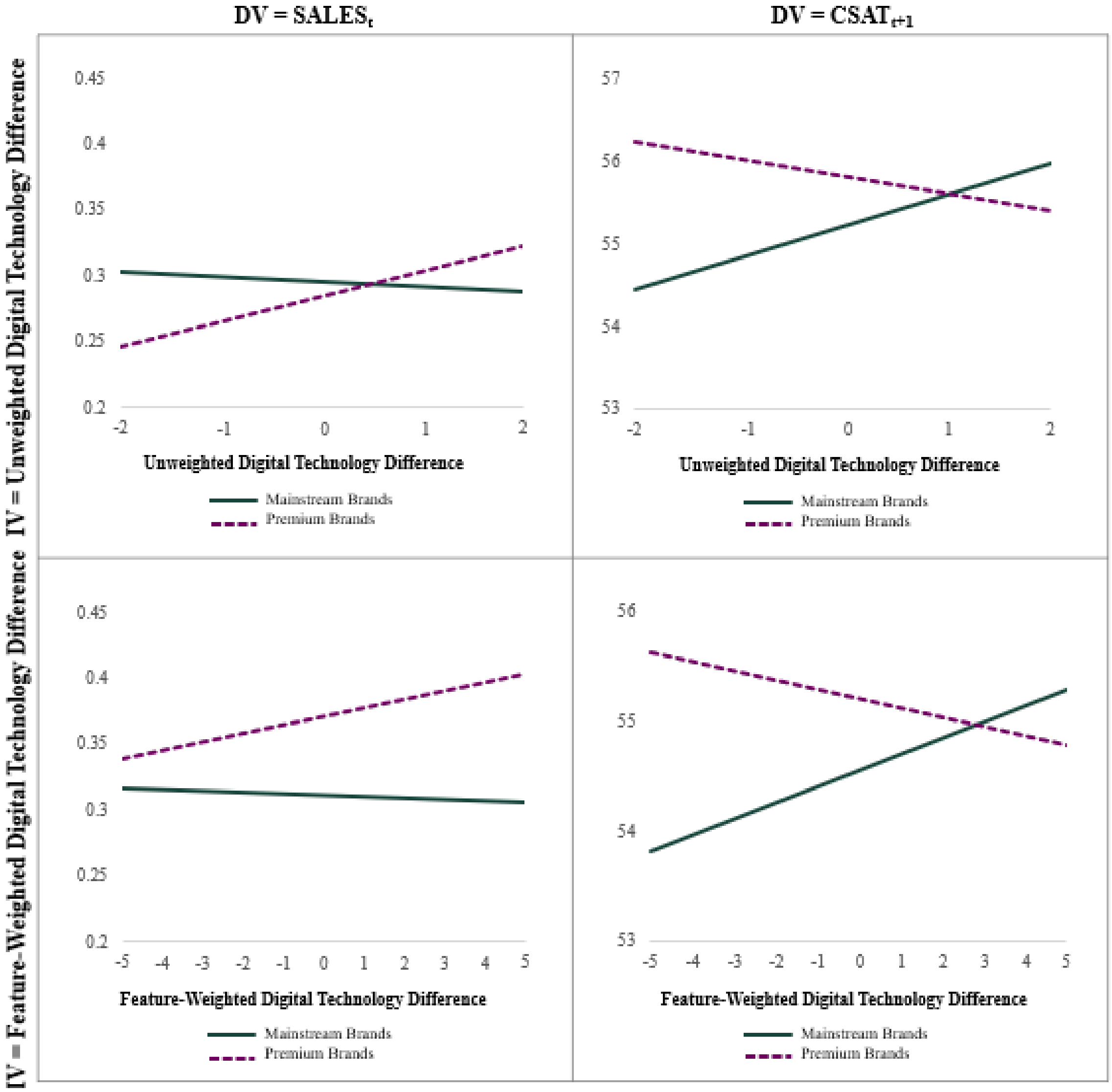


Figure 2-6 Digital Technology Index, Brand Status, Sales, and Customer Satisfaction



Note: The curves represent the unstandardized coefficients and the mean-centered IV.

Figure 2-7 Digital Technology Difference, Brand Status, Sales, and Customer Satisfaction



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DISSERTATION CONCLUSION

In this dissertation, I attempt to address two critical challenges faced by marketing researchers and practitioners posed by the rapid growth of EDTs. From a marketing researcher's point of view, I seek to synthesize and disseminate EDT-oriented knowledge generated by marketing scholars, and to compare, by scholars in neighboring business fields to advance marketing research efforts. From a marketing practitioner's point of view, I seek to investigate the impact of a firm's EDT offerings on marketing outcomes to provide strategic direction for managing the rapid proliferation of digital technologies in a competitive environment. Below, I delineate the theoretical and managerial contributions of this dissertation.

Essay One applies multidimensional scaling (MDS) to examine the intellectual structure of EDT research in marketing and across six other related business disciplines to propose an aggregated, strategic, and integrated view of digital technology's effect on marketing outcomes The scholarly study of EDTs in marketing has led to a substantial body of published works that have significantly advanced our understanding of relevant marketing phenomena, yet calls from prominent scholars and journals continue to emphasize a need for research that outpaces industry practice. Therefore, I put forth a cross-disciplinary and integrative research framework supported by three distinct theoretical perspectives. From a resource-based view (RBV), I propose that emergent digital technologies should be viewed as a resources that, if deployed appropriately, generate a new form of learning and capabilities which should lead to a competitive advantage (or output) which may be sustainable (Barney 1991). I link the RBV-focused portion of the framework to two consumer-focused perspectives: the technology acceptance model (TAM), and the theory of reasoned action (TRA). The user's beliefs and evaluations concerning a new technology can influence attitudes toward the technology based on preexisting perceptions. Jointly, I propose that the competitive use of EDT resources, learning, capabilities, and competitive advantage should substantially influence a user's attitude towards acceptance of EDTs.

Essay Two draws upon the three theories presented in Essay One (i.e., RBV, TAM, and TRA) in conjunction with the economic theory of additive utility to investigate the marketing performance of a firm's digital technology capabilities. In particular, I argue that as brands advance their digital technology capability, they become more capable of offering a greater number and higher technological level of digital technology features, which enhances their product offering's perceived utility (Lancaster 1971). This perceived utility, or value, leads to increased product adoption, evidenced by increased sales (Davis 1989; Davis, Bagozzi, and Warshaw 1992; Fishbein and Ajzen 1975). However, as brands become more capable of offering a greater number and higher technological level of digital technology features, they increase the complexity of product use, triggering a steeper learning curve and potentially igniting a consumer's frustration. This chain of events decreases a consumer's experienced utility, which, in turn, elicits lower customer satisfaction. In other words, while a brand's digital technology capabilities lead to short-term gains, the long-term effect may be detrimental for extremely advanced brands.

Additionally, I integrate brand status literature, which demonstrates that luxury brand products signal the highest level of quality and design, may be purchased for utility, symbolic, and experiential motivations, and promote a plethora of features that may not be functionally necessary (e.g., Berthon et al. 2009; Hagtvedt and Patrick 2009; Silverstein and Fiske 2003). Subsequently, I propose that luxury brands have greater exposure to the positive effects and are more insulated from the negative effects of a brand's digital technology capability than mainstream brands. Finally, I draw upon resource-based theory (Barney 1991), which suggests that a brand’s digital technology capability is inherently a resource that should lead to a competitive advantage for brands that lead within their competitive set, which I refer to as a brand’s digital capability surplus. I posit that as a brand’s digital technology capability surplus increases, they become better positioned to generate greater sales and elicit greater customer satisfaction than their direct competitors. The findings pertaining to a brand’s digital technology capability surplus were surprisingly mixed and strongly suggest that brand status plays a critical role in the target consumer’s perception of and experience with branded digital technology products.

Essay One serves as a practical guide to future EDT-oriented research for marketing scholars and a roadmap of EDT exploration and application for marketing practitioners. Specifically, I describe five predominant areas of interest. First, the impact of design on the belief-attitude relationship has received little attention in scholarly research, yet as digital technologies advance, the need for greater understanding becomes increasingly critical. As such, a firm's ability to design marketing programs and products for customers and marketing processes and tools for employees that address these perspectives should be examined. Second, there has been little distinction between the voluntary and mandatory aspects in this portion of the TAM-related framework apart from sales force automation (Jones, Sundaram, and Chin 2002; Speier and Venkatesh 2002). However, the evolution of digital technologies, particularly AI technologies, brings the potential for the unilateral replacement of many current marketing functions (Huang and Rust 2018). Therefore, firms should assess the differential sentiment regarding the influence of design on the attitude-acceptance relationship. Third, while capabilities have been introduced as relevant to the domain (Humphreys and Wang 2018; Melumad, Inman, and Pham 2019), I argue that decision tools and output should be examined to a significant degree.

Fourth, I suggest that that greater attention should be given to examining EDTs as a resource that provides a sustainable, competitive advantage as it leads to the design of more fruitful consumer-focused programs and marketing organization-focused processes (Huang and Rust 2018). Finally, while a substantial body of research has examined the roles of CRM and customer experience in firm performance (Lemon and Verhoef 2016; Poushneh 2018; Poushneh and Vasquez-Parraga 2017; Rafaeli et al. 2017; Scholz and Duffy 2018; van Doorn et al. 2017), very few studies have examined the importance of trust in this context. Subsequently, I suggest that leveraging EDTs as resources to develop intimacy leads to increased learning and capabilities, which ultimately creates a sustainable position in the marketplace.

Essay Two serves as an expository examination of the nuanced effects of digital technology capability on marketing outcomes. The results suggest that brand managers would benefit from expressly communicating the value of each digital technology offering to enhance the additive perception of utility instead of or in addition to positioning a set of features under a singular technology message. This strategy may be particularly valuable for luxury brand managers as they seek to promote mid-level model purchases over lower-level models. Furthermore, I argue that both luxury and mainstream brand managers should think twice about how their digital technology offerings affect customer satisfaction evaluations 1-2 years after purchase. Strategic plans may include educating consumers on using digital technology features or increasing the accessibility of certain features to enhance consumers' experienced utility. Finally, I find that it is advantageous for brand managers to create competitive benchmarks to establish their relative position on digital technology capabilities (Claycomb, Germain, and Dröge 2000; Kumar et al. 1998; Slater 1993). Specifically, for luxury brands that lead within their competitive set, it is advantageous to focus marketing efforts on developing strategic plans to on feature education and accessibility to enhance experienced utility. Whereas, for mainstream brands, focusing efforts on communicating the additive value of digital technology features would be more instrumental in gaining an advantage over their direct competitors. The methods and calculations are provided for brands to determine their digital technology capability and position relative to the market and direct competition.