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ESSAY

Abstract

This dissertation comprises three essays that conceptually explore the implications of artificial intelligence (AI) in marketing. AI is increasingly becoming integrated into every facet of marketing. As AI reshapes marketing relationships, it provides a path forward toward developing, adopting, or adapting conceptual frameworks, measurements, decision-making logics, and processes to reflect the digital world. Each of the three essays focuses on different facets of marketing utilizing distinct theoretical frameworks, research contexts, and methods. Essay one focuses on text-based communications, essay two focuses on AI personalized environments; whereas, essay three focuses on the new product development process of a business-to-business (B2B) AI marketing firm. These essays advance theory and practice to help us understand the implications of AI in marketing.

In essay one, I provide an evidence-informed answer to the following question: How are text-based communications in the echoverse reshaping marketing tasks and objectives? Given that automated textual analysis (ATA) methods are the window through which scholars and practitioners understand, predict, and co-create text-based communication in the echoverse, a systematic literature review of the marketing literature employing ATA methods is conducted. In doing so, a novel sampling procedure that applies supervised machine learning to rank long-form text assets in terms of relevancy is developed, which was used to identify empirical articles that employed ATA to gain marketing insights and predictions in the echoverse. The synthesis reveals how text-based communication reshapes four key marketing objectives: amplifying and de-amplifying content, tuning content, leveraging product reviews, and enhancing brand performance.

In essay two, I introduce a central concept from the field of ecology— ecological specialization—the breadth of a specie's utilization of resources to the field of marketing and provide a typology of personalized digital environments. Specifically, I conceptualize how the resources within a firm's content library interact with the degree of personalization to curate their digital marketing environment. Using a proprietary dataset including 7,174 email subscribers who opted to receive email marketing communications and opened at least one email between January 1, 2018, and June 30, 2018, from an Artificial Intelligence (AI) email marketing company that employs topic modeling to identify, curate, and deliver personalized emails to each individual customer based on customers' observed preferences, the concept of specialization, along with its implications for AI-personalized digital environments, was examined. I show how the underlying assumptions of traditional marketing metrics may limit marketers' ability to understand AI-personalized environments. The paper provides recommendations to marketers and new pathways for future research.

In essay three, I add the possibility of pivots to popular Stage-Gate® new product development processes (NPD). As conceived and operationalized with Stage-Gate®, one of five outcomes are possible decisions at each gate: go, stop, hold, recycle, or iterate. Borrowing from the entrepreneurship literature, I modify the process to include a sixth possible decision, a pivot. Pivots are triggered when a NPD project yields negative information or management believes that changes are necessary for the organization's survival and growth, i.e., a continuation decision in a failing course of action—an escalation of commitment. Effectuation theory is used to understand how causal/effectual logic informs escalation of commitment decisions, including pivots in an organization's NPD process. Through integrating the literature on Stage-Gate® NPD processes, entrepreneurial pivots, escalation of commitment theory, and effectuation theory, as

well as using a case study of a business-to-business AI marketing organization's NPD project with pivots, research propositions are offered for future research.

ESSAY I

Synthesizing Your Words: Using Automated Text Analysis to Derive Generalizations and Future Research Directions in Marketing

Abstract

Digitalization is revolutionizing marketing communications, whereby a universe of heterogeneous human and nonhuman actors make contributions and influence one another to form a communication landscape of complex feedback loops and reverberations defined as the echoverse. This study aims to provide an evidence-informed answer to the following question: *How are text-based communications in the echoverse reshaping marketing tasks and objectives?* Given that automated textual analysis (ATA) methods are the window through which scholars and practitioners understand, predict, and co-create text-based communication in the echoverse, a systematic literature review of the marketing literature employing ATA methods is conducted. In doing so, a novel sampling procedure that applies supervised machine learning to rank long-form text assets in terms of relevancy is developed, which was used to identify empirical articles that employed ATA to gain marketing insights and predictions in the echoverse. The synthesis reveals how text-based communication reshapes four key marketing objectives: amplifying and de-amplifying content, tuning content, leveraging product reviews, and enhancing brand performance.

Keywords: marketing communication, echoverse, automated text analysis, sampling long-form text assets, brands, systematic literature review

1. Introduction

> There is truth in Marshall McLuhan's asserting that the one thing of which the fish is unaware is water, the very medium that forms its ambience and supports its existence. Similarly, communication, through language and other symbolic forms, comprises the ambience of human existence. (Carey, 1989, p. 24)

In today's hyperconnected world, text-based communications occur between a networked universe of heterogeneous human and nonhuman actors (Price & Coulter, 2019; Swaminathan et al., 2020). Hewett et al. (2016) recognize this new phenomenon as a reverberating "echoverse," in which communication is a complex web of feedback loops. In the echoverse, communications are non-linear, and each communication can elicit a reaction from not only the intended recipient of the message but across the entire ecosystem (Maslowska, Malthouse, & Collinger, 2016). Accelerated by the Covid-19 pandemic (Amankwah-Amoah et al., 2021; MSI, 2021), technology-enabled text-based communication has resulted in an abundance of unstructured text data (Berger et al., 2020) and artificial intelligence's growing influence in marketing (Vlačić et al., 2021) that is revolutionizing society, business, research, and media (Dekimpe, 2020; Lehmann, 2020; Rust, 2020; Shah & Murthi, 2021; Shrestha, Krishna, & von Krogh, 2021).

This paper seeks to illuminate the echoverse in which consumers are immersed by addressing the following research question: *How are texted-based communications in the echoverse reshaping marketing tasks and objectives*? Automated textual analysis (ATA) methods—computer-assisted and automated approaches for mining, organizing, understanding, predicting, conceptualizing, and constructing knowledge from enormous quantities of unstructured text data (Berger et al., 2020; Humphreys and Wang, 2018)—are the window through which scholars and practitioners understand, predict, and co-create text-based

communication in the echoverse. Thus, a systematic literature review of the marketing literature employing ATA methods is conducted. A method adopted from the medical sciences, a systematic literature review is used to summarize and synthesize the literature (Donthu et al., 2021a; Snyder, 2019) to provide an unbiased view of the field, gain insights into knowledge areas, and identify uncharted areas (Parris & Welty Peachey, 2013).

This paper develops a novel sampling procedure that applies supervised machine learning to rank long-form text assets—content with more than 2,000 words (Milligan, 2020)—on the probability of relevancy. Translating words into numbers is core to ATA methods. Bibliometric keyword matching, which is used to find all occurrences of specific keywords, is employed by free and paid databases like Google Scholar and EBSCO (EBSCOhost, 2020; Google Scholar, 2022), which are utilized by researchers to identify articles representative of a subject. However, composing a set of keywords is not trivial. For example, to categorize research on digital, social media, and mobile, Lamberton and Stephen (2016) identified approximately 200 keywords. Furthermore, new phenomena for which descriptor language (i.e., divergent keywords, different context-dependent keywords, sets of linked keywords, or linked concepts) is evolving—or has yet to develop clear signaling words and phrases—compound the challenge as keyword searches result in a paucity of relevant articles. To address this challenge the proposed method employs a dynamic bag-of-words (BoW) approach, which identifies new phenomena not often found using keyword searches.

Despite the evolution of text-based communications in the echoverse, the review shows that extant wisdom frames marketing communications as one-way or two-way interactions between brands and consumers (Yadav & Pavlou, 2014). It emphasizes effective communication between a sender playing a primary role and a receiver playing a secondary role (i.e., receiving

the information or being passive) (Shannon, 1948; Shannon & Weaver, 1949). Such a traditional perspective limits the understanding of echoverse communications, which are dynamic and omnidirectional (i.e., receiving, sending, and echoing signals from every direction). An echoverse perspective is particularly important given the increased prevalence of word of mouth (WOM) (Donthu et al., 2021b) and its value for brand recommendations (Luo, Baker, & Donthu, 2019). Building on Hewett et al.'s (2016) operationalization of the echoverse and communication theory (Barnlund, 1970; Carey, 1989; Rosengren, 2006; Schramm, 1997; Shannon, 1948; Shannon and Weaver, 1949; van Ruler, 2018), this paper proposes *echoverse marketing* as a new marketing communication conceptual framework encompassing the hyperconnected world and involving a "universe" of actors (e.g., consumers, brands, news media, artificial agents) contributing to and "echoing" each other's actions.

The contribution here is three-fold. First, I introduce a new methodology for exploring long-form text that advances sampling methodology, enabling the identification of relevant long-form communications. Second, I offer a conceptual lens for understanding how text-based communications in the echoverse have caused marketing communications to evolve. Third, I provide a state-of-the-art systematic analysis of ATA marketing literature that reveals research is thematically centered around four main marketing communication objectives: amplifying and de-amplifying content, tuning content, leveraging product reviews, and enhancing brand performance. Finally, I provide actionable recommendations to managers as they navigate the echoverse and highlight opportunities for future research.

2. Method

Since Wedel and Kannan (2016) highlighted how ATA methods such as text mining and machine learning were becoming state-of-the-art approaches for marketing analytics, ATA has been increasingly utilized by marketing researchers. Prior reviews on ATA have focused on providing useful guidelines and procedures for employing text analysis methodologies, evaluating method choices, and discussing common challenges (Berger et al., 2020; Humphreys & Wang, 2018). These reviews highlight the plurality of ATA methods and possibilities of their application for gaining and creating new marketing insights; however, they leave the researcher, student, or practitioner pondering how text-based communications in the echoverse are reshaping marketing tasks and objectives. As DiMaggio (1995) pointed out "theory construction is a cooperative venture between author and readers" (p. 396) and ''there is more than one kind of good theory'' (p. 391). The plurality of ATA methods and the accumulation of knowledge from many scholars employing them collectively shape the narrative of what is, and what becomes the echoverse. Given that previous reviews have examined ATA methods, the present review focuses only on empirical studies that have employed ATA methods in an organizational context. To the best of my knowledge, the current study is the first review to provide a synthesis, based upon evidence published in peer-reviewed journals, of empirical studies that employed ATA methods in the echoverse.

Exploring long-form text such as firms' document repositories, databases of scholarly research, magazines, news articles, and with the use of web scraping technologies 1.2 billion publicly accessible websites remains relatively uncharted. This review reveals that, to date, scholars have primarily focused on a short-form text—less than 2,000 words—such as product reviews (Hollenbeck, 2018; Yin, Bond, & Zhang, 2017; Rocklage & Fazio, 2020), Twitter

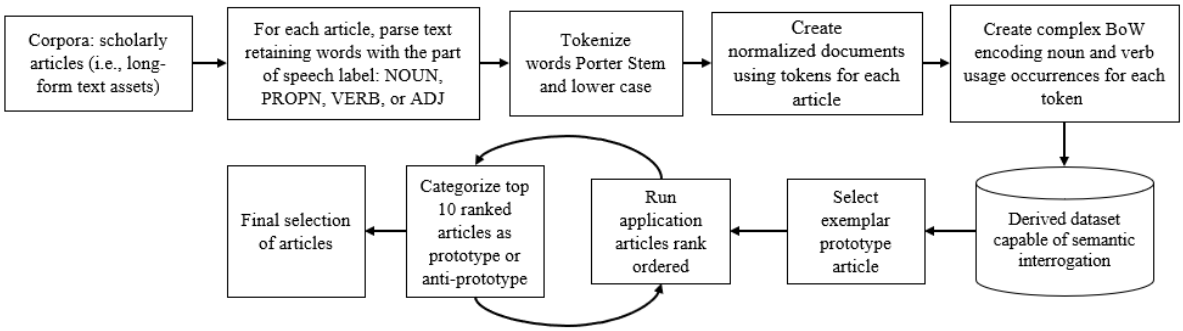
messages (Jalali & Papatla, 2019; Zhang, Moe, & Schweidel, 2017; Berman et al., 2019), and social tags (Ansari, Li, & Zhang, 2018; Nam, Joshi, & Kannan, 2017). Leveraging longform text assets, text assets that are longer than 2000 words, poses significant challenges. Primarily, the identification of relevant documents (i.e., sampling from a broader corpus). Systematic literature reviews, an acknowledged critical, potentially required, step in the scientific process (Palmatier, Houston, & Hulland, 2018) are one instance where scholars encounter this challenge. The objective of systematic literature review sampling is to identify all relevant artifacts (i.e., peer-reviewed articles). However, a unique idiosyncrasy and challenge of longform text analysis is that a topic can be described in many ways (i.e., by specific keywords, different context dependent keywords, sets of linked keywords, or by linked concepts). Thus far, researchers have overwhelmingly employed short-text keyword searches to identify relevant articles, leading to sampling issues (see Table 1). The method for sampling content matters because the choice alters the selection of artifacts and, therefore, the findings (Singh, Hillmer, & Wang 2011). Methods for sampling long-form text borrows from qualitative research and are exceptionally laborious as the process is not random and requires rigorous screening

Table 1. Example of systematic literature review and bibliometric sampling procedure results

Authors	Topic of Interest	Searched Keywords	Sample Pool	Sample	Positive	False Positives
Verma & Gustafsson (2020)	Emerging COVID-19 research trends in the field of business and management	“2019-nCoV” OR “COVID-19” OR “Novel Coronavirus Pneumonia” OR “NCP” OR “2019 novel coronavirus” OR “SARS-CoV-2” OR “2019 Novel Coronavirus Disease” OR “novel coronavirus” OR “pneumonia”	12068	107	0.89%	99.11%
Belitski, Kalyuzhnova & Khlystova (2021)	Impact of the COVID-19 pandemic on the creative industries	A combination of the keywords “creative industry,” “COVID-19,” and “impact”	123825	59	0.05%	99.95%
Parris et al. (2016)	Transparency	"Transparency"	537	46	8.57%	91.43%
Parris & Welty Peachey (2013)	Servant leadership	"Servant leadership"	255	39	15.29%	84.71%
Keegan, Rowley, & Tonge (2017)	Agency–client relationship	"Agency–client relationship" OR "client-agency relationship" OR "ad-client relationship OR “client-ad relationship"	550	114	20.73%	79.27%
Wulff (2016)	Foreign entry mode	"Entry mode” OR “joint venture” OR “wholly owned subsidiary” OR “licensing” OR “franchising” AND "international OR multinational OR foreign" AND "data OR empirical OR test OR statistical OR …”	1,786	119	6.66%	93.34%
Saebi, Foss, & Linder (2019)	Social entrepreneurship	“Social entrepreneur” OR “social enterprise” OR “social venture" OR "social business”	2645	395	15%	85%
Coombes & Nicholson (2013)	Business models in marketing	**Searched Title Only**: ‘business model’ OR ‘business models’	994	405	41%	59%
Galvagno & Dalli (2014)	Value co-creation	Words beginning with the prefix “cocrea,” “co-crea,” OR “co crea”	2,568	711	28%	72%
Hansen & Schaltegger (2016)	Sustainability balanced scorecards	"Sustainability" OR "ecological" OR "eco" OR "environmental" OR "green" OR "greenish" OR "greening" OR "social" OR "societal" OR "community" OR "stakeholder" OR "ethics" OR "ethical" OR "CSR" OR "responsive" AND "balanced scorecard" OR …"	473	69	15%	85%

This paper's proposed method enables effective sample creation from a corpus of long-form text assets by employing a dynamic bag-of-words (BoW) approach, which identifies new phenomena not often found using keyword searches. This BoW is created from the tokenized words of an exemplar document in which the language utilization is encoded, enabling a comparison of documents based on the probability of the researchers' interest. The corpus of artifacts is automatically ranked in order of relevancy to the first prototype/exemplar article. Identifying a seminal article is a recommended approach for systematic literature reviews (Hunter & Schmidt, 1990; Khamitov, Grégoire, & Suri, 2020; Palmatier, Houston, & Hulland, 2018). The method pairs human and machine intelligence to train the application, an effective and proven method in a wide variety of contexts (Qian et al., 2001; Timoshenko & Hauser, 2019). The application is trained by labeling a subsample of the articles as prototypes or an anti-prototype (i.e., an incorrect example). The process is repeated (i.e., iterated) until no new prototype articles are identified to create the final sample. Figure 1 provides an overview of the supervised machine learning approach. Additional details on the application built and the open-source tools which were used are provided in the Appendix and the code is available upon request.

Figure 1. Machine learning sample procedure for document

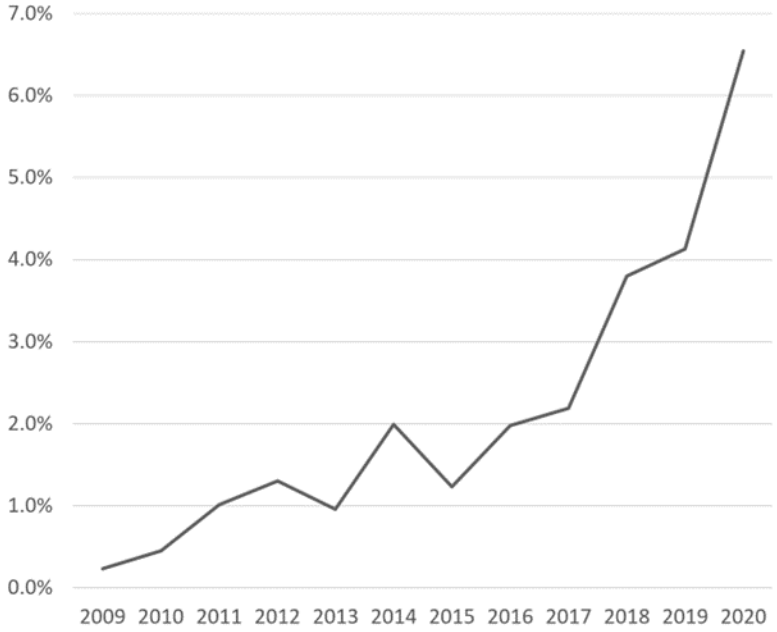


The sample for the review focused on top-ranked marketing journals containing articles utilizing ATA methods comprising at least one percent of the published articles (see Table 2). This systematic literature review was conducted in a disciplined manner but was limited to the journals listed and did not include other indexed journals or peer-reviewed articles. Identifying the sample required 27 iterations identifying 97 prototypes and 173 anti-types beyond the originally defined prototype article. I identified two consecutive iterations without the presence of a prototype article as the point at which performing iterations stopped. Given that ATA's rapid growth started in 2016, as illustrated in Figure 2, the review focuses on the 64 articles (65% of the prototype articles) published between 2016 and May 2020.

Table 2. Percentage of articles per journal utilizing ATA methods

Journal	Article Count (2010-May 2020)	Percentage of Articles Using ATA Methods
Quantitative Marketing and Economics (QME)	146	0.0%
International Journal of Research in Marketing (IJRM)	456	3.5%
Journal of Academy of Marketing Science (JAMS)	573	1.4%
Journal of Consumer Behavior (JCB)	499	0.6%
Journal of Consumer Psychology (JCP)	594	0.3%
Journal of Marketing (JM)	542	2.2%
Journal of Marketing Research (JMR)	693	2.7%
Journal of Public & Policy & Marketing (JPPM)	298	0.3%
Journal of Retailing (JR)	390	0.5%
Marketing Science (MS)	622	4.8%

Figure 2. Rate of growth of ATA methods in marketing journals



The matrix method (Garrard, 2016), an organizational system for abstracting information from empirical research, was applied. The following information was abstracted from each article: the focal marketing task, key findings, and practical implications. Lastly, open, axial, and selective coding were used to cluster and link text artifacts (i.e., articles) together to discover key categories (Neuman, 2006). In this process, the marketing tasks that were linked together revealed four key marketing objectives. These studies' findings were summarized and placed into matrices (i.e., tables), which are discussed next.

3. Findings

In 2016, Wedel and Kannan accurately acknowledged ATA methods' potential to reshape marketing. This study highlights how ATA methods have been progressively utilized by networked consumers, brands, and other entities to understand, predict, and co-create text-based communication. In line with Vlačić et al.'s (2021) review of artificial intelligence in marketing,

this review emphasizes how technologies providing computer-assistance and automation play an increasingly larger role in marketing and society.

ATA methods provide a window into the largely text-based echoverse in which marketing communications are dynamic and omnidirectional, reverberating across a universe of actors. Despite marketing communication's evolution, this study illustrates that scholars are mostly framing the interaction as one- or two-way interactions between brands and consumers. Like a fish being unaware of water—despite water being essential to a fish's very being—this paper's objective is to highlight that marketing communication occurs in the echoverse and, therefore, that marketing communication frameworks should be updated to reflect this reality. Echoverse marketing is proposed as a new marketing communication framework to conceptualize communication encompassing the hyperconnected world in which a universe of actors participate, co-create, co-share, and co-own. The synthesis reveals four key marketing communication objectives: amplifying and de-amplifying content, tuning content, leveraging product reviews, and enhancing brand performance. For each marketing objective, this review highlights the key marketing task and each empirical study's practical implications providing a guide for managers to navigate the ecohoverse, whereas for researchers it focuses on the key findings and future research.

3.1 Conceptualizing the evolution of marketing communications

Historically, marketing communication has been laser-focused on how firms (i.e., brands) deliver messages to their stakeholders with an emphasis on customers and investors. In the echoverse era, with the increasingly blurred and broadened boundaries of branding (Swaminathan et al., 2020), a brand can be a firm (i.e., organization/cooperation), product, service, idea, place, person, or community that can contribute as a human or non-human actor(s).

In an attempt to conceptualize marketing communications' evolution towards a universe of actors understanding, predicting, and co-creating text-based communication in the echoverse, communication theory (Barnlund, 1970; Carey, 1989; Rosengren, 2006; Schramm, 1997; Shannon, 1948; Shannon and Weaver, 1949; van Ruler, 2018) and theories of marketing communications (Harmeling et al., 2017; Hewett et al., 2016; Hoffman & Novak, 1996; Mohr & Nevin, 1990; Yadav & Pavlou, 2014) are integrated. Table 3 shows an organizational typology (Doty & Click, 1994) of four types of marketing communication frameworks.

Table 3. Marketing communication strategies

Marketing strategy	**Promotion marketing**	**Relationship marketing**	**Customer engagement marketing**	**Echoverse marketing**
Assumed Actors	The customer and the brand	The customer and the brand	The customer, other customers, and the brand	A universe of actors: consumers, brands, news media, investors, communities, society
Communication objective	The brand initiates a purchase from the customer	Brands generate loyalty and repeat purchases from the customer	Brands activate customers as participants and contributors to the brand's marketing process	A universe of actors encourages, enables, and observes other actors contributing to the marketing ecosystem.
Learning objective	Brand-directed instruction on the customer buying process	Brand-directed guidance of the exchange relationship	Brand-directed training of the customer to make marketing contributions	A universe of actors—directed learning opportunities to facilitate other actors' learning
Flow of information	One-way communication from the brand to the customer	Bilateral communication between the brand and the customer	Multilateral communication among the brand, the customers, and other customers	Omnidirectional communication within a universe of actors
Model of communication	Linear model: Brand→Customer	Transactional model: Customer ←→ Brand	Interactive model: Triangle of communication	Ritual model: A universe of actors moving, changing, and affecting each other.
Process of meaning construction	The sender constructs the meaning developed by the receiver	Two actors construct new meanings together	Two or more actors construct new meanings together	A universe of actors continuously and simultaneously constructs meaning.
Control of meaning construction	Brand control	Negotiated brand-customer control	The customer exerts high control	A universe of actors exert control.
Assessment of value creation	Customer's purchase power and wallet share	Customer's lifetime value	Customers' owned resources and their future contributions to the brand	A universe of actors co-owning and co-creating resources and future contributions

Communication theory explores how meaning is created, interpreted, and used and how the process of meaning construction works (Rosengren, 2006; McGuire, 1976). Broadly, there are three lenses of how communication processes work: (1) communication as a one-way process of meaning construction whereby the sender (i.e., the brand) attempts to construct or reconstruct the meaning developed by the receiver (i.e., the customer) often viewed synchronically—at a theoretical point in time (Ellis & Mclintock, 1990; Shannon, 1948; Shannon & Weaver, 1949); (2) communication as a two-way process of meaning construction between two or more entities (i.e., the brand, the customer, and/or customers) constructing new meanings together (Barnlund, 1970; Schramm, 1997); and (3) communication as receiving signals from/in all directions, defined as omnidirectional, considering communication's evolution over time (i.e., diachronic), and focused on meaning construction's continuous process (Carey, 1989; van Ruler, 2018). To date, most marketing communication strategies focus only on brands and customers with information flowing in a synchronic one or two-way communication process.

For example, in promotion marketing, the brand is focused on raising awareness and influence (Wierenga & Soethoudt, 2010) to ultimately increase its equity (Valette-Florence, Guizani, & Merunka, 2011). Through the lens of communication theory, this is a one-way process of meaning construction, whereby the brand as the sender constructs the meaning developed by the customer as the receiver. In relationship marketing, exchanges focus on maintaining a relationship (Grönroos, 1999; Morgan & Hunt, 1994, 1999). Through the lens of communication theory, this is a two-way process of meaning construction between dyadic parties (Palmatier et al., 2006), whereby meaning construction is negotiated.

Social media's rapid adoption enabled customers to become active contributors to a wide variety of marketing functions (Malthouse et al., 2013), sparking an explosion of interest in

engagement marketing—a brand's deliberate efforts "to motivate, empower, and measure customer contributions to marketing functions" (Harmeling et al., 2017, p. 312). Through the lens of communication theory, this is a two-way process of meaning construction involving more than two interacting actors with customers exerting high control (Harmeling et al., 2017; Obilo, Chefor, & Saleh, 2021). Promotion, relationship, and engagement marketing share a strategy viewpoint in which the brand is a main actor either as the sender or receiver of the communication. While valuable, these brand strategies bond communications between the brand and customer(s) and may not reflect the digital ecosystem in which the boundaries of communication are broadening and blurring to include a universe of actors playing a role in the communication processes.

Accordingly, the goal of conceptualizing echoverse marketing is to provoke and support the development of marketing communication that embraces the future (Dekimpe, 2020; Rust, 2020; Shah & Murthi, 2021; Swaminathan et al., 2020). It moves toward acknowledging a universe of human and nonhuman actors who can simultaneously listen, decode, and respond to each other as well as develop shared ownership as they co-create in the echoverse. Next, the marketing objectives for text-based communication in the echoverse are synthesized.

3.2 Amplifying and de-amplifying texted-based communications

In the echoverse, marketing leaders and scholars are using ATA methods to understand how to create a message that reverberates with many actors and channels (i.e., amplifying a message) or to explore how to stop a message's echo (i.e., de-amplifying a message), as shown in Table 4. The objective of amplifying and de-amplifying digital communications in the echoverse is to manage their reach and, therefore, effect (i.e., increasing or decreasing big data's five V's—volume, variety, velocity, veracity, and value). Researchers provide insights into

advertising's effect in the echoverse (Joo, Wilbur, & Zhu, 2016; Tirunillai & Tellis, 2017); maximization of rebroadcasts, engagement, and news articles' virality (Heimbach & Hinz, 2016); and increased social media engagement (Jalali & Papatla, 2019; Li & Xie, 2020). Furthermore, Herhausen et al. (2019) have predicted which messages within a brand community are likely to evolve into firestorms.

Table 4. Overview of articles exploring amplifying or de-amplifying text-based communications

Author (Year)	**Marketing task**	**Key findings**	**Practical implications**
Herhausen et al. (2019)	Detect and mitigate negative electronic word of mouth (eWOM)	Emotional arousal, the number of connections between the sender and brand community, and the degree of similarity of the message's linguistic style have distinct impacts on a negative message's likelihood to go viral.	Managers can identify negative messages which are more likely to go viral by using the dictionary created by the authors, measuring the number of connections between the sender and brand community, and comparing the message's linguistic style.
Hewett et al. (2016)	Provide conceptualization and empirically demonstrate the echoverse of eWOM	user-generated content (UGC), brand communication, and news media form an echo chamber where negative news has a greater reach and faster distribution. Furthermore, eWOM can affect business outcomes.	Broadcast strategies appear less effective than personalized responses to individual customers. Brands can adapt communication strategies to leverage social media to drive business outcomes.
Johnen & Schnittka (2019)	Identifying the optimal response to complaints on social media	Observers of complaints on social media may prefer to see a company push back on a negative complaint, particularly in hedonic contexts.	Social media managers should orient responses to fit with the broader content published on their social media so that observers perceive value in the response.
Heimbach & Hinz (2016)	Determining the factors of content virality	Content virality is influenced by positive, emotional, and anger-inducing language.	Managers looking to design content for virality should craft content that is slightly positive.
Jalali & Papatla (2019)	Designing tweets to maximize rebroadcasting	Topic words placed near the beginning of a tweet generate more retweets.	How tweets are composed impacts their potential reach.
Li & Xie (2020)	Increasing social media engagement with the use of images	Image content drives higher engagement on Twitter. Professional high-quality images increase engagement on Twitter and Instagram. Image-text fit encourages further engagement on Twitter.	Managers should consider images, image attributes, and image-text fit when designing content for maximum effect.
Sanchez, Abril, & Haenlein (2020)	Understanding the effects of eWOM's competitive spillover	Helpful information contained in eWOM moderates its competitive spillover effects. Product activities like price changes may be a superior way to generate eWOM.	Brands should consider focusing on creating eWOM content to generate additional eWOM. Furthermore, brands should integrate eWOM efforts into marketing-mix initiatives to assess their effectiveness.

Zhang, Moe, & Schweidel (2017)	Ascertain drivers of rebroadcasting behavior	The fit between message content and consumer interest is a significant driver of rebroadcasting behavior. Influential users can impact others' rebroadcasting behavior, but there is wide variability in the ability to influence and the audience's susceptibility.	Managers seeking to optimize rebroadcasting should match the message's content to the audience's preferences and minimize heterogeneity of interests. Relying on influential users can have varied results depending on the message's content and the interest of the influential users and their audience.
Berman et al. (2019)	Assess how microblogging messages evolve over time during a live event	Messages of a live political event follow a pattern: initial real-time narration followed by retrospective interpretation and then a topical shift from policy topics to abstract themes and combative interactions.	Managers looking to leverage a live event to foster social media activity should design their content to fit into the evolution of discourse around the event.
Colicev, Kumar, & O'Connor (2019)	Model the relationship between UGC and firm-generated content (FGC) to the marketing funnel's stages	FGC has more impact on consideration and purchase intent, whereas UGC has a stronger relationship with awareness and satisfaction.	When customers are in the consideration and purchase-intent stages, FGC distributed on social media with positive valence is not persuasive. Instead, managers should focus on creating objective and vivid content.
Tirunillai & Tellis (2017)	The impact of offline television advertising on multiple metrics of online chatter	Offline television advertising has a short but significant positive effect on online chatter. This effect is stronger on information-spread dimensions (visibility and virality) than on content-based dimensions (popularity and negativity).	Advertising may impact online chatter. Chatter metrics are readily available. Managers and analysts should consider using chatter to assess advertising's impact as a quicker method than assessing sales.
Joo, Wilbur, & Zhu (2016)	Ascertain the relationship between TV advertising and keyword search behavior	There is a significant relationship between TV advertising and the increased use of branded keywords in searches. The greatest increase is for young brands; and the effect on click-through rates is limited, suggesting searchers are exploring.	Managers should consider designing landing pages to coincide with branded-keyword searches following TV advertising.

Critical to understanding content's amplification and de-amplification effects is exploring how texted-based communication channels act, react, and interact with other channels and actors. Hewett et al. (2016) empirically demonstrate the presence of an echoverse while also illustrating how text-based communication evolves over time to become more negative. Studying two fast-moving consumer packaged goods companies, Sanchez, Abril, and Haenlein (2020) illustrate how electronic word of mouth (eWOM) reverberates from and onto other brands within an industry and can affect the brand positively or negatively (i.e., creating new opportunities or threats).

A negative message's impact can also benefit the brand when the brand pushes back on an unfair statement—as Johen and Schnittka (2019) show in the context of hedonic products, a manager's defensive response can lead to positive reactions from observer actors. Nevertheless, different actors within the echoverse can have distinct effects. In modeling the relationship of user-generated content (UGC) and firm-generated content (FGC) to the marketing funnel's stages, Colicev, Kumar, and O'Connor (2019) show UGC has a stronger relationship with awareness and satisfaction, while FGC has a stronger relationship with purchase intent. Additionally, the discourse among actors and across channels evolves in real-time. Examining the minute-by-minute discourse surrounding political debates, Berman et al. (2019) provide a decomposition of the pattern of eWOM as it evolves from play-by-play narration into broader debates around topics highlighting the temporally shifting communication pattern. Collectively, the research on amplification and de-amplification illustrates the omnidirectional impact of a message, which can influence other actors and channels, while the meaning of the message and reactions evolve over time.

3.3 Tuning content

A significant amount of the research applying ATA has assessed how content can be tuned to customers' preferences, as illustrated in Table 5. As Hewett et al. (2016) emphasize, for brands to manage the echoverse there should be a shift from mass advertising toward more one-to-one communication. While ATA enables customization and personalization for one-on-one virtual dialogues, in the echoverse managers must also oversee how these dialogues may be shared and echoed across the universe of actors, who can impact other customers and brands—positively or negatively. The objective of tuning content in the echoverse is to make the intended recipient(s) of the communication feel the messenger responds in a personalized manner to their needs and wants, while also responding in ways that positively influence the universe of actors and revenue.

Table 5. Overview of articles exploring tuning content

Author (Year)	Marketing Task	Key Findings	Practical Implications
Achar, Agrawal, & Hsieh (2020)	Assess the psychological processes that inform customer behavior	Illness detection invokes fear, undermining participation in detection screenings; however, illness prevention aligns with feelings of self-efficacy, increasing the persuasion of marketing messages.	Because fear of detection reduces participation in health screenings, brand managers in healthcare should consider presenting detection as part of a long-term healthy lifestyle.
Chung, Wedel, & Rust (2016)	Assess the value of adaptive personalization for mobile technology	Adapting to customers' observed preferences produces better results than customers' self-customization. Incorporating the customers' social media networks can lead to further improvement.	Algorithmically tuning content based on the observed preferences of a user will produce better recommendations than requiring the user to specify their preferences.
Kanuri, Chen, & Sridhar (2018)	Determine optimum content scheduling	Time of day, content type, and whether the brand pays to advertise the content influence social media post-performance.	To get the greatest return on their investment, managers should strategically time content's publication on social media.
Liu & Toubia (2018)	Infer content preferences by using online search queries	Using hierarchically dual latent Dirichlet allocation (HDLDA) to estimate content preferences and assuming users' use of semantic relationships when querying lead to more accurate estimates than assuming users naively form queries.	To target their promotions, managers should leverage HDLDA to quantify how well their content matches users' content preferences.
Meire et al. (2019)	Investigate the ability to impact the sentiment of customers	Sentiment is a leading indicator of customers' lifetime value. Following an unfavorable event, marketer-generated informational content enhances customer sentiment more so than emotional content.	Managers seeking to influence customer sentiment following an unfavorable event should create and target informational content.
Packard, Moore, & McFerran (2018)	Explore how using personal pronouns impacts interactions	The use of "I" by customer service agents positively affects customers' purchase behavior and satisfaction.	Brands should consider training customer service personnel to use "I" rather than "we."
Rutz, Sonnier, & Trusov (2017)	Forecast comparable ad performance	New ads' performance and perceptions can be forecast by scoring text ads on click performance and perceived ability to generate awareness, interest, desire, and action.	Rather than using traditional ad copy testing (A/B or multivariate), brand managers should consider using the textual characteristics of new ads to forecast their performance.
Toubia et al. (2019)	Create better metadata for content products	Both content-based and hybrid predictive models guided by features of latent Dirichlet allocation (LDA) enable better predictions of movie-watching behavior.	Managers should consider the proposed feature-extraction method to improve content recommendations.
Vermeer et al. (2019)	Identify response-worthy eWOM	Machine learning methods better detect response-worthy eWOM than any variation of sentiment analysis.	Machine learning enables eWOM to be categorized into different dimensions of customer satisfaction, enabling the routing of customer responses to different teams with expertise to respond effectively.

Scholars have explored the timing of social media posts given their emotional content (Kanuri, Sonnier, & Trusov, 2018), selecting ad copy more likely to generate engagement (Rutz, Sonnier, & Trusov, 2017), quantifying how closely brand content aligns with user search queries (Liu & Toubia, 2018), and assessing the methods for curating customer online experiences (Chung, Wedel, & Rust, 2016). Furthermore, Toubia et al. (2019) demonstrate a method to better describe content products by leveraging their product descriptions to create meta-data for recommendation algorithms, and Vermeer et al. (2019) highlight the potential of machine learning to route eWOM questions and complaints to individuals or departments to respond effectively.

With ATA practitioners and scholars are gaining new insights into how customer behavior and sentiment can be influenced by marketing communications with significant impacts on both bottom lines for brands and positive outcomes for customers. Notably, Archer, Agrawal, and Hsieh (2020) find that the marketing message for serious disease screening impacts whether people participate in early-detection behaviors. Meier et al. (2019) demonstrate that brands can influence customers' social media responses following a negative event—through the content the brand disseminates. Packard, Moore, and McFerran (2018) show when responding to customer service complaints or questions the service agent's use of personal pronouns can positively influence the customer's future purchase intention.

Tuning content with ATA can enhance customer engagement, increase persuasive behavior, improve service experiences, and adapt to communication in real-time. Adaptive personalization has the potential to deliver one-to-one communication while also communicating across the echoverse. Thus, the importance of correctly tuning content in messaging, content

mix, timing, language, and emotionality is compounded in the echoverse because it can affect who in the universe of actors will be listening, encoding, and reacting to the message.

3.4 Leveraging product reviews

With ATA capabilities, marketing leaders are leveraging product reviews in a myriad of ways, as shown in Table 6. Product reviews provide insights into customers' post-purchase experiences by making available product and reviewer information. The objective of leveraging product reviews is to impact behavior at both individual and macro levels as well as to identify market opportunities. Brands can leverage reviews to gain positive benefits, such as building trust, influencing sale conversions, increasing revenues, and informing brand strategy.

Table 6. Overview of articles exploring product reviews utilizing ATA methods

Author (Year)	Marketing task	Key findings	Practical implications
Yazdani, Gopinath, & Carson (2018)	Value creation of top- and bottom-ranked online reviewers	Bottom-ranked reviewers have more influence on sales. Top-ranked reviewers can be opinion leaders, but their influence is limited to special cases (i.e., very new products or products with high variance in existing reviews).	Managers should be careful in using reviewer rankings as a measure of opinion leadership.
Yin, Bond, & Zhang (2017)	Emotional expression on perceived review helpfulness	Arousal's marginal effect on perceived helpfulness is positive at low levels but diminishes at higher levels.	Managers may measure reviews' expressed arousal to predict reviews' usefulness and to provide guidelines for reviewers.
Rocklage & Fazio (2020)	Online reviews' emotional content in relationship to purchase intentions	Reviewers who express positive emotions are more positive toward products. However, for hedonic products, high-emotion reviews lead to more trust, review helpfulness, and purchasing intentions than low-emotion reviews. For utilitarian products, high-emotion reviews lead to less trust, review helpfulness, and purchasing intentions than low-emotion reviews.	Managers should ask for low-emotion reviews for utilitarian products and high-emotion reviews for hedonic products.
Melumad & Meyer (2020)	How smartphones enhance consumers' self-disclosure	Consumers tend to be more self-disclosing on their smartphones than on their PCs.	If a brand wants to obtain sensitive or personal information from consumers, it should target them on their smartphones rather than on their PCs.
Liu, Lee, & Srinivasan (2019)	How consumers use review content	Aesthetics and price content significantly increase conversion across almost all product categories.	Managers can automatically extract price and quality information from reviews; use reviews as a part of the marketing mix; and collect real-time information about the consumers' purchase journey to predict conversion more accurately.
Ransbotham, Lurie, & Liu (2019)	How the platform source affects eWOM's consumption value over time	Reviews created on mobile devices are more affective, more concrete, less extreme, and have lower consumption value.	While the act of writing reviews might be therapeutic for consumers, managers should consider discouraging mobile reviews due to their low consumption value.
Hollenbeck (2018)	Online brand reputation mechanisms on franchising	The availability of property-specific information has resulted in greater revenue growth for independent hotels than for hotel chains.	Franchisee/Franchisor relationships may be impacted as location-specific quality increases in importance while chain reputation becomes less important.

Wang & Chaudhry (2018)	Impact of managers' responses to online reviews on popular travel websites	Manager response to a negative review can improve customer perception; however, manager response to a positive review has a negative effect because customers perceive it as a promotion attempt.	Managers should respond to negative comments to manage complaints; however, responses to positive comments should have limited customization.
Ansari, Li, & Zhang (2018)	Improving e-hybrid recommendation systems	Leveraging UGC enables recommendation engines to address the challenges of sparce product-feature data.	Managers may use UGC both to generate insights about consumer preferences and to improve product recommendations.
Büschken & Allenby (2016)	A better understanding of unstructured data	The authors introduce a sentenced-based topic model to improve product reviews' prediction power.	Managers may consider implementing sentence-constrained LDA to improve the predictive power of their topics from UGC.
Marchand, Hennig-Thurau, & Wiertz (2017)	Leveraging consumer reviews and microblogs for new product success	Twitter (volume) is more influential at a new product's launch, and the impact of reviews (volume and valence) increases over time.	When launching new products, managers should focus at different times on leveraging and monitoring Twitter and reviews to influence purchase decisions.
Moon & Kamakura (2017)	Translating reviews into a product positioning map	Reviews reveal information about both the product and the reviewer that can be leveraged to create product positioning maps.	Managers may consider leveraging this novel method to define customer segments and inform product positioning strategies.
Motyka et al. (2018)	Exploring behavioral consequences of writing a review	Consumers who share emotional information in reviews tend to make more impulsive purchase decisions.	The act of writing a review can influence reviewers' own behavior and consumption. Managers can solicit reviewers to maximize future revenue.
Song et al. (2018)	Discovering the role of culture in product evaluations	Cultural congruence alignment between the product and the market has a positive effect on consumer reviews.	Managers should use cultural congruence as a factor in their marketing mix decisions.
Timoshenko & Hauser (2019)	Identifying customer needs from user-generated content	UGC is as valuable a source of customer needs as customer interviews and focus groups.	Managers may consider using UGC to provide customer insight at a greater frequency, comparable value, and lower cost than traditional methods leveraging machine learning.
Puranam, Narayan, & Kadiyali (2017)	The effect of calorie posting regulation on consumer opinion	UGC enables the tracking of changes in consumer opinion over time and the impact of external events.	Automated Bayesian topic modeling can be used to measure and understand the evolution of consumer opinion.

Brands can also leverage reviews to improve recommendation engines (Ansari, Li, & Zhang, 2018), dynamically create product and customer segment positioning maps (Moon & Kamakura, 2017), identify low-frequency customer needs (Timoshenko & Hauser, 2019), track changes in consumer opinion which occur over time and due to external events (Puranam, Narayan, & Kadiyali, 2017), as well as predict review ratings (Büschken & Allenby, 2016). Additionally, reviews can impact how consumers value brands. Integrating hotel revenue panel data with online reviews, Hollenbeck (2018) demonstrates how property-specific information impacts brand value. Results indicate consumers place greater trust in reviews than brand reputation. This finding also contributes to understanding how reviews can impact eCommerce sales, which Liu, Lee, and Srinivasan (2019) explored. They found reviews with favorable aesthetics and price information increase conversion.

Reviews with higher expressions of emotional arousal are perceived as less helpful, but the relationship is mitigated by the customer's perception of the effort invested to write the review (Yin, Bond, & Zhang, 2017). The degree of emotionality expressed in reviews also has different effects: high-emotion fosters less trust, helpfulness, and purchasing intentions than low-emotion reviews with utilitarian products, whereas the degree of emotionality has the opposite effect on hedonic products (Rocklage & Fazio, 2020). Moreover, writing a review and sharing emotional information can lead to more impulsive purchase decisions by the reviewer (Motyak et al., 2018). Furthermore, the expressed arousal may be impacted by the device an actor uses; according to Melumad and Meyer (2020), consumers share more personal feelings, thoughts, and other self-disclosing information on mobile devices. Reviews written on mobile devices are more affective, more concrete, less extreme, and have lower consumption value—i.e., the perceived value of reading a particular review—over time (Ransbotham, Lurie, & Liu, 2019). Accordingly,

managers seeking more direct feedback from customers should encourage reviews on mobile devices, while brand managers maximizing reviews' utility to other customers should encourage reviews written on desktops.

Reviews' consumption value also changes with a product's lifecycle. With new products, microblogs (i.e., Twitter), reviews, and advertising initially drive sales; however, the impact of microblogs decreases over time, while review volume (i.e., number of reviews) and valence (i.e., communication signal of rating, such as a star) becomes more significant (Marchand, Hennig-Thurau, & Wiertz, 2017). Intuitively, the more reviews a product has impacts its success in the marketplace (Marchand et al., 2017), aligning with an echoverse marketing perspective whereby all five V's (Dekimpe, 2020) result in a complex web of echoes across actors.

3.5 Enhancing brand performance

Research employing ATA has provided new insights into drivers of brand value, contributors to brand risk, sales, and a brand's ability to understand the perceptions of customers regarding their place in the market (as shown in Table 7). The objective of enhancing brand performance is to leverage the echoverse to the brand's benefit, which in most research means financial performance. According to a growing body of scholars, brand performance should also include accountability for a brand's societal impact (Crockett & Grier, 2020; Hunt, 2019; Lehmann, 2020; Rust, 2020). Holistically, a brand "is viewed as an institution of and in society, with responsibilities to the local and, at times, global community beyond the maximization of shareholder wealth" (Parris & McInnis-Bowers, 2017, p. 691). How a brand participates in the echoverse can have implications beyond a brand's bottom line because it impacts a broader array of stakeholders, including local communities and the planet. Although marketing is expected to create a better world (Chandy et al., 2021), responsible business and sustainability practices have

not been explored in the marketing literature by leveraging ATA. Instead, the focus has been on financial outcomes.

Table 7. Overview of articles exploring enhancing brand performance

Author	Marketing Task	Key Findings	Practical Implications
Bhattacharya, Misra, & Sardashti (2019)	Determine the impact of entrepreneurial and market orientation on shareholder risk	Idiosyncratic risks increase with entrepreneurial orientation and decrease with market orientation; however, entrepreneurial orientation reduces systematic risk.	Managers should consider the likely risks and returns to be experienced by the brand when determining a strategic orientation.
Dotzel & Shankar (2019)	Determine service innovations' effect on brand value	Business-to-business (B2B) service innovations positively impact brand value and do not affect brand risk. The number of product innovations increases brand value, but the effect is less when the service innovation emphasizes customers.	Managers should consider launching B2B service innovations because there is little effect on brand risk and they positively impact brand value. Additionally, managers should be cautious of emphasizing customers in B2B service innovation announcements.
Gabel, Guhl, & Klapper (2019)	Map market structures	Applying a neural network language model to identify latent product attributes and then reducing their dimensionality produce a two-dimension product map that outperforms econometric methods.	The authors proposed method produces easy-to-interpret product mappings with clear separation between clusters, providing managers insight that may benefit the design of store aisles/shelves and inform cross- selling strategies.
Homburg, Theel, & Hohenberg (2020)	Determine the composition of marketing excellence	Investors place greater value on marketing excellence than on strategies related to market orientation and marketing capabilities.	Managers should consider focusing on achieving organic growth by building marketing ecosystems within and beyond the brand's industry, creating agile market behaviors responsive to new information, and engaging directly with end-users.
Kim & Kumar (2018)	Evaluate the effectiveness of B2B direct marketing communications	Direct brand communications have a cumulative effect on customers' purchase behavior with relationship marketing efforts contributing to customers' goodwill and greater effectiveness than economic marketing.	B2B brand managers should consider that there may not be a fixed number of relationships states applicable to all customers and that customers' perceptions of the importance of brand-offered value changes with time.
Kim, Xiong, & Kim (2018)	Determine the effect of managerial hubris on brand marketing's expenditures	Brands with high corporate hubris place great strategic emphasis on R&D relative to advertising; however, this relationship is mitigated by corporate governance, industry-level strategic emphasis, and brand maturity.	Because increased hubris among executives can lead to underinvestment in marketing activities, managers may need to communicate the value of marketing activities as well as require training and corporate governance oversight.
Klostermann et al. (2018)	Create associative networks from social media content	Clustering posts based on their image and caption text provide unique insights into consumers' perceptions and experiences with brands.	Managers can apply integrative analysis to brand-related social media posts to infer differentiated customer perceptions from brand interactions.

Kübler et al. (2020)	Determine whether product-performance or value-related crises have a greater impact	Product performance and value-related crises have differing impacts with value-related crises causing a decrease in price and product performance elasticity.	Managers should consider that value-related crises have greater potential to evolve from low-level negative eWOM into boycott campaigns or other extreme customer reactions that can extend beyond the brand to other brands within the industry.
Nam, Joshi, & Kannan (2017)	Assess customer brand associations by mining social tags	Analysis of social tags not only shows customers' interpretation of social content and their own mental schema but also can illuminate distinct customer groups with different understandings of content regarding the brand.	Managers can employ social tags as continuous data input to monitor brand associations, evolutions in brand-associated topics, and changes in brand perceptions.
Netzer, Lemaire, & Herzenstein (2019)	Use customer-provided text to predict future behavior	Defaulting borrowers are more likely to reference religion, family, the near future, pleas, general hardship, and use of present and future tense verbs.	Managers should consider that user-provided text can predict the user's financial behavior.
Singh, Marinova, & Singh (2020)	Assess the effectiveness of influence tactics in B2B e-negotiations	Buyer attention mediates the use of influence tactics and provides an early indication on the probability of contract award. The use of competing influence tactics has a negative effect on buyer attention and contract award.	Salespeople should focus their efforts on building buyer attention during the sales process and deploy mixed combinations of complementary influence tactics.
Toubia & Netzer (2017)	Identify promising ideas from unstructured text	Creative ideas can be identified in unstructured text by assessing how well balanced the idea is between familiarity and novelty.	Managers should consider applying the author's method to identify new ideas or to assist in creating new ideas.
Winkler, Rieger, & Engelen (2020)	Determine executives' individual impact on marketing metrics	CMOs possessing high extraversion and low conscientiousness are more likely to convert a new venture's maturity into web traffic.	When selecting a CMO, recruiters for new ventures should carefully consider the candidates' personality traits.
Liu, Singh, & Srinivasan (2016)	Forecast consumer consumption	Information content within tweets and the tweets' timeliness significantly improve forecasting accuracy.	Managers forecasting TV show consumption can significantly improve their models' predictive accuracy with ATA and cloud-computing techniques.
Kupfer et al. (2018)	Assess social media's influence on a prospective partner brand	A partner brand's social media audience size, degree of engagement, and communication forms used to engage the network can lead to higher sales of product offerings, which are the joint creation of both brands.	Managers should consider the partner brands' social media audience and marketing practices as well as request that at launch time the partner brand refrain from posting content that would distract from the joint product.

Specifically, ATA methods provide scholars with new ways to construct meaning from text to identify drivers of brand value (Dotzel & Shankar, 2019; Homburg, Theel, & Hohenberg, 2020), predict product performance (Liu, Singh, & Srinivasan, 2016), assess investment risk (Bhattacharya, Misra, & Sardashti, 2019), specify corporate hubris liabilities (Kim et al., 2018), and predict customer default (Netzer, Lemaire, & Herzenstein, 2019). Exemplifying the risks and opportunities created in the echoverse, Kübler et al. (2020) highlight the differential risk brands face from value-related compared to performance-related crises and illustrate the positive or negative competitive spillover effect value-related crises may have on non-transgressing brands. These spillover effects highlight the omnidirectional flow present in the echoverse.

Research on B2B email communications provides additional insights. First, messages have a cumulative effect, and greater customer goodwill and more transactions result from favoring relationship-building communications (Kim & Kumar, 2018). Second, Singh, Marinova, and Singh (2020) demonstrate buyer attention is impacted by influence techniques and is a robust predictor of contract award. Brand alliances can capture customer attention and drive composite products' sales by leveraging each party's social media reach; however, a partner's network size is only a measure of opportunity. To capitalize on brand alliances, the partner must actively reference the composite product while reducing unrelated, potentially distracting posts (Kupfer et al. 2018)—emphasizing the need to co-create to maximize brand value in the echoverse.

With ATA, brands solicit ideas from new sources (Toubia & Netzer, 2017) and use reams of user-generated data (Klostermann et al., 2018; Nam Joshi, & Kannan, 2017) and basket data (Gabel, Guhl, & Klapper, 2019) to create association and market basket segments. Toubia and Netzer (2017) offer a unique insight: creative ideas are a balance of familiarity and novelty and

can be automatically identified. Thus, opening new opportunities for discovering creative ideas in repositories of unstructured text. While distinct from the research of Timoshenko and Hauser (2019), who demonstrate product reviews can be used to discover customers' unmet needs, the confluence of capabilities highlighted by these authors demonstrate how the echoverse can be an instrumental source of information for new product development and marketing concepts. Although the research on enhancing brand performance is focused on increasing brand value financially, it does not consider a brand's societal impact.

4. Future directions

This review helps researchers and practitioners from distinct fields easily access the marketing literature leveraging ATA methods, it also reveals the following unexplored areas (and related questions) ripe for further investigation.

4.1 Exploring the intent, processes, and effects of amplifying or de-amplifying content

How should marketing mix elements (i.e., the 8 Ps: product, price, place, promotion, people, process, physical, and partnerships) be used in the context of echoverse marketing to amplify or de-amplify content specific to a target audience (i.e., segment) or a target customer (i.e., individual)? If price changes and location openings are effective tools for eWOM generation (Sanchez, Abril, & Haenlein, 2020), what do they mean for pricing and location strategy? What type of eWOM (Luo, Baker, & Donthu, 2019) is likely to cause echoes across channels? What marketing tactics enable eWOM and users' search effects to be harnessed to create echoes, and how can they be tied to business outcomes? If offline content—such as television advertising (Tirunillai & Tellis, 2017)—can impact the echoverse, what other offline elements of the marketing mix can impact the echoverse?

Given the universe of actors in the echoverse, which actors' communications are amplified by whom and how? Furthermore, are different de-amplification strategies necessary for different actors? What is the role of communities (Herhausen et al., 2019) and social network structures in echoverse marketing regarding content's amplification and de-amplification? What are the social and structural mechanisms that influence the echoverse? What is the role of non-human actors, such as chatbots (Kull, Romero, & Monahan, 2021), in amplifying the echo? As brands are being held accountable for their social impact (Parris & McInnis-Bowers, 2017; Hunt, 2019; Russ, 2020), how can they create social network structures to amplify the voices of marginalized groups and social causes to foster change? What is the role of sponsorship, brand alliances, and co-branding in amplifying and de-amplifying communications in the echoverse?

As the global pandemic (Donthu & Gustafsson, 2020) and fake news (Di Domenico et al., 2021) impact society, misinformation's amplification has placed a greater emphasis on the need for governments (national, state, and local), communities, platforms, and brands to de-amplify content, or make their message echo more than the message that is false or misleading. Despite the call for greater transparency (Cambier & Poncy, 2020), "the extent to which a stakeholder perceives an organization provides learning opportunities about itself" (Parris et al., 2016, p. 222). Platforms such as Facebook/Meta are still acting as gatekeepers limiting researchers' ability to explore disinformation (Bond, 2021). With ATA methods, scholars have explored detecting and mitigating negative eWOM (Herhausen et al., 2019) and identifying the optimal response to complaints (Johnen & Schnittka, 2019); however, how to control a negative echo remains elusive and provides enormous opportunities for future research.

4.2 Creating, delivering, and managing the dynamic tuning of texted-based communication

Similar to how dynamic ticket pricing can impact customers' perceptions of fairness and change an industry's marketing strategy (Parris, Drayer, & Shapiro, 2012), what are the impacts of dynamically tuning content in the echoverse? What are the attributes of communication for which consumers expect responsiveness—from whom; in what channel, manner, tone; and with what degree of emotionality, personalization, and customization? How do these attributes vary by platform, device, industry, or brand?

Tuning content can take multiple forms from reacting to individual actors' communications to content curation and generation. However, the demand for brands to generate a tuned response to an actor's interaction is expensive. Nevertheless, new technologies, such as artificial intelligence, are facilitating personalized communications (Perez-Vega et al., 2021), which Riegger et al. (2021) refer to as technology-enabled personalization. How can transaction cost analysis (Anderson, 1985) inform brands' decision-making on the boundaries of the brand to address the human, technological, and content challenges? What strategies are brands employing to address these challenges? What are these strategies' relative opportunities and weaknesses? Are there opportunities for brands to augment their own content libraries and response capabilities with third-party providers; and if so, what kind of business arrangements produce the best outcomes for the brands and the third parties?

Algorithmic discrimination—an algorithm's differential treatment of customers of equal quality, but differing in group membership (Ukanwa & Rust, 2021)—fails to optimize to customers' individual heterogeneity. Therefore, brands risk missing out on profitable customer interactions, but what other opportunities are missed? Algorithmic discrimination also presents potential ethical (Seele et al., 2021), fairness (Morse et al., 2021), and restorative justice (Liu et

al., 2019) concerns. As actors in the echoverse can be automatically classified into groups, such as residents' roles as place-brand ambassadors (Uchinaka, Yoganathan, & Osburg, 2019), what are the risks of misclassification? Is there a risk of excluding certain group members? Can the communication algorithm be trained in a way to avoid ethical concerns and algorithmic discrimination?

4.3 Dive deeper into product review technologies, the five V's, and the effects of online chatter

To date, scholars have not explored the effect of brands' using reviews as a service (RAS)—review technology solutions provided by such brands as Power Reviews, Webimax, Reputation Resolutions, Birdeye, and Podium—as compared to natively submitted reviews. Are there differences in sentiment, emotion, topic, helpfulness, or other review attributes that would influence customer outcomes among RAS providers, as well as among RAS providers and natively submitted reviews, and why? Are there differences in the technical methods RAS providers employ—whether in design, algorithm, review order, or data collection? What are the echo patterns of reviews across different eCommerce channels (i.e., Walmart, Amazon, small and mid-size enterprises)?

In the echoverse, how do the five V's of product reviews impact shopping behavior, echo reach, and the overall relationships with the brand? For instance, is there such a thing as too many or too few reviews? How does the frequency (i.e., pulse) of new reviews affect the echo? What is the pattern of interaction between the echoverse and product reviews? Do product reviews submitted on different sites echo one another? Are there differences in tone, specificity, or sentiment?

Does online chatter inform product reviews or vice versa? What is the interaction of other text-based communication about the product i.e., media content, brand content, consumer-

created content, and other related content that is from competing products/brands, brand communities, or other relevant media? Considering that communication channels echo each other, how can brands manage and influence product reviews and other marketing content to act synergistically?

4.4 Examining the nuances and transparency of public vs. private echoverses

While a few scholars have explored private communications such as email (Singh, Marinova, & Singh, 2020), an enormous opportunity remains for scholars to explore private echoverse environments that are only accessible to invited members. Those environments include proprietary business communication and collaboration platforms (e.g., Slack and Microsoft Teams) as well as long-form text assets often stored in sharing software solutions that help users store and access files across the entire organization. Considering public versus private echoverses, how are social structures and social mechanisms distinct and similar; and can one echoverse influence the other? Given the call for greater brand transparency (Cambier & Poncy, 2020; Parris et al., 2016) and echoverse marketing's learning objective whereby a universe of actors creates directed learning opportunities to facilitate other actors' learning, when should discourse in a private echoverse be shared in the public echoverse and how? Does a private echoverse strengthen brand culture, create internal communities, reinforce brand identity, and encourage participating actors to develop broader identities?

4.5 Measuring the impact of the echoverse and the adoption of ATA methods in practice

Communication in the echoverse provides a greater opportunity to assess not only a brand's effect across multiple actors but also multiple actors' impact on the brand. Communication drives engagement, which drives brand performance (Schaefers et al., 2021). How should marketing metrics evolve to reflect and measure a universe of actors continuously

and simultaneously constructing meaning, exerting co-control, co-owing, and co-creating resources? How can the impact of communications across the echoverse be assessed in terms of brand performance?

What dynamic capabilities of a brand or brand's orientation influence the likelihood the brand will incorporate ATA methods into its marketing practices? Are there differences in brand performance outcomes for brands that do or do not incorporate such methods? Are there differences between industry, product type, or business model that may influence the importance of ATA utilization? Collectively, future research should continue exploring how text-based communications in the echoverse are being used and critically evaluating the ethics and societal impact of doing so. A key question marketers and practitioners should ask is how with the extraordinary mass of material generated in the echoverse does one discriminate between valuable information and noise—notably when one does not know what they do not know? Extending this question further, in scholarly research can ATA methods be used to side-step entrenched thinking and raise up valuable thoughts and perspectives from a marginalized few? Research by Timoshenko & Hauser (2019) showing ATA can discover unmet customer needs, and by Toubia & Netzer (2017) demonstrating novel ideas can be programmatically identified, are but the beginnings of work by marketers to employ ATA methods in the echoverse to look for what is not known as opposed to evidence for what is suspected.

5. Conclusion

In the era of echoverse marketing, communications occur among a universe of actors who are continuously and simultaneously constructing meaning together. The distinction between consumer and brand communications is fading and moving toward multiple stakeholders (i.e., human and nonhuman actors) listening, encoding meaning, and acting in an echoverse. Unlike

traditional marketing communication strategies in which the brand is the initiator, in echoverse marketing the brand is only one actor within the universe of actors who interact in real-time. The focus of brands has shifted from leading to guiding, striving to encourage the universe of actors through participation, actively encouraging, and enabling other actors to contribute to the process of meaning creation, resource co-creation, and future communications.

In short, this study discusses that along with communication actors being defined collectively through an assemblage of heterogeneous human and nonhuman actors (Price & Coulter, 2019), marketing communications have evolved from interactions between the brand and customers to a universe of human and nonhuman actors creating and co-creating meaning in the echoverse. This study contributes to understanding marketing communications in the echoverse and provides actionable recommendations to managers communicating among a universe of actors by systematically reviewing prior research empirically exploring a marketing phenomenon leveraging ATA. Marketing communication's evolution within the echoverse will pose significant opportunities for and challenges to marketing functions and will require developing current and future employee skills (Ostmeier & Strobel, 2022) to lead, manage, and effectively communicate in the echoverse.

This study additionally contributes to the methodology for conducting reviews on emergent phenomena by utilizing a complex BoW and enabling the exploration of long-form text assets. Although this review was conducted in a disciplined manner, potential limitations must be acknowledged. The sampling pool was limited to articles utilizing ATA methods comprising at least one percent of the published articles in top-tier marketing journals. Bibliometric methods, keyword matching, and other ATA methods used to identify scholarly research relevant to a topic of interest that become the building blocks (i.e., the papers cited) of empirical studies and

theoretical foundations of propositions have a profound influence on knowledge accumulation. Given the process of theory building includes abstracting, generalizing, relating, selecting, explaining, synthesizing, and ideating which generates references, data, variables or constructs, diagrams, and hypothesizes or propositions (Weick, 1995), the choice of sampling method alters the nature and insight of the data (Singh, Hillmer, & Wang, 2011). Absent from literature reviews in empirical and theoretical articles is a discussion on the effect of the proprietary algorithms of databases (EBSCOhost, 2020; Google Scholar, 2022) and databases' content limitations (i.e., accessibility and availability) on their selection of articles to support their process of theory building. The method proposed herein addresses these issues by downloading all articles published by the targeted journals and providing transparency into the algorithm employed for ranking them on relevancy.

ATA methods need to be developed for exploring long-form text assets to aid in understanding brands' document repositories, databases of scholarly research, media articles, and 1.2 billion publicly accessible websites with the use of web-scraping technologies. Based on this review, most of the understanding of text-based communication is based on short-form text—fewer than 2,000 words (Milligan, 2020), thus ignoring the diversity of content in long-form texts. This study represents a pioneering effort to review marketing communications' evolution in the echoverse, identify priorities for research and practice, and conceptualize echoverse marketing.

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Appendix

A. Machine learning application

A novel method for sampling longform documents was developed which employed a dynamic bag of word (BoW) approach. In the application the BoW is created from the tokenized words of an exemplar document, and in which the language utilization is encoded enabling a comparison of documents based on the probability of the researcher's interest. Details of the application are provided below and code is available upon request.

A.1 Literature search and extraction to create normalized corpora

Grobid, an open-source machine learning library (Grobid, 2020), was employed to extract text from scholarly article PDFs. Article titles, keywords, abstracts, and bodies were then parsed, retaining only those words that contained the part of speech labels—noun, proper noun, verb, adjective, or adverb—using the open-source Python library, spaCy (spaCy, 2020). Extracted words were tokenized using NLTK Porter Stemmer (NLTK, 2020) and cleaned to remove tokens with only one character, numerals, symbols, and Greek characters.

A.2 Characterizing: Textual analysis for lexical identification

To characterize the word usage in each article, a dynamic BoW was implemented. Usage information was encoded into the BoW by using complex numbers as weighted occurrence counts—whereby the real component represents the word's noun-like usages, whereas the imaginary component represents the word's verb-like usages. Lexical analysis is essential in the early stages of natural language processing because the text is assigned a token value, which serves as the identification of meaning and has been applied in digital marketing contexts (Aggarwal, Vaidyanathan, & Venkatesh, 2009; Moon & Kamakura, 2017; Onishi & Manchanda, 2012). Applying lexical grammar in the BoW enables distinguishing between articles that

discuss a similar topic and those that approach the topic from different perspectives. This approach is exemplified by comparing two documents that each contain two sentences: (Document 1) "*Bob likes big data. Bob likes Judy*." (Document 2) "*Big data likes Bob. Judy likes Bob*." In a traditional BoW, these two documents are identical; however, the sentences have distinct meanings. Applying complex numbers to represent the occurrence counts, whereby the parts of speech are weighted differently, is more aligned with how meaning is constructed. In communication, the noun version of a word has a significantly different meaning than the verb version and, therefore, should be counted separately. Thus, in the followed approach, the lexical identification process interprets Documents 1 and 2 as follows (see Table 1A, 2A, & 3A:

Table 1A. Document 1 lexical identification

Usage	Proper Noun, nsubj	VERB, ROOT	ADJ, amod	NOUN, dobj	PROPN, nsubj	VERB, ROOT	PROPN, dobj
Token	Bob	like	big	data	Bob	like	judi
Points	1.0 + .0*i*	.0 + 1.0*i*	.25 + .0*i*	.5 + .0*i*	1.0 + .0*i*	.0 + 1.0*i*	.5 + .0*i*

Table 2A. Document 2 lexical identification

Usage	ADJ, amod	NOUN, nsubj	VERB, ROOT	PROPN, dobj	PROPN, nsubj	VERB, ROOT	PROPN, dobj
Token	big	data	like	bob	Judi	like	bob
Points	.25 + .0*i*	1.0 + .0*i*	.0 + 1.0*i*	.5 + .0*i*	1.0 + .0*i*	.0 + 1.0*i*	.5 + .0*i*

Table 3A. Identification process of Document 1 & 2 results in the following BoWs:

	Document 1	Document 2
bob	2.0 + .0*i*	1.5 + .0*i*
big	.25 + .0*i*	.25 + .0*i*
data	.5 + .0*i*	1.0 + .0*i*
judi	.5 + .0*i*	1.0 + .0*i*
like	.0 + 2.0*i*	.0 + 2.0*i*

A.3 Article selection and inclusion criteria

The first step in creating the review sample is specifying a prototype, such as an exemplar academic article. Berger et al.'s (2020) article was used as the prototype to identify relevant articles on ATA. To discover similar articles in the corpus, a BoW composed of the tokens taken from the prototype and each article in the corpus individually was built. The occurrence counts were then converted into a frequency distribution to measure the similarity between the two distributions using Jensen-Shannon divergence. The occurrence counts and frequency distributions are built as described below.

The occurrence counts are composed of the combined tokens from the prototype document and the unknown document. If the token appears in the prototype document, the count from the prototype document is used for the prototype occurrence count; and if the token does not appear in the prototype document, an exceedingly small number (1.0e-320 + .0i) is assigned to prevent division by zero in subsequent calculations. The process is then repeated for the unknown document, and the frequency distributions are compared. A weighting factor was used to identify the relevance of a given token to the topic. Weighting started a 1.0 for the first iteration and was adjusted according to the results of the following evaluative iterations. The prototype document's BoW is designated as p and the unknown document's BoW is designated as u. Next, the occurrence counts are converted into a frequency distribution using the following equations.

In Equation 1, the prototype document is defined as

(1) $$\Pi_i = \frac{p_i * w_i}{\sum_j (p_{j*} w_j)}$$

In Equation 2, the unknown document is defined as

(2) $$\mathrm{A}_i = \frac{u_i * w_i}{\sum_j (u_j * w_j)}$$

In Equation 3, Jensen-Shannon Divergence is applied as

(3) $$j = 1 - \left| \frac{\sum_i \Pi_i \log_2\left(\frac{2\Pi_i}{\Pi_i + A_i}\right) + \sum_i A_i \log_2\left(\frac{2A_i}{\Pi_i + A_i}\right)}{2} \right|^2$$

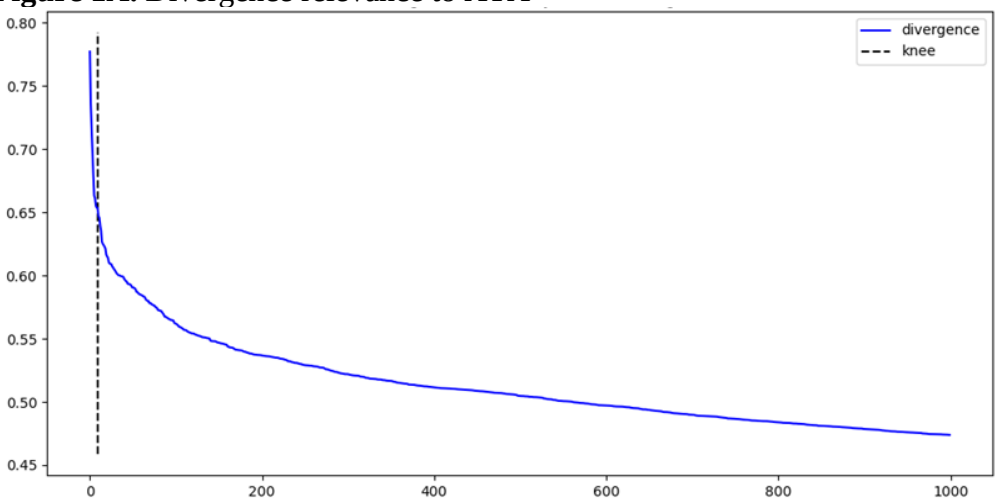
Given the aim to derive a value that could be interpreted as a probability of relevance, the Jensen-Shannon Divergence was subtracted from one. Magnitude squared, rather than magnitude, was selected because of the smoother transition from max to knee in the curve to convert the divergence results to a probability-of-relevance curve. The initial results revealed that the articles with a high score tend to be relevant; in contrast, around the curve's knee, the relationships among the articles cease to be relevant to the prototype. To calculate a document's relative relevance, a final transform was done to suppresses the values beyond the knee. To do so, the divergence value was multiplied by a sigmoid function in Equation 4:

(4) $$r = \frac{je^{\alpha(j-\beta)}}{1 + e^{\alpha(j-\beta)}}$$

Where α controls the crossover's steepness, and β controls the crossover's center-point. The greater the value for β, the steeper the transition. Because the knee in the divergence curve occurs at different levels depending on how well the prototype matches anything in the corpus, a way to dynamically set α and β depending on the prototype-to-entire-corpus results was needed. Thus, the Kneedle algorithm (Satopaa et al., 2011) was used with the following parameters: S = 1; curve = concave; direction = decreasing; online = true. Figure 1A represents the knee identification. The y-value identified by the algorithm as the knee was 0.65 = α; S, controlling the transition's steepness from relevant to not-relevant, was set at 75. These values were used in Equation 5 to calculate β:

(5) $$\beta = \frac{S}{\alpha}$$

Figure 1A. Divergence relevance to ATA



Following this approach, the lower the knee's value, the less the prototype matches the corpus—enabling documents to be quickly identified as irrelevant. The steps above produced a list of documents (i.e., articles) rank ordered in relevancy to the prototype article.

Next, I iteratively reviewed the top-ten most relevant articles as determined by the application. To ensure the analysis was reliable and objective, two authors independently evaluated the articles based on the inclusion criteria (i.e., if the article was an empirical analysis that applied an ATA method), and a third author served as an auditor. The proportional reduction in loss (PRL) reliability measure (Rust & Cooil, 1994; Parris et al., 2016) was not calculated because no inter-rater disagreements emerged. Exemplar articles of the desired subject, ATA, were identified as *prototypes*; and articles which were irrelevant were identified as *anti-types*. With each iteration, the BoW was re-weighted by multiplying the weight of tokens found in the prototype articles by 2 and multiplying the weight of the tokens found in anti-type articles by 0.25. The approach provided an emergent keyword-list containing thousands of keywords ranked by relevance to the topic. The result was a rapid consolidation of relevant articles.

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ESSAY II

Revisiting Personalization: Implications for AI-Personalized Environments

Abstract

This study introduces a central concept from the field of ecology— ecological specialization— the breadth of a specie's utilization of resources to the field of marketing and provides a typology of personalized digital environments. Specifically, I conceptualize how the resources within a firm's content library interact with the degree of personalization to curate their digital marketing environment. Using a proprietary dataset from an email marketing company that employed artificial intelligence to personalize emails based on a customer's observed preferences; this paper examines the concept of specialization and its implications for AI-personalized digital environments. I show how the underlying assumptions of traditional marketing metrics may limit marketers' ability to understand AI-personalized environments. The paper provides recommendations to marketers and new pathways for future research.

Keywords: AI-personalized environments, ecology, specialization, marketing

1. Introduction

Increasingly, artificial intelligence (AI) technologies create personalized environments for consumers by curating the content resources—blog posts, promotions, videos, products, articles, events, images, reviews, audio files, and social media posts—transforming how consumers interact with the digital world (Chung, Wedel, & Rust, 2016; Kumar et al., 2019). Importantly, customers' utilization of content resources influences every stage of the customer journey and is crucial to customer satisfaction and a brand's value (Greene & Kune, 2021). However, while much scholarly attention has been paid to how to make recommendations (Liu, Tsai, & Chiu, 2011; Chung, Rust, & Wedel, 2009) and the financial benefits of personalization (Munz, Jung, & Alter, 2020; Zhang & Krishnamurthi 2004), consideration of the patterns of customer interactions in AI-personalized environments is absent from the marketing literature.

Interestingly, ecologists and evolutionary biologists have long explored a specie's utilization of resources in its environment (Devictor et al., 2010; Futuyma & Moreno, 1988; Hutchinson, 1957) and have shown that the resources present within the environment impact the success of a species (Thompson, 2005). The breadth of a specie's utilization of resources (i.e., its ecological niche) is known as *ecological specialization (specialization)*. In ecology literature and in this paper the following terms are used interchangeably for specialization: specialization, ecological niche (niche), and a specie's utilization of resources. In other words, the specialization/niche of a species (or an individual—i.e., customer) refers to the range of interactions it has with the available resources in the environment. Specialization exists along a continuum from a generalist to a specialist (Forister, Dyer, Singer, Stireman & Lill, 2012). Generalists consume a variety of resources, while specialists are fussier about what they consume. More interestingly, generalist species are increasingly "replacing" specialist species,

whereas specialist species are declining and experiencing higher extinction risk relative to generalist species (Clavel, Julliard & Devictor, 2011).

To apply the wisdom of ecology to marketing, I posit that how consumers (i.e., homo sapiens) explore in digital environments is similar to how bees (i.e., pollinators) search in a field for pollen. As marketers increasingly leverage AI personalization to curate digital environments for individual customers, I argue marketers adopt the concept of specialization from ecology to examine customers' utilization of content resources (i.e., specialization). In doing so, this paper aims to address the following overarching research question: does the breadth of a customer's content interactions (i.e., specialization) influence the extent of their engagement in an AI-personalized environment?

Creating and distributing content is a vital strategic marketing objective (Moutsos, 2022), which represents approximately 25% to 30% of small and mid-size enterprises' (SMEs) marketing budgets (Agius, 2021) and billions of dollars globally (Bauer, Gordon, & Spillecke, 2013). For both B2C and B2B brands, content is increasingly important and requires large investments (Stahl, 2021; Rose, 2022). Hence, an understanding of the breadth of content resources needed to deliver AI-driven personalization can better inform a brand's content strategy. This paper highlights the co-evolution of marketing technology and marketing analytics for personalization, i.e., how AI technologies are reshaping marketing practices (Vlačić, Corbo, e Silva, & Dabić, 2021; Wedel & Kannan, 2016), and proposes a new marketing measure adopted from ecology to shed light on customer's utilization of content.

Through analyzing a proprietary dataset from an AI email marketing company that employs topic modeling to identify, curate, and deliver a personalized email to each individual customer based on the customer's observed preferences, this paper explores the holistic pattern

of customer interactions with digital content in an AI-personalized environment to determine whether a customer's breadth of content utilization (i.e., their degree of specialization) influences their engagement. The contribution of this paper is four-fold. First, I construct a 2 (Content library High/Low) x 2 (Personalization High/Low) typology of personalized digital environments to conceptually illustrate how the resources within a firm's content library interact with the degree of personalization to curate their digital marketing environment. Second, I highlight how the underlying assumptions of current marketing metrics may limit marketers' ability in understanding AI-personalized environments and propose a new marketing measure adopted from ecology in the context of email marketing. Third, to the best of my knowledge, this study provides the first examination of the holistic pattern of customer interactions in an AI-personalized environment by introducing ecological specialization into the field of marketing, as well as testing for its application. Finally, this study provides recommendations to marketers and new directions for scholarly research.

2. Background

2. 1 Personalization

Personalization is one-to-one marketing with a target segment of size one (Arora et al., 2008) whereby marketers tailor one or more aspects of a brand's marketing mix to an individual customer (Peppers & Rogers, 1997; Shaffer & Zhang, 2002). To meet customers' expectation that brands will provide one-to-one interactions aligned with their interests (Parris, 2013), marketers are increasingly adopting AI technologies (Davenport, Guha, Grewal, & Bressgott, 2020; Vlačić et al., 2021) for the generation of content (Persado, 2022), distribution of marketing communications (MailChimp, 2022), and curation of content resources (Retention Science, 2022). While scholars have explored, personalization approaches (Urban, Liberali, MacDonald,

Bordley, & Hauser, 2014), outcomes of biased versus unbiased algorithms (Ukanwa & Rust, 2021), the personalization-privacy paradox (Aguirre, Mahr, Grewal, De Ruyter, & Wetzels, 2015), and proposed personalized marketing frameworks (Kumar et al., 2019), the broader experience of the customer within the personalized environment is often ignored. Furthermore, scholars and practitioners alike are often masking the unique heterogeneity of the individual customer (Ding et al., 2020) and the heterogeneity of personalized environments.

A challenge when exploring the extant marketing literature on personalization is that it is often discussed in binary terms—i.e., personalized vs. not personalized—without distinguishing the degree (i.e., extent) along a continuum ranging from low—no personalization to high personalization—AI adaptive (Arora et al., 2008; Li, 2016). It is important to note that personalized technologies can be adaptive (i.e., iteratively adapt to the evolution of a customer's observed preferences). In contrast, other technologies are not intended or designed to be adaptive. A boundary—tangible restriction—of the degree of personalization an AI technology can employ is the extent of content resources utilized. Content utilization boundaries are conditions restricting the use of diverse content to personalize the digital environment. In other words, when an algorithm selects content resources for a customer, it is limited in the degree to which it can make relevant recommendations by the content library from which it draws. I conceptualize content libraries as existing along a continuum from those with a small number of content resources in only a few topical or categorical domains on the low end to content libraries with large numbers of content assets spanning a wide breadth of topical or categorical domains. Even the most advanced personalization technology is limited in its capacity to explore or exploit an individual's preferences by the breadth and depth of the content resources it can utilize.

To provide an organizing framework (Doty & Click, 1994), I propose that the degree of personalization and content resources within the content library matter and provide a 2 (Content library High/Low) x 2 (Personalization High/Low) typology of personalized digital environments (see Figure 1). A sampling of research on personalization was classified using the typology and the research focus, type of research, and if the personalization approach was adaptive was abstracted (see Table 1).

Figure 1. 2 x 2 typology of personalized digital environments

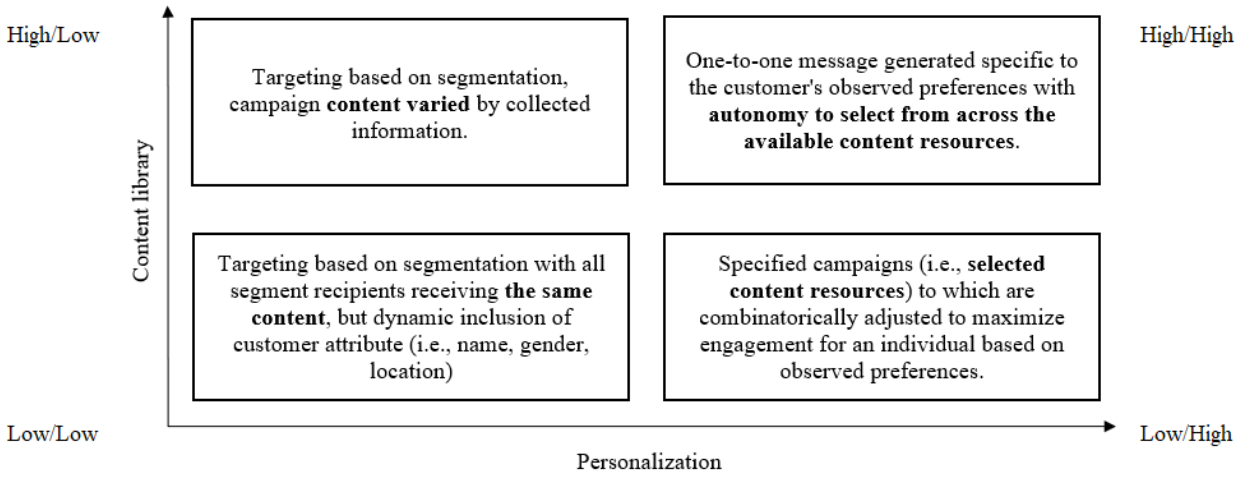


Table 1. A sampling of research on personalization

Paper	**Independent variable**	**Dependent variable**	**Research focus**	**Method**	**Context**	**Content library**	**Personalization**	**Adaptive personalization**
Current paper	d' index for content resource interaction specialization	Customer engagement	Specialization of customer content interactions	Empirical analysis	Retailing emails	**High** – content library of magazine articles, blogs, videos, events	**High –** based on the user's observed preferences	Yes
Munz, et al., (2020)	Surname, surname first letters, demographics	Decision to donate, donation amount	Effect of surname matching	Field experiment	Charitable giving emails	**Low** – same content	**Low** – based on surname	No
Pfiffelmann, Dens, & Soulez (2020)	Presence of personalized add (name and image)	Visual attention, attitude toward the ad	Effect of personalized ads on visual attention and attitude	Experiment	Recruiting ads	**Low** – same content	**Low** – displaying name and photograph	No
Tran, Lin, Baalbaki, & Guzmán (2020)	Perceived personalization, personalized vs generic ad	Brand equity, brand usage intention	Personalization of social media ads effect on brand equity	Survey and experiment	Facebook ads and sunglasses	**High** – one product 8 style choices	**Low** – based on user's collected style preferences	No
Li (2019)	Customer expectation of a personalized message	Attitude toward the ad	Effect of customer's expectation of personalization	Experiment	Promotion of a multivitamin	**Low** – same content	**Low** – based on age and gender	No
Chung et al., (2016)	Self-customization, adaptive personalization, adaptive personalization with social networks	Precision, recall, F1, accuracy, specificity, positive accuracy	Adaptive personalization incorporating social networks	Experiment	News	**High** - RSS feed/news content	**High** - based on the user's social network, and user's observed preferences	Yes
Bang & Wojdynski (2016)	Presence of name and geographic information, high cognitive demand, low-cognitive demand	Visual attention paid, duration till first add fixation, frequency of add attention, perception of add, attitude toward add	Visual attention to personalized banner ads	Experiment	Banner ads on websites	**Low** - same content	**Low** - based on name and geographic information	No

Li (2016)	Generic or personalized ad, perceived personalization, uniqueness need, privacy concern	Attitude toward ad, purchase intention	Differences in effectiveness between perceived and actual personalization	Experiment	Digital ads	**Low** - same content	**Low** - based on name and location	No
Bleier & Eisenbeiss (2015)	Time passing, degree of content personalization, perceived informativeness, perceived intrusiveness, congruency of banner displaying website	Click-through, view-through	Timing and placement of banner ads	Field and lab experiments	Banner ads on websites	**High** - product catalog	**High** - based on the customer's most viewed items from the prior session	No
Kaptein, Markopoulos, Ruyter, & Aarts (2015)	User persuasion profile, Persuasive psychological principle	User influence	How persuasive technologies can adapt to influence user's	Case study experiments	Text and email for healthy lifestyles, emails for a travel agency	**High** - library of messages	**High** - based on the user's observed preferences	Yes
De Keyzer, Dens, & De Pelsmacker (2015)	Perceived personalization, attitude toward the platform, perceived ad relevance	Brand attitude, intention to click	Customers' responses to personalized social media ads	Experiment	Social media ads	**Low** - same content	**Low** - based on collected information	No
Aguirre et al. (2015)	Information collection strategy, website reputation, presence of trust-building cues	Click through intention, feelings of vulnerability	Exploring the personalization -privacy paradox	Experiment	Social media ads	**High** - multiple variations of ad	**Low** - based on collected information	No
Hauser, Liberali, & Urban (2014)	Website morph timing	Switching costs, potential website exit, total clicks	Optimal timing of website morphing	Proof-of-feasibility	Banking website	**High** - 8 morphs	**Low** - based on segment	Yes

Urban et al. (2014)	Cognitive style, customer buying process, product characteristic	Click-through, brand consideration, purchase likelihood	Optimal selection of banner ads	Field test and experiment	Media website and automotive information website	**High** - multiple morphs with varied content	**Low** - based on segment	Yes
Ho & Bodoff (2014)	Attitude formation	Item selection	Consumer attitude formation toward personalization agent	Lab and field experiment	Book and music retailing websites	**High** - thousands of books or music tracks	**Low** - based on user's collected preferences and external information	No
Tucker (2014)	Personalized advertising pre-change in Facebook privacy controls, personalized advertising post-change in privacy policy.	Click-through	Influence of privacy controls in personalized ads	Field experiment	Non-profit social media campaigns	**Low** - same content	**Low** - inclusion of user's institution or celebrity's name whom they follow	No
Lambrecht & Tucker (2013)	Generic or dynamically targeted ad, visited a review site	Customer purchase, time to purchase	Effectiveness of dynamically vs generic retargeted online ads	Field experiment	Travel firm advertising on external websites	**High** - varied content	**Low** - based on single product view	No
Liu et al., (2011)	Content recommendation method	Hit ratio (number of clicked articles/number of recommended articles)	Development of recommendation model	Online-experiment	Blog article recommendation	**High** - content library of blog posts	**High** - based on user's observed preferences and popular topics	Yes
Atahan & Sarkar (2011)	Profile learning approach	Identification of user age	Development of a method for active profile learning	Simulated experiments	Customer web browsing	**High** - library of offer sets--web pages	**High** - based on the user's observed preferences	Yes
Chung et al., (2009)	Minimum dissimilarity model, Adaptive personalization	Percentage of song played, percentage of songs finished,	Method for adaptive personalization of digital audio	Experiment	Digital audio on a mobile device	**High** - library of digital audio	**High** - based on observed preferences	Yes

Frias-Martinez, Chen, & Liu (2009)	Version of adaptive digital library: adaptive and adaptable; cognitive style;	User performance (amount of time and transactions required to complete a task) Perception of digital library	Comparison of adaptive or adaptable personalization on cognitive style for digital library interface	Experiment	Customization of digital library search interfaces	**High** - 3 three search interfaces	**Low** - based on assignment to defined cognitive style	No
Khan, Lewis, and Singh (2009)	Customization of marketing promotions, purchase cycle temporal differences between customers, cross sectional differences between customers	Decision to purchase, purchase expenditure	Comparison of one-to-one, segmented, and mass marketing	Simulation	Promotions for online grocery and drug retailer	**Low** - selected price promotions	**High** - based on the user's transaction history and preferences	No
Hauser, Urban, Liberali, Braun (2009)	Website characteristics, user cognitive style	Purchase probability	Adapting a website's look and feel to match the cognitive style of the user	Experiment	Dynamically adapting a broadband provider's website	**High** - multiple website morphs with varied characteristics	**Low** - based on the user's cognitive style segment	Yes
Liang, Yang, Chen, & Ku (2008)	Semantic-expansion, traditional Bag-of-words method	Number of articles identified of interest	Development of personalization method	Experiment	Library information retrieval	**High** - 200 master's theses/doctoral dissertations	**High** - based on the user's stated preferences	No
Zhang & Krishnamurthi (2004)	Customized promotions	Purchase probability, brand selection, purchase quantity, promotion, expected promotion cost, expected profit	Development of recommendation model	Simulation	Online grocery retailing	**Low** - price discount and timing	**High** - based on the user's transaction history	No
Ansari & Mela (2003)	Email content and design	Click-throughs	Development of	Simulation	Promotional emails to drive web traffic	**High** - varied content	**High** - based on user's usage history	No

			recommendation model					
Moon (2002)	Message style, customer personality type	Manipulation of user's ranking, attitude, and evaluation of information	Effect of tailoring message style to customer's personality	Experiment	Vehicle comparisons and online content consumption	**High** - varied content	**Low** - based on the user's assignment to dominate or submissive personality type	No
Ansari, Essegaier, & Kohli (2000)	Individual expressed preferences, other customer preferences, evaluations, product characteristics, customer characteristics	Recommendation accuracy	Development of recommendation model	Simulation	Movie recommendations	**High** - library of movies	**High** - based on user's preferences, preferences of other customers, expert evaluations, item characteristics, and individual characteristics.	No

As illustrated in Figure 1 and Table 1, content resources and the degree of personalization interact to create different types of personalized digital environments. An example of scholarly research which employs high personalization and a high content library (i.e., an AI personalized adaptive environment) is Chung et al.'s (2016) experiment which recommends news articles to a user based on their social network and observed preferences. In contrast, an example of scholarly research that uses a single content resource (i.e., low content library) and a low degree of personalization is Munz et al.'s (2020) field experiment that distributed identical content to every email subscriber altering only one attribute to the message recipient. Two other possible personalized digital environments are either a high content library with low personalization or a low content library with high personalization. Tran et al. (2020) provide an example of scholarly research which has a high content library with multiple resources (i.e., 8 variations of a social media ad) but relies on a low degree of personalization by leveraging information collected from users on their style preferences as opposed to their observed preferences. Zhang & Krishnamurthi (2004) provide a contrasting example of a low content library with high personalization, as the algorithm can tailor the promotion price and timing to the customer's observed preferences.

In the extant literature on personalization, there is limited discussion on where a study falls on the continuum of possible personalized digital environments. At present, to determine the personalization context, one must carefully examine the method section for details about the content resources and the degree of personalization applied, which I argue limits the generalizability of marketing research on personalization. Furthermore, to the best of my knowledge, this is the first paper to conceptually discuss how the interaction of content resources and the degree of personalization form the personalized digital environment.

To date, when scholars have explored personalization, they have relied on simulations, field studies, and case studies while using outcome measures that capture the recipient's immediate response to personalized treatments, such as click-throughs (Bleier & Eisenbeiss, 2015; Urban et al., 2014), recommendation accuracy (Liu et al., 2011; Liang et al., 2008), and purchase, purchase intention, or attitude (Li, 2019; Li, 2016; Lambrecht & Tucker, 2013). To the best of my knowledge, this is the first project which empirically explores an AI-personalized environment as opposed to a personalized treatment or recommendation method. Additionally, this is the first project to explore personalization through the perspective of holistic patterns of user interaction and to investigate if personalization leads to more customer engagement. Despite significant scholarly attention paid to personalization, there remains limited research on personalization in the context of email marketing despite its wide use.

2. 2 Email marketing

Given email's ubiquity—more than 4 billion people use email daily, and eight of ten email users under thirty admit to checking it while using the restroom (Holland, 2022; Phrasee, 2022). It is not surprising that email marketing drives more sales than any other digital channel and generates $42 for every dollar spent (i.e., a 4,200% ROI) (Campaign Monitor, 2022; Kirsch, 2022). Furthermore, AI-personalized email technologies are going mainstream with application services providers such as Intuit acquiring Mailchimp in 2021 for approximately $12 billion to provide an AI-driven customer platform for SMEs (Mailchimp, 2021) and Constant Contact, one of the largest email marketing software providers serving 600,000 companies (Cudmore, 2022), purchasing Retention Science, an AI email marketing startup, in 2020 for $35 million (Jao, 2021).

However, despite email marketing's wide use, it has received scant scholarly attention. To date, that research has followed two tracks. The first focused on how customers respond to email campaign attributes through either subscriber engagement, such as opens and clicks (Balakrishnan & Parekh, 2014), purchases (Goic, Rojas, & Saavedra, 2021; Kumar, 2021; Munz et al., 2020; Sahni, Wheeler, & Chintagunta, 2018; Thomas, Chen, & Iacobucci, 2022), or performing a desired action (Ding, Poquet, Williams, Nikam, & Cox, 2018). The second focused on disentangling subscriber engagement with email program outcomes like email list churn (Ascarza, Netzer, & Hardi, 2018), program profitability (Zhang, Kumar, & Cosguner, 2017); or timing consumer opt-in and out (Kumar, Zhang, & Lou, 2014). Table 2 is a sampling of the email marketing literature.

Table 2. A sample of email marketing empirical studies

Paper	Independent variables	Dependent variables	Research focus	Context	Personalization	Adaptive personalization
Current Paper	d' index for content resource interaction specialization	Customer engagement	Utilization of digital resources on customer engagement	AI personalized retailer emails	Yes	Yes
Thomas et al. (2022)	Type of email: promotional, CRM, alerts	Email opening rate, spending amount, shopping cart abandonment rate	Type of email on customer engagement and purchasing	Email campaigns for a reseller of live entertainment tickets	Yes	No
Kumar (2021)	Email design elements	Email open, click, and repeat open, consumer purchases	Email newsletter design on subscriber response, and subscriber purchases	Retail promotional emails	No	No
Goic et al. (2021)	Received triggered email, the configuration of triggered email	Customer revenue	The effect of cart abandonment emails on customer purchase	Triggered retail email campaigns	Yes	No
Singh, Marinova, & Singh (2020)	Influence tactics, buyer's attention	Contract award	Sales tactics effectiveness in B2B email negotiations	B2B email negotiations between buyers and sellers	No	No
Munz et al., (2020)	Surname, surname first letters, demographics	The decision to donate, the donation amount	Effect of matching potential donor and receipt names on charitable giving	Charitable giving email campaign	Yes	No
Mark, Bulla, Niraj, Bulla, & Schwarzwäller (2019)	Dynamic segment	Channel choice, purchase frequency	Understand customer path to purchase accounting for dynamic channel choice and purchase frequency	Multi-channel retailer employing catalogs and email strategies	No	No
Ascarzaet al., (2018)	Email opens, email clicks	Overt or silent churn	Observed and unobserved customer attrition	Email messages from a daily deals website and performing arts organization	No	No
Sahniet al., (2018)	Presence of the recipient's name	Campaign profitability	The role of non-informative advertising content	Incorporating email recipient's name into email communications	Yes	No
Kim & Kumar (2018)	Effect of economic and relational marketing communications	Customer purchase	How customers evaluate marketing communications	B2B service firm direct marketing messages	No	No

Zhang et al., (2017)	Number of purchases, emails sent, emails opened, time since last purchase, time since last email opened, an indicator variable for email opened per month, an indicator variable of purchase during month	Email open behavior on customer purchases	Maximizing profitability for email marketing	Home improvement retailer promotional emails	No	No
Reimers, Chao, & Gorman (2016)	Receive permission email marketing	Perception of usefulness, ease of use, perceived risk, and enjoyment of shopping online	Email marketing role in influencing consumers' perceptions of online shopping	Survey of Australian online shoppers	No	No
Wu, Li, & Liu (2018)	Email campaign promotional attributes, customer characteristics	Customer purchases	email marketing and customer characteristics effect on purchasing behavior	Email campaigns for an online ticket marketplace	No	No
Kaptein et al. (2015)	User persuasion profile, one of three influence principles: authority, scarcity, and social proof	User influence	How persuasive technologies can be rendered adaptive users	SMS and email on healthy lifestyles (Case 1 and 2). Email for a travel agency (Case 3).	Yes	Yes
Kumar et al., (2014)	Demographic categorization, customer contacts, coupon utilization, return utilization, email opens and clicks	Subscriber opt-in, opt-out, average transaction amount	Timing of customer decision to opt in and out of marketing communications	Retail promotional email campaigns	No	No
Merisavo & Raulas (2004)	Customer email content evaluations measured through survey response	Email marketing effect on brand loyalty	Email marketing’s effect on brand loyalty	Manufacturer email campaigns	No	No
Ansari & Mela (2003)	Email content and design	Click-throughs	Development of recommendation model	Promotional emails for a media website	Yes	Yes
Chittenden & Rettie (2003)	Factors influencing campaign response: customer demographics, email characteristics	CTR, Unsubscribe Rate	Factors affecting email subscriber response to individual emails	Promotional email campaigns from multiple retailers	No	No

The above review highlights three gaps in the extant email marketing literature that this paper aims to address. First, to date, scholars have explored email marketing contexts by examining customer attributes, subscriber engagement (i.e., the subscriber's open, clicks, and/or purchases), and email campaign attributes—either at an aggregated or granular level. However, despite research by Kim and Kumar (2018) highlighting the cumulative effect (i.e., totality) of email communications influences customer purchases—this remains a largely uncharted area. Second, there is a need for new measures to capture individual customers' utilization of content resources as the traditional email marketing metrics, such as open, click, conversion, and unsubscribe rates, assume identical content per campaign per customer segment (i.e., list). Table 3 provides a summary of traditional email marketing measures and their assumptions. Third, despite AI personalization's rapid adoption in email marketing, there has yet to be an empirical study employing field data capturing customers' use of an AI-personalized email marketing environment.

Table 3. Email marketing metrics

Email marketing metrics	What is it?	How is it calculated?	What are the assumptions?	How is it used?
Click through rate	The percentage of unique subscribers who clicked on content within an email	(Unique users who clicked ÷ number of emails delivered)	Identical content is distributed to all campaign recipients	Assess email list subscribers' engagement with distributed content
Conversion rate	The percentage of email subscribers who both clicked a link AND completed a desired action (i.e., make a purchase, fill out lead generation form)	(Number of subscribers who completed the desired action ÷ emails delivered)	Identical content is distributed to all campaign recipients	Show the extent to which marketing communications are contributing to marketing goals.
Bounce rate	The percentage of the total emails sent in a specific campaign that were not successfully delivered	(Number of bounced emails ÷ number of emails sent)	N/A	Assess the percentage of valid email addresses as well as provide an indication of the sender's reputation with the email service provider
List growth rate	The email list's rate of growth	New subscribers-lost subscribers ÷ total email list count	N/A	Determine whether the customer base is expanding or contracting
Email sharing rate	Percentage of email subscribers who forward to a contact	Number of subscribers who forward ÷ number of emails delivered	Identical content is distributed to all campaign recipients	Identify what kinds of articles and promotions generate rebroadcasting behavior
Overall ROI	The return on investment for an email campaign	Sales made – amount invested in campaign ÷ amount invested in the campaign	N/A	Monitor the value of the email marketing channel
Open rate	The percentage of email list subscribers who open a given email	Unique users who opened ÷ number of emails delivered	Identical content is distributed to all campaign recipients	Assess the overall interest from the customer base in the brand and message
Unsubscribe rate	Percentage of email subscribers who explicitly opt out of receiving future communications	Number of users who opt out of future communications ÷ number of emails delivered	Identical content is distributed to all campaign recipients	To determine whether marketing messages are valued by email subscribers

3. Specialization and hypothesis

The degree to which an organism interacts with the resources in its environment—i.e., specialization—is a main concept in ecology and conservation (Devictor et al., 2010). It has been over 30 years since Futyman and Moreno's (1988) seminal review on specialization, during which time the concept has continued to flourish, spawning further reviews (Armbruster, 2014,

2017; Clavel et al., 2011; Devictor et al., 2010; Kay & Sargent, 2009), empirical and theoretical work (Pilott, Haubrock, Sundermann, Lorenz, & Haase, 2022; Schluter, 2000), as well as measurement development (Blüthgen, Menzel, & Blüthgen, 2006; Blüthgen, Menzel, Hovestadt, Fiala, & Blüthgen, 2007; Blüthgen, Fründ, Vázquez, & Menzel, 2008; Dalsgaard, Martín González, Olesen, Timmermann, & Andersen , 2008; Dormann, 2011). As stated in the introduction in the ecology literature and in this paper, the concept of specialization is referred to interchangeably as: specialization, ecological niche (niche), and a specie's utilization of resources.

Specialization is defined with respect to a particular environmental factor, such as focusing on the interaction of one trait of an organism and a specific condition of the environment (Forister et al., 2012; Irschick, Dyer, & Sherry, 2005). The specialization concept can be distinguished by its ecological dimension. Ecological dimensions describe the relationship between a species and its environment. Two important ecological dimensions to consider are the Grinnellian—response of a species to a set of resources (Grinnell, 1917), and the Eltonian—a species' impact on the environment (Elton, 1927). Both the Grinnellian and Eltonian niches can be extended to Hutchinson's (1957) ecological niche concept (Devictor et al., 2010). As this paper focuses on the response of a consumer to the set content resources in their environment, I am considering the Grinnellian dimension.

Data on niches can be used to understand an individual's, species', or population's utilization of resources (abiotic and biotic), as well as examinations of the resources used compared to their availability, and comparisons of an individual's resource interactions to the population (Devictor et al., 2010). Specialization has been used to explore diversity, community ecology, assembly of communities, community complexity, evolution, extinction, functional-

group specialization, and interaction networks (Armbruster, 2017). In adopting a key measure of specialization in an AI-personalized environment, I seek to address whether the specialization of a customer's content interactions informs their engagement in an AI-personalized environment.

Specialization is often measured using quantitative indices of observed interaction frequencies of species (i.e., consumers) with resources in the environment (Blüthgen et al., 2006) which is emphasized by González-Castro, Morán-López, Nogales, and Traveset (2022) statement "interaction frequency is the most common currency in quantitative ecological networks" (p. 2). Specialization asserts that the resources available within an environment affect the breadth of a species' ecological niche (Futuyma & Moreno, 1988). The niche is represented as an n-dimensional hypervolume where the dimensions are environmental conditions or resources (Hutchinson, 1957). In an AI-personalized environment, content resources are curated for a customer as the algorithm serves content to match the observed preferences of the individual. Chung et al. (2009) show adaptive personalization leads to greater consumption and increased usage duration, and Ansari and Mela (2003) show content targeting in the context of email marketing increases click-throughs. However, the extant research on personalization in marketing has focused narrowly on an individual's immediate response to a personalized treatment and not the cumulative effect of the consumer's interactions with all digital content (i.e., resources) present within the environment. In an AI-personalization context, the algorithm makes repeated content recommendations to explore and exploit the individual's preferences. It is the sum of these recommendations which forms the user's experience.

I propose that the specialization concept can be used to explore consumers' interactions with content resources by adopting how it has been used in research on plant-pollinator interactions. All organisms have environmental condition requirements, including the types of

resources they must obtain to thrive (Forister et al., 2012). Implicit in the concept of specialization is the understanding that organisms will have a tendency or ability to use only a subset of the potential resources in an environment (Armbruster, 2017). Central to this paper's proposal is that consumers of content resources in an AI-personalized environment are like any organism in the natural world, requiring a specific subset of environmental conditions to thrive.

Furthermore, research by ecologists has shown tradeoffs between the two ends of the specialization continuum. Notably, in the right environment, specialists will have a greater growth rate than generalists, who are more likely to have a consistent growth rate (Caley & Munday, 2003). Changes in the environment may have the same positive or negative effect on both specialists and generalists, but generalists are more likely to succeed (Clavel et al., 2011). Considering the comparative tradeoffs between specialists and generalists, I hypothesize the relationship between specialization and a customer's engagement with marketing messages is curvilinear. Following the continuum of specialization from a generalist to a specialist I predict on the left side that those with more generalized consumption patterns will succeed in the environment, and on the right side that the favored specialists will thrive in the environment, whereas in the middle, those not favored may struggle. Next, I discuss the data and measures.

4. Specialization measurement assessment

4. 1 Data

When ecologists collect data on interaction frequency to measure specialization between pollinators and plants, they often mark plots on the ground where they observe the species interacting, as described by Dalsgaard et al. (2008). The data for this study includes the interactions of customers in an AI-personalized environment. Specifically, to address my hypothesis I use a proprietary data set from a brick-and-clicks retail chain operating in the central United States which includes 7,174 email subscribers who opted to receive email marketing

communications and opened at least one email between January 1, 2018, and June 30, 2018. The dataset was provided by a technology firm that develops AI-driven personalization technologies for the retail, real estate, and collegiate recruiting industries.

The technology firm used AI to create a unique email for each customer specific to their observed preferences selecting autonomously from a content library of marketing resources approved by the firm, which included both the firm's owned marketing assets (i.e., blog posts, events, products, videos, images, etc.) and third-party marketing assets provided by manufacturers and magazines with which the company had a re-distribution agreement. The technology firm employed a proprietary topic modeling approach that assigned the content library contents to predefined "interests" (n=28) which had been preselected by the retail firm's marketing manager for use in their email marketing messages. When creating email communications, the technology firm's engagement algorithm would programmatically explore each customer's preferences by selecting content from across the specified interests to identify customer preferences and tailor the content experience to the user. The dataset includes a unique anonymized ID for each email subscriber and the complete record of all content distributed to each subscriber, including whether the user viewed the content, from the time the subscriber opted-in to the email list until March 2019 or when the user stopped receiving emails due to un-subscription or in-activity.

4. 2 Measures

4. 2.1 Specialization. There are multiple characteristics of specialization, and for each characteristic scholars have developed measures. To measure a species' absolute degree of specialization, ecology scholars quantify the species' discriminatory behavior—operationalized as the extent to which a species consumes what is presented in the environment or shows

preferences beyond what would be encountered during a random search (Dormann, 2011). The d' index (d') was proposed by Blüthgen et al. (2006) to account for such a degree of specialization. It measures both proportional resource utilization and proportional availability such that a species that utilizes resources in proportion to their availability is considered more generalized than one which uses rare resources disproportionally. A benefit of the d' index is it accounts for the availability of resources in the environment. Using the quantitative data in a weighted network to incorporate both the species' interaction intensity and the resources' abundance d' controls for instances such as when a pollinator is found exclusively on one species of plant, but the plant is the most dominant in the environment. In this case, the pollinator would receive a low d' value, whereas a pollinator appearing only on the rarest of the plant would receive a higher d' value. Values of d' can range from 0 when the subject has no specialization to 1 when the subject is a perfect specialist. In the context of email marketing technologies that deploy high content resources (i.e., extensive content libraries) and high personalization, it is still frequently the case that certain content topics, such as sale announcements, corporate announcements, or brand positioning campaigns, are distributed without regard to the customer preferences (i.e., not personalized) and distributed to all customers. In these cases, d' accounts for customer interactions with topical domains which are more abundant to provide an unbiased estimate of customer specialization. Of particular benefit to marketers d' can be used to rank consumers, and by correcting for resource availability does not require comparison to null models (Dormann, 2011). Ecology scholars have recently employed d' to explore pollen use and seasonal shifts by pollinators (Bertrand et al., 2019), biogeography history on the functional traits of animals, such as the length of a bird's bill, and resource specialization (Dalsgaard et al., 2021), as well as virus evolution (González et al., 2021).

4.2.2. Customer engagement. I operationalize customer engagement as the ratio of the number of emails a customer opens relative to the total number of times the individual was emailed (Thomas et al., 2022).

4. 3 Analysis and results

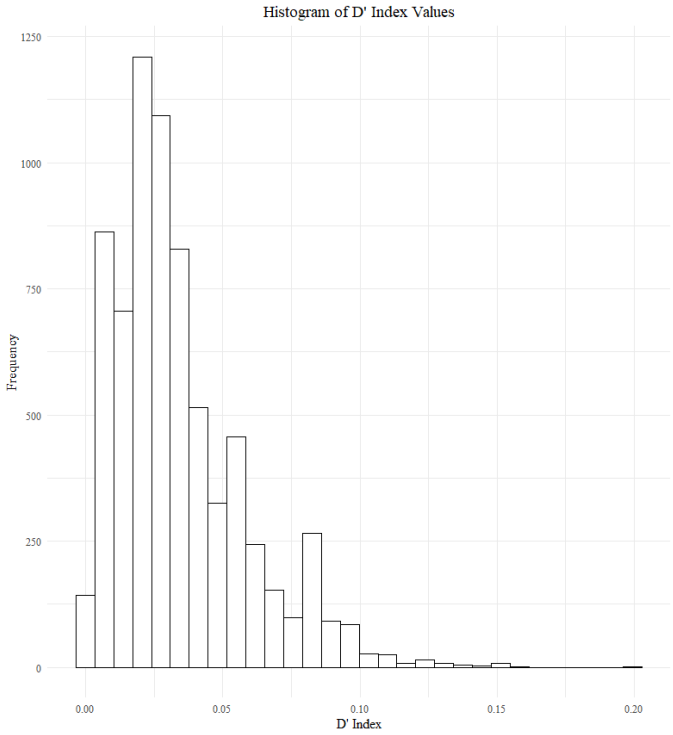
Consistent with Hutchinson's (1957) representation of a species' ecological niche as a n-dimensional hypervolume where the dimensions are environmental conditions or resources, I created an interaction frequency matrix, whereby cells with positive integer values reflect the frequency an email subscriber viewed content assigned to a topic. In total, there were 1,961,816 content-viewing interactions. Next, to calculate d' I used the 'bipartite' package version 2.16 in RStudio (Dormann, Gruber, & Fründ, 2008). Descriptive measures for d' values are presented in Table 4.

Table 4. D' index descriptive measures

	Min	Q1	Median	Mean	Q3	Max
d'	0.0004	0.0181	0.0284	0.0340	0.0450	0.1998

The observed degree of specialization of consumers in this study is consistent with the analysis of pollinators at the individual and species levels as most are generalists (Waser, 2006) but some degree of specialization is normal (Jordano, 1987; Vázquez & Simberloff, 2002; Vázquez & Aizen, 2004; Vázquez & Aizen, 2006; Bascompte, Jordano, & Olesen, 2006; Blüthgen et al., 2007) as shown in Figure 2.

Figure 2. Distribution of d' index values



As a second step, I computed the dependent variable, customer engagement, by extracting for each user the total number of times they opened an email divided by the number of times they were emailed. Values for customer engagement ranged from a min value of 0.07 to a maximum of 99.08 with a median value of 0.93 and a first and third quartile of 0.44 and 2.25. To account for customer engagement being positively skewed, the variable was log-transformed. The Pearson correlation coefficient between the independent and transformed dependent variable is -0.4. Descriptive measures of customer engagement following log-transformation are presented in Table 5. Next, I split the dataset to create a holdout validation dataset comprising twenty percent (n=1,435) of the total observations. Finally, I test my hypothesis of a curvilinear relationship between a customer's degree of specialization and their engagement using the stats package in RStudio version 1.4.1103 and perform a holdout validation.

Table 5. Customer engagement descriptive measures

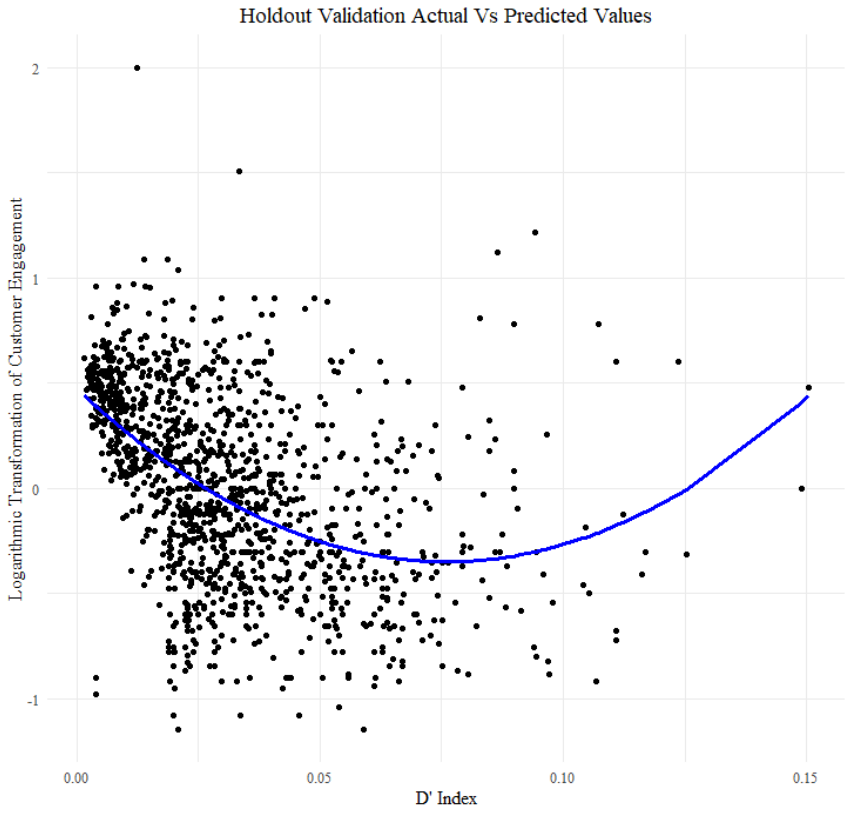
	Min	Q1	Median	Mean	Q3	Max
Customer Engagement	-1.15	-0.35	-0.03	-0.02	0.35	1.99

The results are presented in Table 6, which shows strong support for my hypothesis. Not only is a customer's specialization, operationalized as the extent to which a species consumes what is presented in the environment or shows preferences beyond what would be encountered during a random search, a significant predictor of a customer's engagement with marketing messages, but a quadratic model specifying d' values as the sole predictor explains twenty-five percent of the variation within the model—a surprising result. When modeled as a curvilinear relationship, d' has improved model fit with a R^2 value of 0.25 (F-statistic 939.4 on two and 5736 degrees of freedom) as compared to a R^2 of 0.16 (F-statistic 1117 on one and 5737 degrees of freedom) when excluding the quadratic term. The holdout validation of the quadratic model shows consistent results with a nearly identical R^2 of 0.25. In Figure 3, I show the actual vs predicted values from the holdout validation. Furthermore, visually inspecting Figure 3, it is evident that for each level of elevated customer engagement, there are many more generalists than specialists, consistent with the insight from ecology that both specialists and generalists can succeed, but generalists are more likely to succeed.

Table 6. Model results

Modeling Results				
	R^2	B	SE B	P
	0.25			<0.001
Constant		0.47	0.01	<0.001
d'		-21.64	0.6	<0.001
d'^2		142.14	5.63	<0.001

Figure 3. Holdout validation actual vs predicted values



Next, the findings and implications are discussed.

5. Discussion and conclusions

Prior research into the effects of personalization in marketing has primarily found positive results: higher click-throughs (Bleier & Eisenbeiss, 2015), more accurate recommendations (Chung et al., 2016), and increased purchase likelihood (Urban et al., 2014). However, this paper argues personalized digital environments should be considered similarly to ecological environments–where through interacting with the resources in the environment customers have the potential to develop specializations. The extant logic in marketing holds that environments tailored to customer preferences improve user experience and produce greater benefits for the firm. This reasoning ignores what is known by ecologists. Specialists are more susceptible to disturbances (Vázquez & Simberloff, 2002) and less likely to succeed in environments subject to change (Clavel et al., 2011), a weakness in digital environments which are dynamic. Furthermore, the breadth of dietary preferences (i.e., specialization) is a key predictor of extinction (Mckinney, 2003). Consistent with findings in ecology, this paper shows within a digital AI-personalized environment, both specialists and generalists can succeed, but generalists are more likely to succeed.

How do marketers reconcile the findings presented in this paper with a substantial body of knowledge highlighting AI-personalization's positive effects? First, to date, research on AI-personalization has relied on laboratory experiments, field studies, and simulations. To the best of my knowledge, this is the first study to empirically explore the effect of AI-personalization in a real-world setting where customers have had repeated interactions over weeks and months. Second, in this paper, I am not considering whether a personalized treatment induced the customer to take action, rather, I am looking at the cumulative effect of interactions in an AI-personalized environment on the customer's engagement with marketing messages. And third, specialists in the right environment can outperform generalists (Caley & Munday, 2003). I argue

marketers adopt the perspective that just like all other living things email marketing consumers (i.e., homo sapiens) have a set of environmental conditions necessary to thrive. Therefore, marketers should seek to identify in AI-personalized environments whether a customer is a specialist or generalist and seek to provide the resources necessary for that customer.

Intriguingly, research and theory development by ecologists may be useful in helping marketers address this task. For example, consider the bee searching for pollen in a field where the pollinating flowers are patchily distributed e.g., patches where the pollinating flowers are found in greater concentration than others. The bee will spend time and energy moving between areas of the field, searching and consuming pollen; further, as it does so, it is depleting the supply of pollen within that patch such that the availability of food diminishes with time. This scenario is identical to a consumer of digital content foraging across a digital ecosystem in which the content, information, and products they wish to consume are found in different concentrations on different platforms and websites. Ecology scholars have sought to understand and model the movement of foraging animals leading to the development of optimal foraging theory.

According to optimal foraging theory, an animal should leave any patch when the expected gain from remaining is equal to the anticipated gain from traveling and searching another patch (Bartumeous & Catalan, 2009). Therefore, if a consumer were to perceive that the digital patch in which they were foraging for content was beginning to deplete, and recognizing digital environments are easy for consumers to travel and search, one might expect a consumer to depart quickly in response to perceived changes in the available content on which they have become specialized. For marketers, optimal forage theory holds promise as a way to provide a theory-informed answer to why customers unsubscribe or silently churn (Ascarzaet al., 2018).

Potentially by exploring the customer's use of digital resources in the environment, marketing scholars and practitioners can develop and co-develop new methods for creating, curating, delivering, and managing AI-personalized environments. Adopting an ecological lens to understand and predict marketing outcomes could optimize content generation and methods for profitably managing marketing programs as well as reframe customer churn as a natural cycle of search and consumption patterns.

Another intriguing question for scholars and practitioners is why and when a consumer would change their content consumption from a generalist to a specialist or vice versa. Ecologists' exploration of animal dietary preferences and switching to eat other prey has led to the development of optimal diet theory. In his seminal paper, on the theory of optimal diets Pullman (1974) contends that a predator's determination to switch between specialization and more general eating patterns is a function of the density of the preferred prey type, the physical area the predator can cover per unit of time, and the energy value of the prey. There are several essential propositions for marketers to consider.

Pullman's (1974) proposition, the presence of alternative prey options does not inform the animal's decision to switch—only the density of the preferred prey, and the greater the availability of resources, and notably increased density of the preferred items, leads to increased predator specialization—has implications for marketers as how content topics are concentrated in the digital environment may influence the extent to which a consumer specializes and may be used to induce a switch from specialized to generalized consumption patterns. Furthermore, Pullman contends an animal's only estimate of food abundance is from the frequency with which it encounters prey which means an isolated, starved animal that has not been encountering prey will have a low estimation of prey density and therefore be more likely to eat any prey which it

encounters (i.e., show a generalist pattern); however, as the animal has encounters its estimates of prey density update, and it would begin to show specificity for preferred prey. If Pullman's proposition is accurate in digital content consumers, one might expect people's consumption patterns to vary on the time of day as the consumer would have been isolated and content deprived during their sleeping hours. And finally, Pullman argues that predators will become more specialized on highly conspicuous prey, which he defines as the extent to which prey are clumped in the environment. Implications from this proposition are that digital environments with evident content clumping, such as newspapers and streaming services are more likely to produce specialized content consumers than environments in which content topics are more distributed.

Additionally, exploring biodiversity, the variety of life in a particular habitat, which ecologists recognize as critical to ensuring a stable and sustainable ecosystem, holds promising possibilities for research and practice. Mutualistic interactions between species shape and maintain the earth's biodiversity (Bascompte et al., 2006) and may provide marketers with new ways to understand customer churn in digital environments. A common example of a mutualistic interaction in nature is a bee's pollen consumption, which can be comparable to consumer interaction with digital content. When a bee consumes pollen from a flower, it increases the probability that flower species will procreate and thrive. In digital environments, when a consumer engages with a content resource, the algorithm serving that content becomes more likely to select that content for inclusion in other communications (in many applications of AI curation). Through studying environments with greater biodiversity, Bascompte et al. (2006) found the following pattern. These environments are highly asymmetric such that when a plant species depends strongly on an animal species (i.e., the plant species is highly specialized) the

animal species is weakly dependent on the plant species. Recognizing asymmetric coevolutionary networks are critical to the maintenance of biodiversity, and biodiversity is a requirement for ecosystem stability and sustainability marketers should explore whether digital environments with stable customer life cycles are typified by a similar pattern of asymmetric networks, where if the content is highly dependent on a consumer or segment of customers for its interactions, the consumer or segment is weakly dependent on the content for their consumption.

A further finding in ecology that marketing scholars and practitioners should explore is the tendency for species to become more specialized, which can lead to an array of species all sharing a common lineage known as adaptive radiation (Schluter, 2000). A population of customers interact with a personalization algorithm that learns about the users' preferences and offers increasingly specific recommendations—the same trend documented by ecologists of species' tendency to become more specialized. Darwin was the first ecologist to consider and document a species fragmentation from a common ancestor with the classic example of Darwin's finches. Future research in marketing should explore how digital consumers develop specializations and how the sequence and formation of interaction patterns develop and lead to specialization.

Adding to the new research directions and managerial implication for marketing is research by Herath, Wat, Banks, and McArthur (2021) that shows that the individual animal's personality influences dietary specialization. Specifically, in possums, proactive individuals have broader and higher quality diets than reactive individuals within the same landscape. Can marketers use the range of consumer content interactions to inform their understanding of the consumer's personality? And if so, can marketers adapt the digital experience for those users to better align with their inferred personality and drive improved marketing outcomes?

In today's hyperconnected digital environment, content resources are created and co-created by a universe of heterogenous human and nonhuman actors (Price & Coulter, 2019; Swaminathan, Sorescu, Steenkamp, O'Guinn, & Schmitt, 2020). Hewett, Rand, Rust, and Van Heerde (2016) conceptualized today's digital environment as an echoverse in which communication is non-linear, eliciting a reaction from the intended recipient and the entire ecosystem (Maslowska, Malthouse, & Collinger, 2016), and forms a complex web of feedback loops. As marketing communication evolves from interactions between brands and consumers to a constellation of nonhuman and human actors co-creating meaning in the echoverse scholars have begun to ask: how is the echoverse reshaping marketing? This paper argues one way marketing should evolve in the echoverse marketing era is by adopting an ecological perspective of the consumer, viewing the consumer as something akin to a pollinator moving between foraging patches encountering both their preferred content and communication as well as a smorgasbord of communication. Using this perspective, marketing scholars and practitioners can adopt measures from ecology to quantify the extent to which a consumer is developing a preference for its offering, how important a consumer or group of consumers is to the brand's ability to generate reverberations in the echoverse, and ways for marketers to understand customer movement in the echoverse.

As scholars and practitioners adopt AI-supported marketing practices, there will be an increasing need to distinguish best practices and determine the optimum place along the personalization continuum for a given setting and context. A task made difficult by scholars presenting personalization research as a binary treatment. For example, Khan, Lewis, and Singh (2009) provide a comparative study of mass marketing, segmentation, and one-to-one marketing through a series of dynamic optimization tests. Someone considering these results may come

away perceiving segmentation offers nearly the same results as personalization; however, using the proposed typology it is more accurate to state this may be the case only when the marketer has a limited content library—low content resources—but ample personalization capability.

Furthermore, research in the low content library low personalization area often employs a form of mass marketing with eye-catching personalized effects, such as Bang and Wojdynski (2016) distributing identical banner advertisements in an experimental setting where the only manipulation is the presence of the potential customer's name and geographic information. While their experiment meets the definition of personalization, the ad's contents (i.e., product and ad copy) were not selected to align with a customer's preferences. Thus, the marketing insights gained from the experiment may have implications about how customers respond to the inclusion of their name and geographic information and may not be generalizable to other kinds of personalized treatments.

Similarly, research in the high content library low personalization area is often a form of segmentation as customers are grouped based on responding similarly to the marketing effort (Grewal & Levy, 2021). For example, Tran et al.'s (2020) experiment show one of eight sunglass styles to potential customers based on the customer's direct response to a survey asking about their style preferences, and Hauser et al.'s (2014) method identifies latent customer segments and then morphs a website by selecting from eight website variations designed to appeal to a specified segment. Segmentation enables marketers to create content for specific groups. These studies provide valuable marketing insights on the effectiveness of doing so; however, they do not explore each customer within a segment individually. I acknowledge there is value for all types of personalized environments and their exploration of them; however, it is critical that scholars and practitioners recognize that the interaction of content resources and degree of

personalization can alter the nature, insight, and generalizability of personalization research and technologies.

For over 50 years, ecology scholars have recognized that the synthesis of interactions is meaningful for understanding nearly all aspects of the natural world; however, in the marketing field, this remains an uncharted area. This paper is the first to explore a holistic pattern of interaction between customers and the environment in a marketing context, specifically in a high content resources high personalization AI environment. To deepen our understanding of customer interactions in digital environments, this paper explores a central concept in the field of ecology—ecological specialization—by adopting a key measure of specialization, it shows that the holistic pattern of customer interactions in a digital space influences customer engagement with marketing communications. Finally, we highlight some of ecology's most extensively developed theories utilizing specialization to propose new research directions in marketing.

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ESSAY III

Pivoting During New Product Development: Another Pathway for Escalation of Commitment

Abstract

This article adds the possibility of pivots to the popular Stage-Gate® new product development processes (NPD). As conceived and operationalized with Stage-Gate®, one of five outcomes are possible decisions at each gate: go, stop, hold, recycle, or iterate. Borrowing from the entrepreneurship literature, I modify the process to include a sixth possible decision, a pivot. Pivots are triggered when a NPD project yields negative information or management believes that changes are necessary for the organization's survival and growth, i.e., a continuation decision in a failing course of action—an escalation of commitment. Effectuation theory is used to understand how causal/effectual logic informs escalation of commitment decisions, including pivots in an organization's NPD process. Through integrating the literature on Stage-Gate® NPD processes, entrepreneurial pivots, escalation of commitment theory, and effectuation theory, and using an autoethnography case study of a business-to-business AI marketing organization's NPD project with pivots, research propositions are offered for future research.

Keywords: new product development, pivots, escalation of commitment, effectuation theory

1. Introduction

Most organizations use a Stage-Gate®[1] system, a comprehensive "plan-driven" idea-to-launch system, for new product development (NPD) (Cooper, 2014, 2017). The COVID-19 pandemic and global supply chain disruptions have complicated the business environment and called for organizations to pivot— "a structured course correction designed to test a new fundamental hypothesis about the product, strategy, and engine of growth" (Ries, 2011, p. 149). Pivots are triggered when a NPD project yields negative information (Kirtley and O'Mahony, 2020) or when management believes changes are necessary for the firm's survival and growth (Hampel, et al., 2020). In recent years, the decision to pivot has gained traction as an additional decision outcome in the popular press driven by Silicon Valley stories of businesses such as Slack rising from the ashes of a NPD failure (Clark, 2019). However, according to extant wisdom in NPD, a pivot also reflects a continuation decision in a failing course of action—an escalation of commitment (Schmidt and Calantone, 2002). While the lexicon of pivots has become popular in practice, there is limited research to date (Chaparro and Gomes, 2021, Shepherd, et al., 2019).

In each stage of the Stage-Gate® system for NPD (Cooper, 2014, 2017), activities are performed, problems are solved, information is generated (e.g., sales forecasts), and decisions are made. Each gate results in one of five possible decision options (Cooper, 1990): (1) go—the project is tolerably acceptable to continue development; (2) stop—terminate the project permanently as it is deemed unacceptable to continue (now or later) for various reasons; (3) hold—the project is in a holding pattern until problems can be solved, more information can be generated, or the market conditions become clearer; (4) recycle—the project is tolerably

[1] State-Gate® is a registered trademark of the Product Development Institute, Inc.

acceptable to continue development albeit with minor changes which need to be addressed in the previous stage (Cooper, 1990, 2017); and, (5) iterate—the project adopts a series of more experimental design-build-test spirals (i.e., cyclic processes of prototyping, testing, and refining a product) (Cooper, 2014, 2017). Similarly, yet distinctly, the entrepreneurship literature includes the same five possible decisions with the additional possibility of pivoting.

Entrepreneurship and B2B scholars have explored cognitive processes to understand how managers make decisions (Parry, 2020; Pedersen and Ritter, 2022). To aid in the understanding of pivots as an additional decision-making outcome of Stage-Gate®, I use effectuation theory, which aligns with the recommendation from Mansoori and Lackéus (2020, p. 812) that scholars "take advantage of the theoretical strengths that effectuation is grounded in" and the illustration by Klenner, et al. (2022) of how effectuation theory can be integrated into NPD. Based on cognitive behavioral studies of expert entrepreneurs who founded companies from $200M to $6.5B, effectuation theory distinguishes between causal and effectual logics, which can be used independently, jointly, or in non-sequential orders (Sarasvathy, 2001). The manager who applies causal logic assumes that the environment is fairly stable, controllable, and views contingencies as undesirable deviations, which is the familiar approach of Stage-Gate® systems, as well as by many financers (Fisher et al., 2016, Osiyevskyy et al., 2013, Shirokova et al., 2021). Unlike casual logic, which is an ends-driven reasoning, effectual logic is a means-driven reasoning that takes "a set of means as given and focuses on selecting between possible effects" (Sarasvathy, 2001, p. 245). In a NPD context, Berends et al. (2014) illustrated how causation and effectuation can be leveraged in small firms' NPD processes while Klenner, et al. (2022) shed light on how effectuation theory can be integrated with other NPD processes. To the best of my knowledge,

this is the first paper to explore pivots as an escalation of commitment in NPD processes and how casual/effectual logics can inform decision-making.

In exploring a case involving a B2B artificial intelligence (AI) marketing organization's NPD process with pivots, this article addresses the following research question: How do causal/effectual logics inform escalation of commitment decisions, including pivots in an organization's NPD process? An autoethnographic approach is utilized to draw on lived experiences, which has been used to develop new insight into organizational contexts (Bourguignon et al., 2021, Kelly et al., 2021, Whitehurst and Richter, 2018) and address calls for scholars to turn their critical analysis onto themselves by inquiring into how, why, and to what effect are theories 'performed' in practice (Manson et al., 2015).

The contribution of this study is twofold. First, this article addresses the calls for research on pivoting (Kirtley and O'Mahony, 2020; Parry, 2020, Shepherd et al., 2019), which likely will play an increasingly important role in accelerated NPD (Slotegraaf, 2021). Second, through integrating effectual and causal logics, this paper explores pivots as an additional decision outcome and method for escalation of commitment in the Stage-Gate® system. In brief, the findings of this study contribute to the bodies of knowledge in the areas of NPD, entrepreneurship, and escalation of commitment.

The organization of this article is as follows. In the next section, I review the relevant literature streams and conceptualize Stage-Gate® with pivots. Then, I detail the methodology followed by presenting the findings and discussion. I close by discussing theoretical and managerial implications, along with future research directions.

2. Theoretical background

To understand how causal/effectual logics inform escalation of commitment decisions including pivots in an organization's NPD process, I utilized and integrated the following four literature streams: Stage-Gate® NPD processes (Cooper, 2014, 2017), entrepreneurial pivots (Hampel, et al., 2020, Kirtley and O'Mahony, 2020, Parry, 2020), escalation of commitment theory (Staw, 1976), and effectuation theory (Sarasvathy, 2001, 2008). These four lenses were combined because they have been used to assess outcomes of B2B organizations (Mero & Haapio, 2022, Sarangee et al., 2019), and their underlying frameworks complement and reinforce each other. Such a process of theoretical triangulation is an important approach to challenging extant inherent assumptions and biases (Miles and Huberman, 1994) and offers different yet potentially complementary insights. Triangulation of bodies of knowledge, such as knowledge sourcing (Endres et al., 2020), sharing (Nguyen et al., 2018), integration (Jin and Shao, 2022), and creation (Ba et al. 2021) are practices of B2B organizations as well as provide intriguing research possibilities. Aligned with a knowledge-based view of the firm (Kogut and Zander, 1992) whereby knowledge can be recombined to expand and create new knowledge, my awareness of theories and perspectives across the business administration discipline (i.e., new product development, marketing, management, and entrepreneurship) enabled the process of theorizing—"abstracting, generalizing, relating, selecting, explaining, synthesizing, and idealizing" (Weick, 1995, p. 389) in order to "uncover the nonobvious and to render the obvious less so" (Weick, 1947, p. 501). Moreover, these four lenses represented bodies of knowledge embedded in the organizing principles of the B2B AI marketing organization explored in this autoethnographic case study.

2.1. Stage-Gate® and the determinants leading to escalation of commitment

Stage-Gate® systems enable managers to make sequential investments in a NPD project, whereby the managers can adjust the investment planning for a subsequent round on the performance of the previous round (Yang et al., 2022). However, NPD project decisions are recognized as being prone to managerial decision errors (Schmidt et al., 2001). Yet, stringent decision-making is strongly associated with successful NPD (Cooper, 1996). Given that the decision to throw good money after bad is one of the costliest decisions in the organizational sciences (Sleesman, 2012), and new products have a significant rate of failure (Boulding et al., 1997, Victory, et al., 2021) research into the determinates of continuation decisions has been an active area of research for the last 45 years. Next, we review the relevant literature on the environmental, project, and individual determinates of continuation decisions that can lead to an escalation of commitment.

Environmental determinates. Continuation decisions are influenced by the environment in which they are made. Managers in environments with greater uncertainty are more likely to make continuation decisions (Boulding et al., 1997), while product leaders in environments where the decision risks or opportunity costs are better known are less likely to continue Sleesman (2012). Notably, the distribution of information within the environment has been shown to influence the quality of continuation decisions as teams with shared information make worse decisions than teams relying on information possessed by a subset of the team (Zhang et al., 2014).

Project determinates. Scholars have identified numerous project-level determinates of continuation decisions, including product innovativeness (Schmidt and Calantone, 1998, 2002), project team stability (Slotegraaf and Atuahene-Gima, 2011), project proximity to completion

(Conlon and Garland, 1993, Schmidt and Calantone, 2002, Sleesman, 2012), physical distribution of the team and temporal distribution of decision making (Schmidt et al., 2001), and prior project performance (Sleesman, 2012).

***Individual determinates*.** Research into decision makers' traits and project continuation decisions has yielded valuable insights. These insights include factors influencing a continuation decision such as whether the individual initiated the project or expressed a preference for the initial decision (Schmidt and Calantone, 2002, Sleesman, 2012) and whether the individual is likely to bear the negative responsibility of a termination decision (Sleesman, 2012, Staw, 1976). Furthermore, insights into the decision to stop a project have shown a manager's sense of anticipated regret (Sarangee et al., 2019), and the act of information acquisition may lead to the decision to kill a project (Sleesman, 2012).

2.2. Pivoting: Another pathway for escalation of commitment

A pivot decision is made after a setback in the NPD process (Chaparro and Gomes, 2021) or management believing changes are necessary for the organization's growth and survival (Hampel, et al., 2020), which leads to a continuation decision in a failing course of action—an escalation of commitment (Schmidt and Calantone, 2002). Early studies suggest the determinates of pivots (i.e., triggers) are similar, if not the same, as when managers make a continuation decision. For instance, pivots are also triggered by environmental determinates, such as disruptive business-model innovations (Dewald and Bowen, 2010) and the emergence of new information from external sources (Kirtley and O'Mahony, 2020); project determinates, such as changes in leadership (Wasserman, 2003), the emergence of new information from internal sources (Kirtley and O'Mahony, 2020), and institutional context (Shirokova, et al., 2021); and individual determinates, such as a manager's identity (Grimes, 2018), grit and impulsiveness

(Wood et al., 2019), experience (Marvel et al., 2020), and prior learning from failure (Eggers and Song, 2015). Given the similarity of the determinates of continuation across decision-making outcomes (i.e., pivot or continue), a manager's and the institutional cognitive approach, causation and/or effectuation, will influence if a pivot decision is a possibility.

2.3. Effectuation theory

The Stage-Gate® systems' planned approach assumes a high degree of certainty, predictability, budget, and the gate decision outputs are either go or stop (permanently or temporarily) (York and Danes, 2014). Causal logic frameworks focus on preset goals, rules that define expectations of what follows an action, expected returns, and avoiding surprises through gaining insights and predicting outcomes (Parris and McInnis-Bowers, 2017). A lesson from COVID-19 is this is not always the case; often managers are presented with roadblocks during the NPD process that cause uncertainty. Furthermore, managers often find the best-laid plans still result in product failure rates of 25% to 40% (Victory et al., 2021).

A distinct logic that can be exhibited in combination with causal reasoning, is effectuation which views the world as "dynamic, nonlinear, and ecological environments" (Sarasvathy, 2008, p. 251). Effectuation is linked to entrepreneurship which assumes less logical decision decision-making (Read et al., 2009). This approach views the future as emerging and can be shaped by a manager making decisions to act with their available means. Sarasvathy (2008) specifies three categories of means as 'Who I am?, What do I know?, and Who do I know?', which one uses to imagine possibilities originating from their means. Possibilities created from one's means form goals that are non-teleological, changeable, flexible, and allow for pivots based on learning, new effects created, and the development or acquisition of new means during the NPD process.

Effectuation and causation are two distinct logics - ways of thinking, a set of heuristics, and a paradigm for making decisions - that can be utilized at different times in the NPD process. Adding effectuation to the traditional Stage-Gate® system expands managers' decision-making logics by giving them two ways of thinking to guide their decisions. Importantly, throughout the NPD process, a manager can shift decision-making logics. For example, often during the initial conceptualization of a new product, there are unknowns with many future possibilities. In this stage of uncertainty, effectual logic is useful. Cooper (1988, 1990) proposed the traditional NPD Stage-Gate® process, and he later emphasized customer discovery at the earliest stages of NPD (2011, 2013) recognizing the need for next-generation systems that are more agile, adaptive, and accelerate innovation in NPD processes (Cooper, 2008, 2014, 2021). Similarly, if a Stage-Gate® system is in place and suddenly an unplanned event occurs (i.e., a surprise), such as product, technical, or market failure, sudden loss of resources, a global external shock like COVID-19, or leadership succession, which results in uncertainty, an effectual logic can serve managers in shaping the future that may include a decision to pivot.

An effectual logic encourages and enables managers to question the status quo and imagine the possibilities (Parris and McInnis-Bowers, 2017) with the resources they have, and what they can afford to lose, by interpreting the 'bad' or 'new' information as clues to new markets, building partnerships, and focusing on activities within their control (Read, et al., 2009, Sarasvathy, 2001). Effectuation can enable managers to celebrate a failure by providing them with a way of thinking in a changing environment that allows new ideas, such as pivots from an initial plan, to emerge from existing resources (Mero et al., 2020).

The theory of effectuation (Sarasvathy, 2001, 2008) provides five guiding principles, a set of heuristics (i.e., mental shortcuts), to serve as foundations for making decisions in times of

uncertainty. The five principles work in harmony with each other and can be applied iteratively, simultaneously, or in any combination or sequence. Managers can use the following five principles to guide their decision-making when they are presented with a failure, a surprise, or operating in a situation where the future is unknown:

1. *Bird-in-the-hand principle*: When viewing the NPD failure, managers applying effectuation will look at the resources they already have and start to imagine different possibilities by leveraging what is on hand and what can be done by asking: who are we? what can we do? And who do we know? In contrast, a manager taking a causal logic approach will first develop pre-set goals of what they want to do and then seek to assemble resources.
2. *Affordable loss principle*: When designing a course of action in an effectual way, managers will begin by understanding what loss the organization can afford at each step and then select actions where there is benefit even if a shortcoming occurs. In contrast to a causal logic approach that starts with managers focusing on maximizing the potential financial gains and minimizing the associated risks of what actions to take next.
3. *Lemonade principle*: When the inevitable surprises or unexpected events occur (i.e., lemons) managers with an effectuation approach view the surprises as an opportunity to create and identify new possibilities (i.e., make lemonade). In contrast, a manager who adopts causal logic will avoid surprises and view them as negatives, possibly leading to a kill decision, whereas a manager adopting an effectual logic will see it as an opportunity leading to a pivot decision or at minimum a 'what-if exploration' of different pathways from failure to success.

4. *Patchwork quilt principle*: To reduce uncertainty, managers embracing an effectual approach will seek out and form partnerships with interested stakeholders who can co-create, co-own, and co-share in developing new possibilities. In contrast, the causal logic approach assumes other stakeholders are competitors and seeks to retain ownership.
5. *Pilot-in-the-plane principle*: Mangers embracing an effectuation approach view the future as something they can make, instead of predict or find through understanding established market forces. When leading pivots, effectual managers make decisions that incorporate only resources and actions within their control.

As organizations respond to times of uncertainty by adopting accelerated innovation NPD systems and need to pivot due to internal or external changes, the guiding principles of effectual logic could be a valuable extension of the causal logic informed Stage-Gate® systems. Table 1 illustrates the differences in effectual and causal logic.

TABLE 1. Differences between causal and effectual logic.

Distinctive ways of viewing the NPD Process	**Causal logic (traditional approach)**	**Effectual logic (entrepreneurial approach)**
Process	Predictive process (i.e., linear, static, and independent environments)	Iterative learning process (i.e., dynamic, nonlinear, and ecological environments)
Starting point of NPD	Effects are given, the choice of resources (i.e., means) is driven by what the decision-maker wants to create/develop	Only some resources are given, the choice of possible effects can be created with given resources
Goal selection criteria	Based on expected return, maximize risk-adjusted return	Based on affordable loss, should not risk more resources than can be afforded to be lost
Goal setting	Define goals→create a plan→seek resources→begin working towards goals	Identify resources→use existing resources to set potential goals→begin working towards goals
Investment decisions	Invest based on the potential upside of the goal	Invest based on what you can lose
Outside organizations	Seen as potential competitors, protecting ideas is paramount to position in the competitive environment	Seen as potential collaborators, stakeholders can emerge as partners who can commit resources to common goals and influence development
Challenges, contingencies	Viewed as something to be avoided, focus on planning	Viewed as an opportunity to develop something new, focus on leveraging surprises
View of the future	Predictable and something to be planned	Constantly changing, but can be navigated with skill

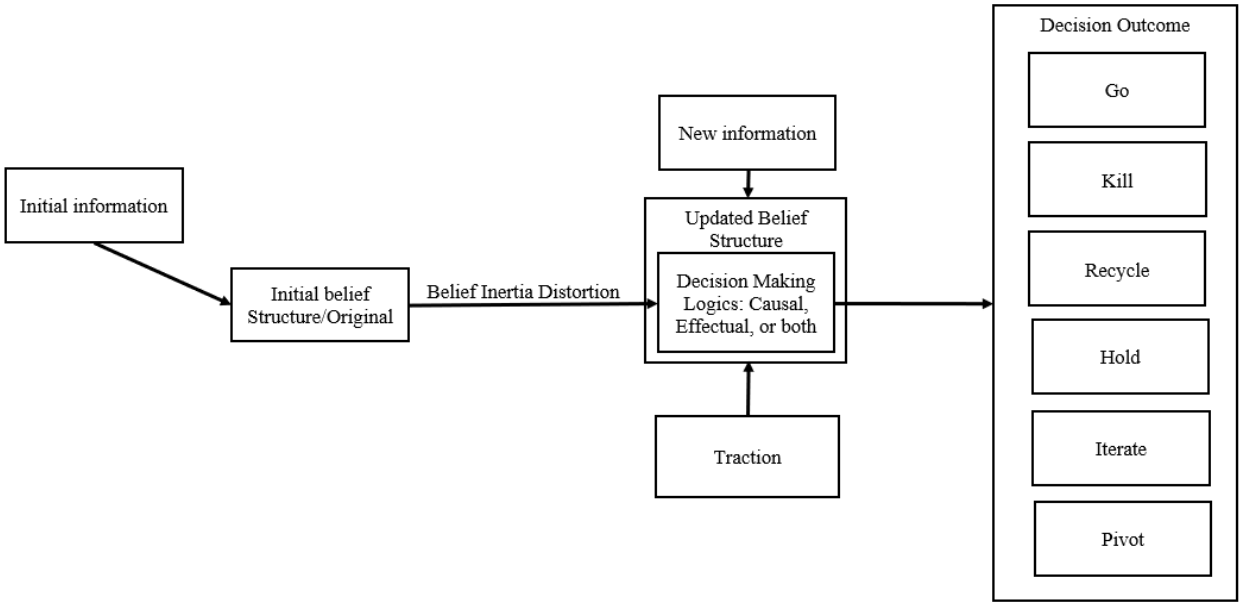
Even though scholars have called for more research on accelerated innovation NPD processes (Cooper, 2021, Slotegraaf, 2021) to the best of my knowledge, this is the first article to argue for the integration of effectuation and causation logics into Stage-Gate® systems to expand decision making possibilities to include pivots. To date, the majority of NPD research has focused on methods (i.e., ways of doing) accelerated innovation—rapid validity testing, design thinking, lean development, startup lean methodologies, agile, Stage-Gate® systems—without exploring ways of thinking (i.e., reasoning) that provide managers heuristics for doing the do-

able. Effectual logic can serve managers in stages of uncertainty, while causal logic is valuable in stages of predictability and controllability. It is important to acknowledge causal and effectual logics can be used jointly, and the decision maker's logics can change as they engage in strategic decisions, such as continuation decisions (Reymen et al., 2015; Sarasvathy, 2001, 2008) If, during the NPD process, milestones determined by pre-set goals are progressively being achieved, expected returns are being realized, resources are fixed, and market forces are stable, a causal logic comes into play. Alternately, effectuation can be useful at the earlier stages of development, in response to periods of uncertainty, or in situations when the assumptions of causation are not met (Edelman and Yli–Renko, 2010). The focus of this article is exploring the use of effectual and causal logics for managers who during the NPD process find themselves in situations whereby they need to decide on how to continue. Next, I conceptualize how in a Stage-Gate® NPD system a manager can shift between causal logic and effectual logic, as well as simultaneously use both logics to expand their decision-making paradigms.

2.4. Conceptualizing Stage-Gate® with pivots: causal-effectual decision-making logics

I conceptualize the path leading to a pivot decision as moving through the belief-updating model (Biyalogorsky, et al., 2006) and shifting from a causal logic to an effectual one. Figure 1 illustrates how causal and/or effectual logics inform Stage-Gate® decisions with the addition of a pivot outcome. First, the decision-makers craft the original product concept from an initial set of information which shapes their initial belief structure. Over the NPD process, new information and traction (e.g., marketing, technical, and/or financial) act upon this initial belief structure to form an updated belief structure—shaping this belief structure is the logic of the manager causal, effectual, or both.

FIGURE 1. Figure 1 how causal and/or effectual logics inform Stage-Gate® decisions with the addition of a pivot outcome**.**



A manager's updated belief structure can be distorted by belief inertia, especially through the lens of a causal logic approach, where they fail to "sufficiently adjust prior beliefs" (Biyalogorsky, et al., 2006) and interpret the new information similar to what happens with confirmation bias (Jonas et al., 2001). The determination as to whether the manager will continue the same failing course of action or pivot is determined by whether their belief structure and logic update. If a manager applies an effectual logic, they may imagine new possibilities that can lead to making a pivot decision. A pivot might be viewed as an escalation of commitment since it is a continuation decision in face of the failure of the prior product concept or belief that changes are needed for the organization's survival and growth. Albeit a pivot is not a typical escalation situation since the pivot provides some possible path forward with potentially higher odds of success than straight continuation without the pivot. Additionally, if a manager applies causal logic or effectual logic, they may select to escalate their commitment through holding or recycling, but to a lesser extent than continuing full speed ahead. Moreover, a

manager may apply both logics, causal and effectual, and decide to iterate. It is important to remember the logics can be used interchangeably, simultaneously, or one logic may be more dominant when the scope of the organization's activities is wider leading more to an effectual logic or narrower leading to the usage of casual logic.

3. Methodology

3.1. Research approach and empirical data

Consistent with prior work on effectuation theory (Auernhammer and Roth, 2021, Mero, et al., 2020, Parris, et al., 2018) and decision-making frameworks in NPD (Antioco et al., 2008, Beverland et al., 2016, Kester et al., 2011), a case study design was used. Case studies allow for an in-depth, exhaustive, and rich description of individuals immersed in the experience, which emphasizes the "voice" of the storyteller—those engrossed in the experience—which can include the researcher (Lieblich et al., 1998, Yin, 2014). Given pivots are a nascent topic in entrepreneurship and NPD literatures, and since the aim of this paper is to contribute to escalation of commitment theory, effectuation theory, Stage-Gate® systems, and entrepreneurial pivots the author team selected an extreme example (Dane et al., 2012, Parris and Welty Peachey, 2013, Pratt et al., 2006) in which the first and second authors had lived experience of being the subjects immersed in making the decisions throughout the NPD process. Thus, a B2B AI marketing organization was selected that made pivots during its NPD process, ultimately escalating before it was eventually terminated. Autoethnography exploratory-naturalistic case studies utilize the experiences of the researcher as the subject of study, which crosses disciplinary boundaries and has been used in anthropology, marketing, education, entrepreneurship, sociology, medicine, and other fields (Belkhir, et al., 2019, Ellis, 2004, Riessman, 1993). A benefit of autoethnography exploratory-naturalistic case studies is the data

are owned by the researcher(s) since they are the same as the subject of investigation. Unlike most case studies, in an autoethnographic case study, the researcher's in-depth, lived experiences and narrative recollection facilitates the collection of large quantities of datum and the lucidity of the breadth, depth, and complexity of social and environmental dynamics (Lieblich, et al., 1998, Yin, 2014).

The case example is a B2B AI marketing organization that operated between 2015 and 2019 and was founded by the first and second authors. Data for this study were collected by the first author's participation in the organization, which included gathering over one thousand agendas and supporting documents from meetings with the development team, potential and existing customers, investors, partners, tradeshows, and presentations as shown in Table 2. Additionally, data were gathered from company documents (n=146), artifacts from presentations (n=42), reports (n=17), and historical records from the company's product development management software (n=802) were collected. Table 3 illustrates the organization's NPD timeline, which illustrates how the company pivoted multiple times and how the founders applied effectual and casual logics during their NPD process to make continuation decisions.

TABLE 2. Company events in which the first author participated

Meeting type	**2015**	**2016**	**2017**	**2018**	**2019**	**Total Meetings**
Engineering and project meetings	83	154	138	159	40	574
Sales meetings	2	117	113	100	1	333
Customer management meetings	0	1	28	46	10	85
Tradeshows attended	1	9	6	6	0	22
Industry presentations	0	3	2	4	0	9
Venture capital/investors meetings	3	6	3	4	0	16

TABLE 3. The B2B AI marketing organization's NPD timeline.

Year	NPD stage	Decision	Product concept	Effectuation or causal logic utilized
2015	Stage 0 - Opportunity identification	Go	An AI classification engine for events whereby users can find and register for social and competitive activities as an affiliate business model	Bird-n-hand principle, Affordable loss principle, Patchwork quilt principle, Pilot-in-the-plane principle
		Iterate	Added create alert feature whereby users could user set alerts to receive an email of upcoming events, specific to their interest, within the distance they were willing to drive	Patchwork quilt principle
2016	Stage 1 - Preliminary marketing and technical assessment	Hold	Same product concept as above	Pilot-in-the-plane principle, affordable loss principle
	Stage 2 - Development and testing	Pivot 1	Co-branded partnership with retailers whereby the organization built a list builder to register retailer web traffic to opt-in to a weekly email of local events	Bird-in-hand principle, Lemonade principle
	Stage - 3 Commercialization	Iterate	B2B SaaS business model offering a white-labeled email marketing service	Affordable loss principle and causal logic
2017	Stage 2 - Development and testing	Pivot 2	Autonomous personalized email marketing company - delivering one-to-one personalized emails tailoring email content to the observed preferences of the user	Affordable loss principle and causal logic
2018	Stage - 3 Commercialization	Pivot 3	Autonomous marketing company – auto-classifying content from numerous sources, partners, and customers to deliver personalized content to users	Bird-in-hand principle, Lemonade principle, Patchwork quilt principle, Affordable loss principle
2019	Stage - 3 Commercialization	Kill	Close the company	Bird-in-hand principle

3.2. Data analysis

A qualitative study has trustworthiness, an accurate representation of the phenomena, if it has credibility—an analogy to internal validity, transferability—an analogy to external validity,

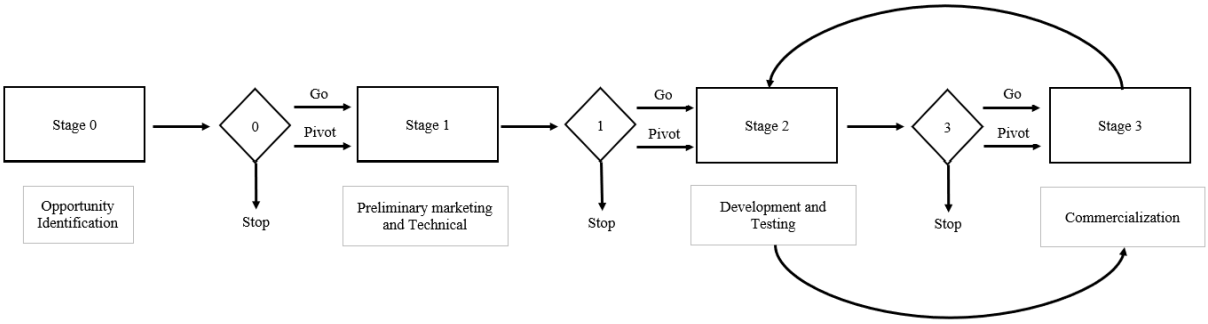
dependability—an analogy to objectivity, and confirmability—an analogy to reliability (Lincoln and Guba, 1985, Wagner et al., 2010). Credibility was established by using triangulation of measures. Triangulation was achieved by a detailed review of the organization's product development management software which provided a granular day-by-day perspective of the product's journey, as well as calendar records, sales presentation PowerPoint decks, and industry presentation PowerPoint decks. Narrative recollection of the events was checked against calendar records and records from the company's software development management platform to enhance credibility. Transferability was achieved by the first author keeping a reflective journal, documentation of personal observations and perspectives, which provides a contextual narrative and ensures transferability (Glesne, 2016, Lincoln and Guba, 1985). To improve dependability and confirmability, the first author collected and analyzed the data, while the second, third, and fourth authors served as auditors that reviewed and confirmed interpretations (Erlandson et al., 1993). Additionally, as recommended by Pratt (2009) direct quotes (i.e., power/proof quotes) are provided to illustrate the findings.

4. Findings and discussion

The case study revealed effectual and causal logics were applied interdependently and independently when the organization made continuation decisions during NPD, which included the traditional decisions of Stage-Gate® (i.e., go, stop, hold, recycle, and iterate) in addition to the decision to pivot. Figure 2 illustrates the B2B AI marketing organization's evolution with pivots in a Stage-Gate® system. Exploring the NPD process of the technology startup and the logics utilized by the founders provokes several interesting research propositions, which are integrated into this section. These findings suggest incorporating effectual logic and causal logic

into a NPD Stage-Gate® system provides the manager, founder, or product leader a logic with which to update their belief system that supports pivots in the NPD process.

FIGURE 2. The B2B AI marketing organization escalation of commitment with pivots.



4.1. Stage 0: Opportunity identification

The B2B organization on which this case is based started as a business-to-customer (B2C) organization. In the process of planning a vacation whereby the founders attempted a road trip connecting mountain bike and paddleboard races, they became frustrated having to navigate to multiple websites, event registration platforms, knowing the names and locations of various associations, social clubs, and informal networks. Aligned with the bird-in-hand (i.e., starting with one's means) principle of effectuation theory, the two founders envisioned an AI classification engine that monitored the web for interest-specific outdoor sporting events and made them available from one central location. Based on their backgrounds the founders knew the idea was implementable, could be built for $30,000 dollars which they had on hand (i.e., bird-n-hand principle), could afford to lose (i.e., affordable loss principle), and did not exist in 2015.

In applying the bird-in-hand principle of effectuation in stage 0 of the NPD process, opportunity identification—where actions are taken to identify or create new business or product ideas, the founders' started with their means by asking: 'who are we, what can we do, and who

do we know?' (Sarasvathy, 2001). In answering, "who are we" the founders discovered complementary skills and experiences. One founder, the first author, had experience leading technology NPD projects in multiple industries, which included working with off-shore and on-shore development teams. The other founder, the second author, had experience in the sports industry as an entrepreneur and professional athlete, as well as in developing artificial intelligence models. In answering, what can we do?, the founders could design a technology product that applies artificial intelligence to classify sporting activities, such as the difference between kayaking, running, climbing, mountain bike riding, or hiking events, as well as distinguish between the level of difficultly of the event—beginner friendly to professionally competitive from the plethora of digital content published online.

Developing technology products can be expensive, especially if it is not within the means - human, social, and financial resources (i.e., who are we, who do we know, and what can we do?) of the company or managers. By building the product concept, leading project development themselves, and employing an off-shore development team they could launch a minimal viable product (MVP) - a version of the product with a tolerably acceptable number of features that would be useful to customers who can provide feedback. In asking who they know, the founders had worked with a local organization that facilitated hiring and working with offshore development and were able to leverage this past relationship to be a client at a discounted rate. The bird-n-hand principle also aligns with self-authorship, reflecting on one's beliefs, identity, and relationships to inform one's decision-making (Kegan, 1998, Magolda, 2020). This requires questioning the status quo, exploring possibilities, and constructing one's decision-making logic (Parris and McInnis-Bowers, 2017). A critical component of effectual logic is starting with

one's means; whereas, in causal logic often resources to execute the new product concept are sought after the opportunity identification stage is passed with a "go".

Another key difference between effectual and causal logic is the selection criteria for defining NPD goals. In the case of causal reasoning, the goals are defined by minimizing risk and maximizing expected return, which is the taken-for-granted norm (i.e., institution logic) (Oliver, 1997) of business school education and most companies (Parris and McInnis-Bowers, 2017). Despite their MBA training and experience in enterprise settings where technology innovation often faces resistance (Parris et al., 2016), the founders applied effectual logic when deciding to pursue the opportunity. Effectuation is a way of seeing the world (i.e., logic, paradigm, belief system) that individual actions can make the future, also known as the pilot-in-the-plane principle; whereas causation attempts to predict the future and accepts the future will unfold following established market forces (i.e., what can be predicted). In this case, the founders simultaneously applied bird-in-hand, affordable loss, and pilot-in-the-plane principles as illustrated in Table 3. As highlighted above, the founders assessed their means including their financial resources, and then asked themselves, what could they afford to lose if this product concept failed (i.e., affordable loss)? Their answer was $30,000 dollars for the MVP, in addition to one of the founders resigning from their current position to work on the startup full-time. Together they focused on taking actions to develop the initial product concept (i.e., pilot-in-the-plane principle).

Next, the founders applied the patchwork quilt principle of effectuation theory where they sought out potential collaborators by sharing their initial product concept with colleagues, strangers, and investors. A former colleague who is a developer started building prototypes as a way to learn new skills and help friends out in the process, which resulted in weekly lunches in

the park. These brainstorming sessions led to an iteration that added a key feature to the MVP. The feature was a "Create Alert" function which enabled a user to receive an email of upcoming events, specific to their sport interest, within whatever distance they were willing to drive. Additionally, the founders began competing and participating in social and competitive events they identified with the organization's initial prototype - an Excel sheet of events. At each event, the founders spoke to the organizer and participants to build a list of beta users and partners who expressed an interest in the product. In contrast, if they applied causal logic, they would have viewed everyone else as competitors and kept their product concept a secret.

On November 21st, 2015, the platform was released to nearly 400 beta users.

Research proposition (RP1):

> *The speed of Stage 0 – opportunity recognition, is faster with effectual logic than causal logic. As the boundaries for starting the NPD process and criteria selection of goals are based on the resources on hand, what can be lost, and collaboration instead of needing to gather resources, avoid risks, competitive analysis, and create a plan to clarify expected returns.*

4.2. Stage 1: Preliminary marketing and technical assessment

As the founders' MVP was tested in the marketplace, the site utilization metrics immediately showed a troubling pattern. Site users came to the site once a week, consistently week after week, demonstrating consistent but low-frequency use. While the week-to-week organic growth rate—the number of new users per active user—was 0.005. A massive volume of users would be required to make the web traffic produce revenue, but the marketing effort to get those users would never result in profitability. The business model—earning a commission for each paid event registration originating through the platform (i.e., an affiliate marketing model)—did not make financial sense. It was beyond the founders' financial, human, and social capital (i.e., means) to adopt a push marketing strategy—take the product to consumers making them aware of the product and its benefits or to influence consumers behavior by providing

incentives, shaping habits with new features, and using contextual tools to reinforce actions. The founders quickly acknowledged changing consumers' behavior on their site was beyond their control. This could have resulted in a decision to kill the product concept.

However, even though the initial business model was not adequate (i.e., viability) users were coming back indicating the product provided value to them (i.e., desirable). As highlighted by Klenner, et al. (2022) and Parris and McInnis-Bowers (2017) effectuation principles can encompass design thinking, as both are mindsets and approaches for building innovative products that test and integrate the following three critical pieces for product success: (1) *desirability*—a unique value proposition that people want, need, or makes sense for their lives, (2) *feasibility*—the technology is possible and executable at scale, and (3) *viability*—meets the requirements for a successful business/revenue producing unit (Brown, 2008). In addition to ascertaining whether their product had desirability, the product itself met the feasibility criteria as it was scaling well beyond their initial expectations such that the platform was automatically collecting over 500,000 unstructured events and categorizing them daily.

At this time the founders decided to hold and began to focus on the technology solution which was within their control. The approach of focusing on what you can do with the resources and actions within the managers' or founders' control, aligns with the pilot-in-the-plane principle of effectuation. In contrast, if the founders had applied causal logic, they would have accepted the market forces and sought to find or predict the future. In this case, the founders' effectual logic was rooted in a belief that the future could be made by creating new possibilities with actions they could take, which were within their means and what they could afford to lose.

Research proposition (RP2):

> *In light of negative feedback, using an effectual logic will be more likely than using a causal logic to lead to escalation of commitment as decision makers believe the future*

can be made, as well as they are more likely to accept predictions are false and seek to identify and create new effects with their existing means if the initial product concept is not tolerably acceptable.

4.3. Stage 2: Development, testing, and commercialization

In contrast to causal reasoning that avoids unpredictable events, effectual logic welcomes surprises as potential insights to create new possibilities—also known as the lemonade principle of effectuation (Read, et al., 2009, Sarasvathy, 2001, 2008). The organization's initial product concept with a B2C business model was failing; however, through leveraging an unexpected outcome (i.e., contingency), they escalated their commitment by making the decision to pivot, which resulted in significantly modifying the product and switching to a B2B business model.

4.3.1. *Pivot one—a B2C event aggregator towards a B2B email marketing company*

Each January, Orlando, Florida hosts one of the largest tradeshows for the specialty outdoor sports industry. It is attended by manufacturers and retailers. From past industry experience, one of the founders had extensive contacts within the industry. Leveraging who they knew and what they could do (bird-in-hand principle), the founders used their technology platform to send to their industry social network upcoming events that would be happening near the tradeshow while they were in town. While standing on the floor of the tradeshow, a retail store owner who had received a forwarded email from a manufacturer representative surprised the founders by asking if a similar email could be sent weekly to his customers. Standing in a tradeshow aisle the founders leveraged this surprise and crafted a plan whereby the retailer and the organization would partner to send co-branded weekly upcoming event emails. The organization benefited from the arrangement by getting an infusion of target market web traffic and users. The retailer benefited by reporting which provided insights on the interests of its customer base. This concept gained traction when a manufacturing representative group took notice and connected the founders with several "influential" retailers.

Research proposition (RP3):

> *An organization or individual who embraces an effectual logic when confronted with a surprise (positive or negative) will be more likely to update their belief structure and leverage the new information to pivot by either creating new effects (i.e., outcomes/goals) or modifying the product concept; thus, being more likely to escalate their commitment to continue in light of an unpredictable event.*

4.3.2. *Stage 3: Commercialization through an iteration of pivot one*

Nevertheless, by the summer of 2016, the founders concluded earning commissions from event registrations was not a viable business model. Thus, the founders made the decision to kill (i.e., discontinue) their affiliate business model and remove the "Get Alert" functionality from the company's website. On the other hand, the founders had partnered with five specialty retailers who viewed the co-branded emails as part of their marketing mix often supplanting their own direct marketing programs. So, the founders decided to pivot the business from a B2C organization partnering with retailers to generate web traffic to a B2B organization providing email marketing services for specialty retailers. The response from the retail partners was overwhelmingly positive as stated by the president of a specialty outdoor chain operating in the southeastern US in an email communication on 11/29/2016 "Let's roll this asap. I plan to dump constant contact soon." However, this iteration required the development of marketing tools common to email service providers such as a list builder, a pop-up that appears on a website requesting the visitor's email, as well as email templates with the retailer's branding and color schemes.

Prior to investing to become a B2B email marketing company, the founders applied both the affordable loss principle and causal logic. The founders again asked: how much can we afford to lose if this fails (i.e., affordable loss principle)? In using causal logic, they sought to predict their desired outcome of becoming the email marketing company of choice for specialty retailers. Based on promising financial modeling and possessing the means (bird-n-hand

principle) to invest more in developing a software as a service (SaaS) business model the founders decided to iterate. As a positive sign of traction, 100% of the retailers who used the list builder purchased the email marketing solution.

Research proposition (R4a)

> *The decision maker's logic when choosing to iterate is distinct from the decision to pivot. When making a pivot decision the decision maker is more likely to employ effectual logic, whereas when making an iterate decision the decision maker will combine effectual logic and causal logic.*

Research proposition (R4b):

> *If an NPD project develops traction and thus, predictions are possible, a decision maker who applies effectual logic historically is more likely to combine effectual logic and causal logic to inform their next decision instead of switching to causal logic only. In this case – causal logic will likely be used to model the viability, feasibility, or desirability of an effect created, but what to do next will likely be informed by effectual logic if continuation is within the individual's or organization's means (bird-in-hand principle) or affordable loss.*

Research proposition (R4c):

> *If a decision maker applies both causal and effectual logics simultaneously, he/she is more likely to make an iterate decision (i.e., make minor changes) than a kill, go, hold, or pivot decision.*

During this transition, the founders continued to develop and assemble new means (bird-in-hand principle) and expand their social network to proactively create new possibilities by combining means, organizations, and people in new combinations, which aligns with the theory of effectuation and Obstfeld et al.'s (2020) assembly perspective of entrepreneurial action. In September 2016 they connected with the president of the industry association representing independent specialty retailers through one of their customers. The founders shared examples of the organization's beta customers use of the new B2B solution and described how, with their technology, the president's vision of hundreds of independent retailers operating distinctly but joined as a single marketing channel could be achieved. The president responded by saying

“Thank you. Let me move this forward on my side. Love this” (email communication September 2, 2016). Although the President found this desirable, feasible, and viable, he needed buy-in from across the association to move forward. Jointly, they planned to introduce the concept at the organization’s next tradeshow in November.

In preparation for the show, the founders studied the email marketing practices of the membership by registering for all 121 of the retailers’ email lists through their websites and then, coding each email the retailer sent between August 16, 2016 and October 16, 2016 to assess their practices. At the show, the founders presented their findings: only 31% used email but of those most were using it infrequently averaging .8 emails per week, 84% of those emails were promotional with an average discount off the manufacturer’s suggested retail price (i.e., MSRP) of 38%, while only 14% were following best practices for email formatting. In contrast, the large chain and online retailers of specialty goods engaged their customers via email an average of four times a week, with a broader marketing message mix, a lower average discount of 32%, and 100% applying best practices for email formatting. The response as measured by a feedback survey of the presentation administered by the association showed 58 percent of respondents (n=22) found the presentation excellent or very good. While text comments on the survey furthered this sentiment “Data is key on talking about stuff. They called us out on our practices, gave recommendations, offered services and most of all talk trends on what works and what doesn't.” As well as messages like “Plan to reach out to [organization’s name].” To get retailers to visit their booth the founders’ offered analysis of each retailer’s email marketing program which generated 19 sales leads coming out of the show. Following the tradeshow, the founders and the president of the association sat down and agreed if ten of the retailers became customers

of the organization the association would allocate funds to pay for the service for all retail members.

Concurrently, the founders were introduced to another B2B organization who were working to make brick-and-mortar stores in-stock inventory searchable online. The two companies determined by integrating the founders' organization could use their expertise in AI to match the retailer's inventory to the content it distributed. Doing so, enabled the organization to create a fully automated email marketing program for retailers.

4.3.3. Pivot two: Launch into autonomous personalized email marketing

To deliver emails with both content and products autonomously posed a challenge. Space in an email is limited. Therefore, the content delivered to the individual has to be relevant to them. Otherwise, the engagement algorithm would in effect just be sending randomly selected content. As of the fourth quarter of 2016, the founders had invested approximately $40,000 dollars. With this pivot, however, the founders were going to have to invest considerably more since they would need to design algorithms to select content and products. The implementation of these algorithms had to be done in such a way that hundreds of thousands of emails could be crafted and distributed daily. This pivot represented the largest escalation of commitment as the founders would need to invest nearly $120,000 dollars in the first quarter of 2017 into software and hardware. However, consistent with the principle of affordable loss the founders could afford the investment and knew if the opportunity with the buying group failed to materialize the technology would be applicable in other settings. Additionally, the founders applied causal logic modeling the potential of the products desirably, feasibility, and viability in distinct settings, which all reaffirmed the decision to pivot.

Research proposition (RP5):

> *A decision maker's escalation of commitment has an upper bound set by the organization or individual's affordable loss. At an organizational level once the resource commitment exceeds what the organization can lose on the project the organization will terminate it. At an individual level, the loss could be both financial or social, such as loss of reputation and prestige.*

4.3.4. *Pivot three: Impacts of the Facebook—Cambridge Analytics scandal*

Following the 2016 election, organizations that integrated with Facebook were holding their breath to see how the company would respond to criticism of Facebook's data policies. In response, the founders had to make a significant pivot in their technology and business model. From a technology perspective, the organization had to broaden the kinds of content it could acquire and categorize. This led the founders to build partnerships with magazine publishers and develop the technology to harvest and categorize magazine content so that articles could be included in user emails consistent with the product catalogs of the retailers and the interests of the subscribers. Fortunately, the organization had an attractive offer for publishers as in August of 2017 their emails were reaching 200,000 email subscribers 4 times a month, with expected distribution of 500,000 email subscribers by year's end (company communication dated April 1, 2017). Furthermore, the publisher only needed to provide permission. Publisher responses were positive as typified by the director of digital media for a large publisher of specialty magazines statement "I enjoyed the talk, I think this has lots of possibilities for both companies" (email communication on August 13, 2017). Throughout 2017 and 2018 the organization secured content distribution agreements with three large publishing organizations to broaden the content mix on the platform.

In April 2018, Facebook stopped third-party companies from requesting data from the platform (Seetharaman et al., 2018). While Facebook was one of over thirty sources of content for the organization it provided the lion's share of content specific to the retail customers. This

forced the founders to further expand their content acquisition capabilities to include consuming, filtering, and categorizing web content scraped from the retailers' owned digital channels.

However, both the development and cost to operate this technology drastically increased the costs for the organization. Recognizing these costs could not be passed onto the retailers the founders applied the patch-work-quilt and bird-in-hand principle. The founders recognized the new technology capabilities could be used to catalog the marketing materials of the manufacturers. Once the marketing materials of the manufacturer were associated with the products the organization could automatically include the manufacturer's marketing assets in the emails of retailers. Furthermore, with the connections they had built through the industry group, they were able to sell this content integration service to four manufacturers quickly.

4.3.5. The kill decision

While the organization grew quickly to have one-third of the membership of the industry group as customers, as an association no progress was made to purchase a group-wide solution. Starting in the second quarter of 2018 the organization had exhausted the supply of early adopters within the trade organization. For many retailers, email marketing is their most profitable digital channel (Campaign Monitor, 2022, Kirsch, 2022), and therefore, plays a large and central role in the daily life and job of a retail marketing manager. A good indication of the barrier which was to come was included in the survey results from the founders' first presentation to the association in 2016, "If only I could get my marketing guy on board with their concept." Consistently the founders encountered where usually the owner, CEO, general manager, sales leader, or store operations leader was fully committed, and on one occasion had already purchased the organization's email marketing service, only to have the marketing manager stonewall the implementation to prevent losing control of the email marketing program.

An irony of running a fully autonomous direct marketing company was despite producing email open rates which were 59% greater and click rates that were 44% greater than the retail industry average, as well as increasing the number of transactions per customer from 1.53 to 1.95 a 26.7% increase (Company promotional material in 2018) some customers wanted greater control of the content distributed. Unfortunately, the conflict between a desire for control and the benefits of AI automation was the leading cause of customer cancelation as reported in the email communications from canceling retailers in 2018, "The biggest thing for us to have more control of what goes out," (email communication with the owner of a single store retail operation in the southeast on December 21, 2018) and "we feel we can send emails to our customers that have more control over products presented" (email communication with the owner of a multi-store retail chain in the central US February 19, 2018). Even customers who were evangelical about the benefits they received routinely requested to override the personalization algorithms, "please be sure the Locals'Night/ Luminaries event is listed on our emails mañana," (Marketing manager of a multi-store retail organization in Western US on December 18, 2018).

Furthermore, in selling the content integration solution the founders were confronted with a long-existing tension between the manufacturers and their supply chain partners—the retailers. As stated by the marketing manager of a globally known manufacturer of specialty products during a meeting at the manufacturer's corporate headquarters, "We spend an enormous amount to produce these marketing assets. Allowing you to use them for the retailers would be helping our competition," (First author meeting notes from onsite discussion on January 11, 2018). While many manufacturers rely on wholesale retail partners, many also operate direct-to-consumer channels. In these organizations often there was a distinction between the wholesale sales manager and the marketing manager. The wholesale manager's performance was measured

on sales through the wholesale channel while the marketing manager often had their performance measured by customer engagement and sales through the manufacturer's direct channels. The perspective adopted by the marketing manager quoted above was if someone wants to purchase our product the independent retail channel is competing with me for that sale. In one instance the head of wholesale sales for a globally known manufacturer based in the pacific northwest stated, "I'll pay for it—we just have to get marketing to sign off" (email communication June 19th, 2018). While again control was a recurring theme as one marketing manager stated during a zoom call, "How do we make sure our assets are not in the same email with other [manufacturers]").

The combination of increasing sales cycle time, increasing cost to manage the service expectations of the customer base, customer attrition, as well as the inability to sell more manufacturers on the content integration service quickly enough, while the cost to develop and operate the email marketing solution continued to increase rapidly forced the founders in early 2019 to kill the autonomous marketing service.

Research proposition (RP6):

> *Using effectual logic the determination to pivot is based on whether a decision maker has a means which enables him/her to imagine possibilities. Once the decision maker no longer sees how his/her means can generate new possibilities, he/she will kill the project.*

5. Implications and conclusion

This paper makes multiple theoretical contributions. First, I have sought to push NPD research beyond thinking about ways of doing i.e., focusing on NPD methods to consider ways of thinking, and how logics influence the kinds of decisions made by NPD managers. Second, through integrating the entrepreneurship and NPD literature I have added a new decision outcome to the established Stage-Gate® outcomes, which provides an additional pathway to escalating commitment in the NPD process. Third, the case illustrates how the causal-effectual

process of belief updating can lead organizations to escalate their commitment, as well as show how the logics of managers can be adaptable to a changing operating environment.

Furthermore, this case illustrates that during NPD, decision-makers can shift between and combine causal and effectual logic. Stage-Gate® NPD processes are commonly used and borrowing from entrepreneurship research, the concept of a pivot is added to the possible gate decision outcomes. Pivots arise when decision-makers receive negative feedback, and they result in a redirection of the NPD project. Since pivots result in substantial changes to the product concept, they give the underperforming project a potentially greater chance for success. Alternately, pivots provide another potential pathway for the escalation of commitment during NPD. In addition to adding pivots to the well-known Stage-Gate® NPD process, an effort has been made to postulate how escalation of commitment can occur once pivots are added as a possible outcome. Furthermore, I argue that during NPD, decision-makers should consider shifting between or combing causal and effectual logic.

For scholars, the purpose of this case study is to dive into the nuances of a B2B organization's NPD process and generate research propositions that can be explored through empirical and mixed-method approaches. Beyond the research propositions proposed above, this study has shown the causal-effectual process of belief updating can lead organizations to make pivot decisions, as well as provide decision-making logics that are adaptable to a changing operating environment. Scholars should seek to explore if these findings are applicable to all B2B organizations or only a subset, as well as the conditions under which managers can optimally apply effectual-causal logics. As well as, whether organizations who employ pivots as a decision outcome in their NPD processes have greater NPD success rates when compared to organizations who do not. Furthermore, while scholars have pointed to distortion in the belief

updating process as the mechanism leading to escalation of commitment, scholars should explore if there are differences in the degree and type of distortion between managers who are a.) trained in causal reasoning, b.) trained in effectual reasoning, and c.) trained in both logics. The implications of these future research directions could result in significant improvements in NPD outcomes for organizations.

For practitioners, this research points to value in managers possessing both effectual and causal decision-making logics. Furthermore, decision-makers should be aware of the logic with which they are approaching NPD gate decisions (i.e., a causal, effectual, or combination), and assess whether the decision-making logic should shift to meet changes in the operating environment. Taking this approach, managers who encounter a significant unexpected contingency, such as the covid-19 pandemic, may choose to shift from a causal logic to an effectual logic or integration of the two to do the doable and keep worthwhile new product initiatives advancing through the NPD process. Finally, managers should recognize pivoting is a continuation, and a continuation when the project has yielded negative results i.e., an escalation of commitment. While pivoting likely increases the probability of success over a straight continuation decision it is not an escape from a project failure.

Despite these theoretical and practical contributions, as with every study, this study has its limitations. The findings are based on one case study and may not be generalizable. While the exploratory case study suggests pivots can be an escalation of commitment during NPD and that the casual-effectual process of belief-updating is further associated with escalation of commitment, this does not indicate it will be the same in all B2B organizations. As a qualitative study, the data represent the perspectives, observations, and experiences of the participants which may lead to biases (Miles & Huberman, 1994). Specifically, in this case, the first and

second authors are the participants. To mitigate bias the first author collected and analyzed the data, while the second, third, and fourth authors served as auditors that reviewed interpretations and confirmed the findings (Erlandson et al., 1993). As this case study only provides one perspective, future research should include the perspectives and contributions of other B2B organizations and management teams.

Finally, I present the result of an autoethnography, exploratory-naturalistic case study of an actual NPD project which included pivots. Not only do the results of this case study help to develop and test the theory developed herein, but they also facilitate the development of research propositions. I believe that these propositions offer ample pathways for future research efforts. Managerially, expanding the possible decision outcomes of NPD review points gives under-performing projects the chance to be redirected – which also opens significant research opportunities.

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