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The Future of Digital Communication Research: Considering Dynamics and Multimodality ☆

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Abstract

Digital communication, the electronic transmission of information, reflects and influences consumers' perceptions, attitudes, behaviors, and shopping journeys. Thus, data stemming from digital communication is an important source of insights for retailers, manufacturers, and service firms alike. This article discusses emerging trends and recent advances in digital communication research, as well as its future opportunities for retail practice and research. The authors outline four consumer–retailer domains relevant to digital communication, which in turn frame their discussion of the properties of communication dynamics (e.g., trends, variations) within messages, communicators, and their interaction, as well as communication multimodality (i.e., numeric heuristics, text, audio, image, and video). These factors are critical for understanding and predicting consumers' behaviors and market developments. Furthermore, this article delineates conceptual and methodological challenges for researchers working in contexts that feature dynamics and multimodality. Finally, this article proposes an agenda for continued research, with the goal of stimulating further efforts to unlock the "black boxes" of digital communication and gain insights into both consumers and markets.

Keywords: Digital communication; Dynamics; Multimodality; Big data; Marketing analytics

Taking advantage of the vast increases in digital communication data (Bradlow et al. 2017) would prove enormously beneficial for retailers, manufacturers, and service firms (De Luca et al. 2020; Dekimpe 2020; Shankar 2019). Digital communication describes any electronic transmission of information that has been encoded digitally and transmitted via digital media.

These available data span multiple communication formats and various communicators (e.g., consumers, retailers). Digital communication also can be categorized broadly as involving one-way (e.g., digital ads, customer reviews; Minnema et al. 2016; Pauwels et al. 2011) or interactive (e.g., e-service chats, online brand communities; Jin, Hu, and He 2014; Van Dolen, Dabholkar, and De Ruyter 2007) pathways, and it occurs on a vast number of platforms (e.g., Instagram) and stores (e.g., digital signage; Roggeveen, Nordfält, and Grewal 2016).

Because digital communication is purposefully constructed, recurring, and subject to change, its dynamic development is equally as relevant as its current content. Thus for example, providing content in a sequence that matches customer journey stages might increase conversion (Humphreys, Isaac, and Wang 2020). Other dynamic components, such as trends or variability in the communicators and interactions, provide additional insights (Palmatier et al. 2013; Villarroel Ordenes et al. 2019). In addition to its dynamism, digital communication features various modalities (e.g., numeric, text, audio, image, video). Most retail research and analytics still rely predominantly on numeric or text data, but richer images or videos might be more powerful for reflecting and influencing consumers' preferences (Li, Shi, and Wang 2019), such as by supporting service interactions through smart speakers (Shankar et al. 2020) or crafting targeted video messages (Hess et al. 2020). Because consumers and retailers tend to combine various modalities (e.g., likes, text, pic-

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tures, videos) in their efforts to convey information, all of these different modalities need to be considered jointly to determine their impact (Li and Xie 2020).

Such efforts may be enabled by the extensive records of digital communication data that get automatically stored and frequently updated, such that they are traceable and readily available to retailers and researchers. For retailers, digital communication provides particularly rich and valuable data for several reasons. First, it offers first-hand, unobtrusive insights on consumers' perceptions, attitudes, and behaviors. Even if a retailer does not actively participate in the communication, simply listening in may help it understand its consumers (Schweidel and Moe 2014). Second, digital communication influences shopper journeys. Ratings, reviews, and images across platforms and sites all matter for consumers. Recent evidence indicates that only 53% of consumers would consider a retailer that earns fewer than 4 stars on a rating site; that most people read reviews for local retailers, as well as the retailers' responses, prior to undertaking a purchase (Murphy 2019); and that in the fashion and beauty sectors, 72% of purchases result from influences by Instagram (Arnould 2017). Third, digital communication data can provide insights at a greater level of detail and scale than traditional methods like surveys or focus groups (Balducci and Marinova 2018). Because these data from digital communications also get constantly created, they are particularly well suited for longitudinal studies of developments or changes exhibited by consumers or retailers.

Within the emerging domain of digital communication research, we aim to make four main contributions. First, as the structure in Fig. 1 details, we introduce four domains of digital communication between consumers and retailers to frame our discussions. Second, instead of being timeless states, digital communications are processes that develop and change. The importance of such process dynamics is often emphasized (e.g., Babić Rosario et al. 2019; Zhang and Chang 2020) but rarely addressed in marketing and retailing research. Accordingly, we delineate illustrative dynamic communication properties (e.g., trends, variation, peaks) which likely provide valuable new insights for researchers and retailers. Third, we propose an overview of different modalities in digital communication (i.e., numeric, text, audio, image, and video communication; Balducci and Marinova 2018) and likely spillovers effects between them, as input for further research and retailer insights. We provide suggestions on key conceptual and methodological considerations when working with digital communication. Finally, we offer a set of expansive research propositions pertaining to using dynamics and multimodality to understand the meaning and effects of digital communication.

Domains of digital communication

Data stemming from different domains of digital communication reflect and influence consumers' (favorable or unfavorable) perceptions of and attitudes toward a retailer, behaviors (e.g., recommending the retailer or not), and overall shopping journey (Holmlund et al. 2020). We might classify these data broadly as internal and external. Internal data come from the direct communication between retailers and consumers (e.g., digital ads, digital service interactions). Retailers communicate substantially and directly with consumers, and through this practice, they also can capture first-hand data. External data instead stem from digital communications among consumers, without any direct retailer involvement (e.g., online reviews, online communities). They therefore need to be actively collected and analyzed, using netnography approaches, statistical software, or machine learning tools. Data from such external communication can complement retailers' internal data to establish better consumer insights (de Haan and Menichelli 2020). Each of these forms also can exhibit either one-way or interactive communication (Herhausen et al. 2019a). Accordingly, we identify four domains of digital communication (see Fig. 2): retailer-to-consumer messages, retailer–consumer interactions, consumer-to-consumer messages, and consumer–consumer interactions. Of course, in practice, these categories may be blurred when messages are further exchanged and become interactions.

In detail, *retailer-to-consumer messages* refer to one-way communication from the retailer, including targeted messages and display or mobile advertisements (Lee et al. 2018; Shankar et al. 2020), as well as direct messages sent to customers online or through mobile channels (Shankar and Balasubramanian 2009). *Retailer–consumer interactions* involve e-customer service, chatbots, or call center conversations, usually employed to provide frontline services and complement the efforts of employees. For example, retailers might handle customer complaints via email (Packard, Moore, and McFerran 2018) or social media (Herhausen et al. 2019b); even if service recoveries are handled by phone, today's call centers usually record the call, so the communication becomes digitized. In addition, in *consumer-to-consumer messages*, such as online consumer reviews or electronic word of mouth (eWOM), consumers report on their retail experiences and make recommendations to their peers (Duan, Gu, and Whinston 2008; Jin, Hu, and He 2014; Minnema et al. 2016). Finally, consumers discuss and exchange information about retailers and products in *consumer–consumer interactions* in brand communities and online forums.

We leverage this proposed typology and also integrate insights from review articles that suggest ways to derive quantitative insights from unstructured data in digital communication domains (see Table 1). These review articles have (1) introduced broad perspectives about using and handling big data in marketing (Wedel and Kannan 2016; Balducci and Marinova 2018) more specifically in retail (Bradlow et al. 2017; Dekimpe 2020), and (2) provide more focused methodological guidelines into one or two modalities (Pollach 2012; Kern et al. 2016; Humphreys and Wang 2017; McKenny et al. 2018; Li, Shi, and Wang 2019; Berger et al. 2020; Hildebrand et al. 2020; Schwenzow et al. 2020; Villarroel Ordenes and Zhang 2019). Extending the work of these articles, the sections below offer a new perspective concerning dynamic developments in digital communication data, beyond visual variation in video content (Li 2019), and discuss a full range of digital communication modalities (numbers, text, audio, image and video). We both discuss conceptual issues (e.g., theoretical underpinnings)

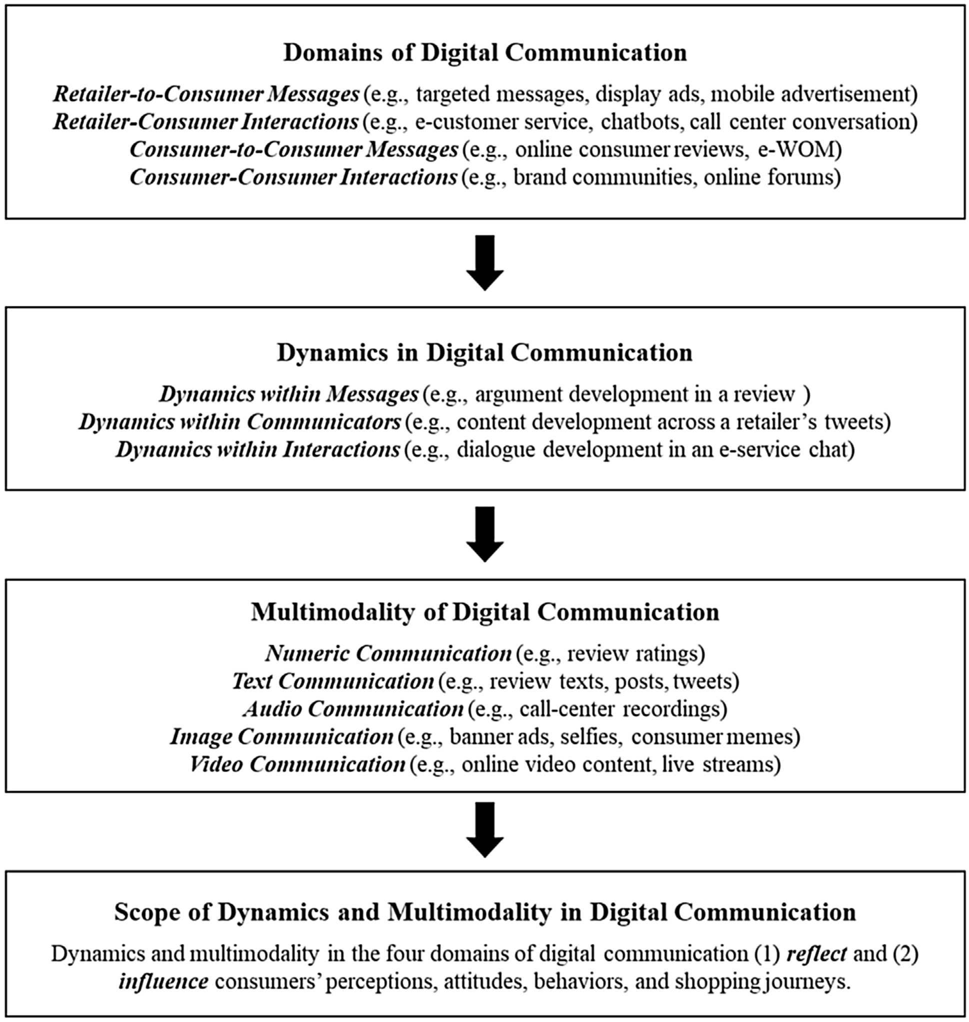

Fig. 1. Conceptual framework.

and methodological challenges (e.g., spillovers effects between modes).

Dynamics of digital communication

The content of digital communication accumulates, develops, and changes over time. Conceptually, considerations of how processes unfold, rather than timeless states, reflect the very definition of marketing and consumer behavior (Bartels 1968; Zhang and Chang 2020). Consumers inevitably evolve and change with their interactions, experiences, and shifts in the market environment (Hunt and Morgan 1996), as does their digital communication. Relevant insights for retailers thus may be derived from not only the current content of digital communication but also its dynamic development over time.

Every digital message (e.g., tweet, blog, post) contains contents and a developmental structure, determined by the order in which information in the message is presented. This structure is theoretically relevant. It might define a message's narrative genre (e.g., comedy, tragedy; Genette 1992) or level of drama (defined as a narrative discourse element that emerges due to oddities or twists in the story; Burke 1962). By considering developmental structures, researchers can discern a reviewer's sentiment or the impact of a review on prospective customers more accurately (van Laer et al. 2019). Thus, a gradual increase, rapid decline, or (in)consistency in digital messages might lead to different conclusions about the communicator.

Each message also comes from a communicator (whether consumer or retailer), whose presentation format or frequency (e.g., daily, weekly, monthly) might change. The patterns of changes can offer relevant market cues. Kanuri, Chen, and Sridhar (2018) determine that rhythms in content scheduling (i.e., time of day) influence the virality of social media posts. Therefore, retailers need to consider the dynamics in their own communication patterns, whether their digital communication is one-way or features ongoing digital interactions with consumers.

In the latter case, relational features (e.g., commitment, trust, gratitude, satisfaction) likely develop during the interaction, which may further explain or predict relationship performance. Palmatier et al. (2013) establish that commitment velocity, defined as the rate and direction of change in commitment over time, predicts sales performance better than a static, overall commitment level. Similarly, in digital interactions of consumers and

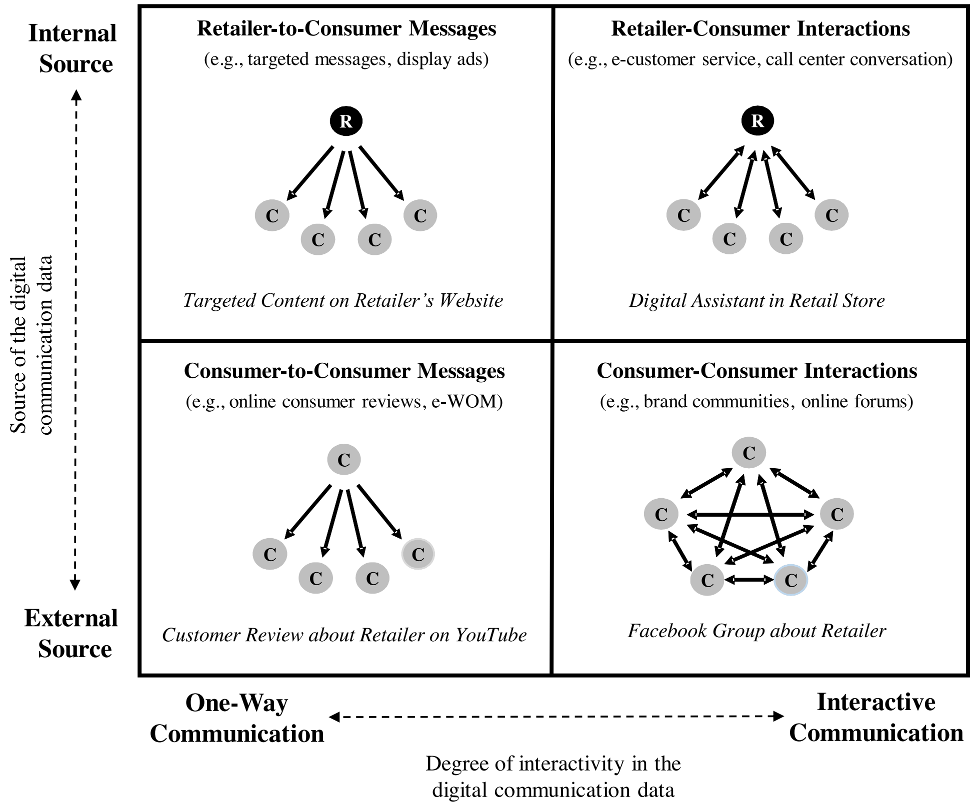

Fig. 2. Domains of digital communication.
Note: C = consumer, R = retailer. The same communication domains can be found for manufacturers or service firms, and the domains also apply to digital business-to-business communication (Herhausen et al. 2020a).

retailers, dynamic communication properties that reflect how the interactions develop likely can predict interaction outcomes and retail performance.

To study all three of these dynamic developmental properties, retailers can leverage digital communication data, which are both longitudinal and frequently updated. Their dynamic developmental properties better than static measures can, reflect the sender's perceptions, experiences, and behaviors and also influence communication recipients. Yet most existing research considers digital communication only at a given point in time or in aggregate (Table 1). We propose instead that researchers should recognize the implications of dynamic developments that occur in messages, communicators (consumers or retailers), and their interactions.

Dynamic Developmental Properties

A dynamic approach systematically theorizes and captures developmental properties along a sequential or temporal progression. Such properties can be operationalized for various types of digital communication data (numeric, text, audio, image, video), for which the information transmission sequence (e.g., order of reviews, sentences in emails, conversation turns, scenes in videos) likely has implications for relevant outcomes. In this sense, a wide range of possible dynamic developmental properties should be meaningful for studying digital communication. We consider six example dynamic developments in Table 2, for which we found robust effects across various research domains and contexts. *Displacement* refers to a specific level or state (e.g., end, maximum, mid-way) relative to a reference level (e.g., start, average) in a sequence. *End point* refers to the final moment of a sequence (e.g., last sentence in a message, last post by a communicator, final interactive exchange). A *peak* is the most intense instance or state in a sequence (e.g., the sentence with the maximum positivity in a message, the communicators most detailed post, the happiest point in an interaction). A *reversal* is a change in direction of content, behavior, or state from one stage to the next in a sequence (e.g., following a few positive sentences, the next sentence in a message is very negative). *Trend* is a measure of the overall direction or rate of change in a sequence (e.g., the communicator becomes increasingly anxious in her posts, formalities decrease as the interaction continues). *Variation* refers to the dispersion of a data series around the mean level (e.g., variation in positivity of a communicator across posts). For each of these dynamic developments, in the following sections, we provide operationalization examples, illustrate their uses and issues, and list some illustrative references. We consider (1) the order in which the message presents content, (2) sequential or temporal developments in the communicator's behavior, and (3) the sequences of any interactions. The overview in Table 2 does not portray all possible dynamics but provides rather a starting point for considering how developmental properties may offer important, unique new insights gleaned from digital communications.

Table 1
Reviews related to digital communication research.

Article	Context	Dynamics in communication	Differentiation of data types	Multimodality of communication				
				Numeric	Text	Audio	Image	Video
Pollach (2012)	Automated text analysis in organizational research				√			
Kern et al. (2016)	Gaining insights from social media language				√			
Wedel and Kannan (2016)	Marketing analytics for data-rich environments			√	√	√	√	√
Bradlow et al. 2017	Big data and predictive analytics in retailing			√				
Balducci and Marinova (2018)	Unstructured data in marketing				√	√	√	√
Humphreys and Wang (2018)	Automated text analysis for consumer research				√			
McKenny et al. (2018)	Accuracy of text mining in management				√			
Li, Shi, and Wang (2019)	Video mining in marketing research	√						√
Villarroel Ordenes and Zhang (2019)	Text and image mining for service research		√		√		√	
Berger et al. (2020)	Automated text analysis for marketing insights				√			
Dekimpe (2020)	Retailing in the age of big data analytics			√	√	√	√	√
Hildebrand et al. (2020)	Voice analytics in business research					√		
Schwenzow et al. (2020)	Video mining in business research							√
This article	Digital communication in retailing and marketing	√	√	√	√	√	√	√

Dynamics within Messages

Beyond considering the content of a message, additional insights can be gained by noting how a message's content is ordered. For example, the degree of positivity or negativity within a digital message may vary across sentences or subsections (Variation in Table 2). This variation may yield insights about the sender and determine the impact of the message. For example, inconsistent positivity within a review predicts sentiment (Villarroel Ordenes et al. 2017), and changes in emotionality over the course of a review's story line influence helpfulness perceptions and the impact of the review (Van Laer et al. 2019).

In Fig. 3, Panel A, we illustrate positivity across sentences in three customer reviews about shopping experiences. They are equally positive on average, so each review arguably could boost retail performance. However, Review 1's consistent positivity level (i.e., lack of variation) might have a different impact than the U-shaped trend in positivity of Review 2 or the regressing trend in Review 3 (Trend, Table 2). These observable developments also might reflect vastly different evaluations. Therefore, simply aggregating digital communication content aspects, like positivity, may lead to insufficient or inaccurate insights. Instead, researchers should identify the order (as a gestalt characteristic; Reb and Cropanzano 2007) in which the message is structured. Dynamics within messages also are not unique to text, so dynamics exhibited by images (e.g., left-to-right flow), videos (e.g., sequence of scenes), or audio data (e.g., intonation sequences) can be conceptualized similarly.

Dynamics within Communicators

Digital data may provide insights into communicators (e.g., customers, customer segments, retailers) by studying their communicative changes across multiple communication instances (e.g. multiple posts by a customer segment). Any dynamic developments in their digital communication might explain their overall evaluations or changing expectations. For example, online reviews, blog posts, and search entries offer insights into consumers' views of and interest in brands (Aggarwal, Vaidyanathan, and Venkatesh 2009; Lee and Bradlow 2011; Netzer et al. 2012), and their dynamics reflect how those views and interests develop over time. A sharp reversal, such that the number of times consumers search for a specific brand attribute decreases rapidly, could signal weakened brand associations or reduced interest (Reversal, Table 2).

Changes in communicators' digital content also can determine their impact on receivers. Pauwels et al. (2011) show that retailers that digitally communicate price promotions may increase their short- and long-term revenues, but trends or

Table 2
Selected Dynamic Developmental Properties.

Dynamic Property	Description	Operationalization Example	Illustration	Issues to Consider	Illustrative References
Displacement	The current level of an attribute, state, or behavior relative to a reference level of a progression or sequence.	Divide the final level of an attribute, state, or behavior by the reference level in a progression or sequence.	Positivity in the concluding sentence, the final video shared by a firm, or the last interactive turn in a service chat, divided by the positivity in the first sentence, first video, or first interactive turn.	Choosing appropriate comparison points along the progression or sequence is critical.	DeKinder and Kohli 2008; Hsee and Abelson 1991
End Point	The level of an attribute, state, or behavior at the final observation point of a progression or sequence.	The final level in the normalized attribute, state, or behavior in a progression or sequence.	The positivity in the concluding sentence, the final video shared by a firm, or the last interactive turn in a service chat.	Researchers may need to consider the starting point as well.	Ariely and Carmon 2000; Baumgartner, Sujan, and Padgett 1997
Peak	The size of the maximum level of an attribute, state, or behavior across a progression or sequence.	The maximum level in the normalized attribute, state, or behavior in a progression or sequence.	The maximum positivity in the sequence of sentences, the videos shared by a firm, or the interactions in a chat.	The relative position of the peak along the sequence or the absolute low point (valley) might be informative.	Ariely and Carmon 2000; Baumgartner, Sujan, and Padgett 1997
Reversal	Within-communicator frequency of change in the direction (or slope) across a progression or sequence.	Sum of slope changes in a progression or sequence.	The number of slope reversals in positivity in the sequence of sentences of a text, the videos shared by a firm, or the interactions in a service chat.	When dealing with different amounts of observations, the sum of reversals must be divided by the number of units.	DeKinder and Kohli 2008; Ludwig et al. 2014
Trend	Direction or rate of change (slope) of an attribute, state, or behavior of a progression or sequence.	Linear (or nonlinear) regression line through the progression stages or sequence points, according to the least square method.	The linear (or non-linear) degree of increase/decrease of positivity in the sequence of sentences, videos shared by a firm, or interactions in a service chat.	Whether a direction or rate of change truly reflects an actual decrease or increase needs to be assessed.	van Laer et al. 2019; Villarroel Ordenes et al. 2017
Variation	Degree of dispersion of attribute, state, or behavior levels across a progression or sequence.	The ratio of the standard deviation to the mean in the normalized attribute, state, or behavior levels in a progression or sequence.	Degree of variation in positivity in the sequence of sentences, videos shared by a firm, or interactions in a service chat, relative to the base level of the sequence/progression.	Alternative operationalizations relate to alternative conceptualizations.	Harrison and Klein 2007; Ludwig et al. 2014

variations relative to previous communications about price promotions likely have distinct impacts on consumers. For example, Ghoshal et al. (2014) establish that a well-designed brand message sequence can foster message sharing, beyond the effects of each individual message, and Villarroel Ordenes et al. (2019) and Herhausen et al. (2019b) find specific sequences in digital communications increase or reduce consumer sharing. Studying numerical data, Wu, Jin, and Xu (2020) also confirm that the variance of reviewers' historical ratings influences the persuasiveness of those reviews.

In Fig. 3, Panel B, we illustrate differences in successive tweets by customer segments about a new movie series. The average positivity is the same, but customer segment 1 seems to be losing interest (negative linear trend), customer segment 2 offers consistently increasing positivity with each week (increasing linear trend), and customer segment 3's positivity varies drastically (three slope reversals). These different patterns might reflect different experiences with the new movie series, such that the patterns have differential impacts on tweet readers.

Dynamics within Interactions

A digital communication interaction is inherently dynamic (Batra and Keller 2016), because they involve consumers and retailers constantly creating and sharing information. Obviously, the content of these interactions matters. For example, Van Dolen, Dabholkar, and De Ruyter (2007) show that customers' chat session satisfaction is stronger when the representative is oriented toward the task rather than socially oriented. Dynamic developmental properties along interaction sequences also can provide relevant insights; whether a chat between a customer and a service employee ends with positivity, or when the relative positivity peak occurs during the interaction, might be even more important than the average positivity in the chat. Considering displacement, or the comparison of the use of positive words at the end of the chat rather than at the start, also can be informative about the customer's service experience (End Point, Peak, and Displacement, Table 2).

In Fig. 3, Panel C, we illustrate positivity in three interactions, involving service chat sequences between a customer and a retail

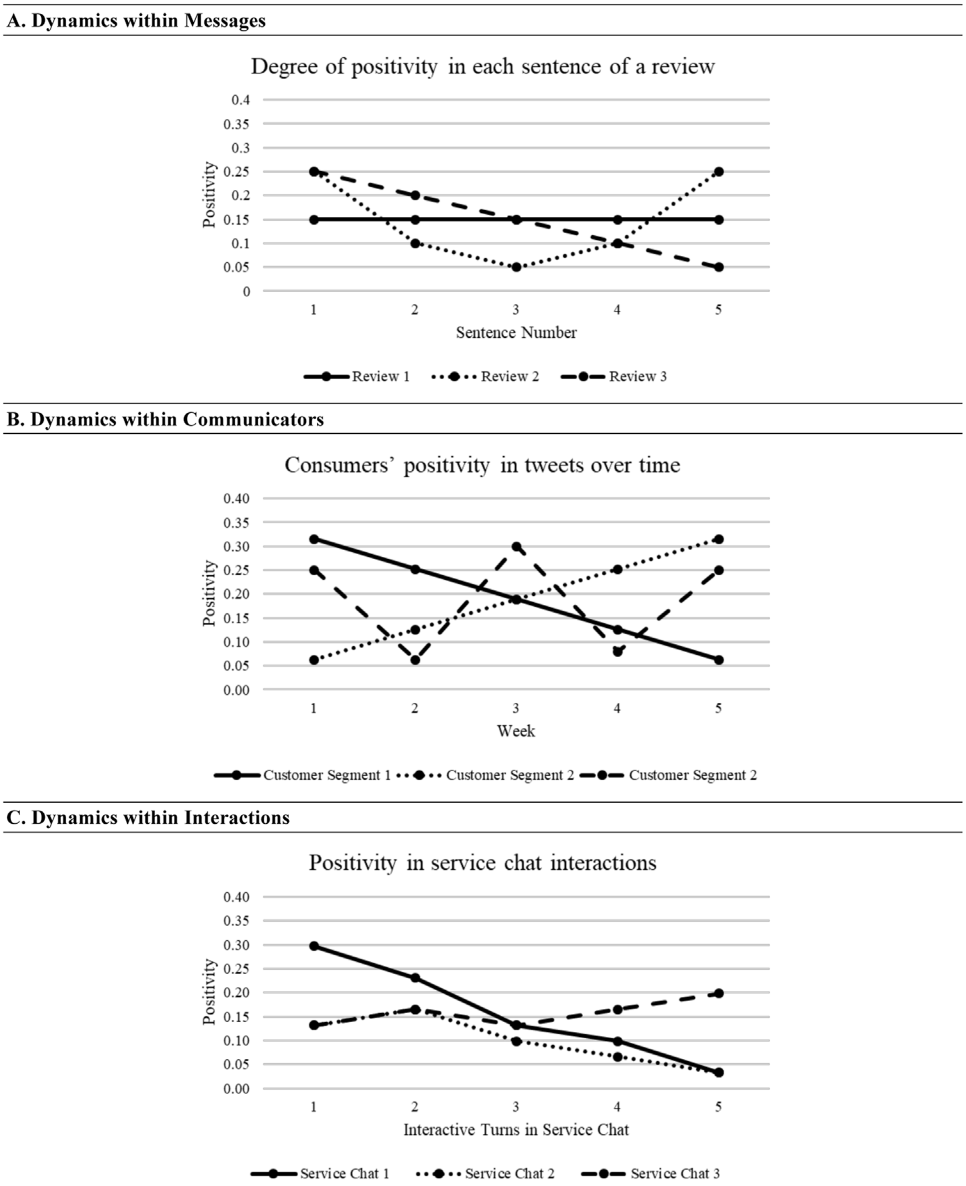

Fig. 3. Dynamics in digital communication.

firm representative. On average, they exhibit the same positivity. However, in Service Chat 1, positivity decreases steadily across five interactive turns. Positivity also decreases in Service Chat 2, in a more rugged manner. In contrast, positivity increases in Service Chat 3 with each interaction turn. The outcomes of these service chats likely differ, and retailers should leverage the interactive patterns captured by digital communication data. Here again, we illustrate interaction dynamics with text data, but they could be derived from other modalities too (e.g., development of pitch in an audio conversation).

Challenges of Studying Dynamics in Digital Communication

Researching dynamic communication properties creates several conceptual and methodological challenges. Conceptually, any study that investigates dynamic developmental properties in digital communication must provide conceptual rationales for how, why, and which types of information can be leveraged over time to understand the content, communicator, and impact on receivers. For theory development, the conceptual model and development also must adequately reflect the dynamic, complex view of digital communication.

The methodological challenges relate broadly to the validity of dynamic developmental properties and the time-invariant and time-variant endogeneity present in the data. First, to assess the *validity of dynamic developmental properties* (i.e., truly evident in the data or just spurious properties), researchers should test different cut-off levels. For example, they might consider only changes of direction or maximum levels that are at least one or two standard deviations above the normalized mean to represent "real" reversals or "real" peaks. Alternating the cut-off level of trend coefficients could provide another robustness check, such as to test whether a positive rate of change really represents a statistically significant increasing trend.

Second, *time-invariant unobserved differences*, such as the communicators' education, country of origin, or gender, as well as the communication context, evoke differences in the data and may lead to spurious relationships. To account for such unobserved heterogeneity across communicators and contexts, researchers need to estimate their models using fixed-effects, or else apply dynamic panel models (Ludwig et al. 2013) to remove time-invariant differences.

Third, if multiple sequences are observed for each communicator, *time-variant endogeneity* may arise, because omitted variables could influence both the time-variant dynamic property and the respective outcomes. Communicators may learn through time or alter their behaviors if they anticipate certain outcomes. For example, a brand's current tweet sequence might be the result of its success (or failure) with earlier tweet sequences. To correct for this endogeneity, researchers could use instrumental variables (Singh, Marinova, and Singh 2020) or a control function approach (Villarroel Ordenes et al. 2019). Alternatively, instrument-free approaches, such as latent instrumental variables (Herhausen et al. 2020b) or Gaussian copulas (Ludwig et al. 2020), might correct for time-variant endogeneity in communication.

Multimodality of digital communication

Digital communication in retailing consists of multiple modalities, such as a consumer's TikTok video describing a store, the text of a paid search ad, or a call center voice interaction. These different communicational modes all provide retail insights. The primary modes of digital communication are numeric heuristics (e.g., number of likes, stars, thumbs up), text, audio, image, and video (Table 3). Numeric communication is structured, with predefined representations (e.g., more likes represent more positive reactions) and a single facet (e.g., score, count). The quantitative surrogates are used extensively across digital domains, but their value in terms of consumer and market insights is limited (Ludwig et al. 2013). In contrast, text, audio, image, and video-based communication offer richer, more naturally occurring insights. Unlike numeric heuristics, information contained in textual, audio, and visual data are unstructured, so extracting meaningful insights from them can be difficult (Balducci and Marinova 2018). We discuss each type of data in detail, to delineate its challenges and opportunities.

Communication with Numbers

Perhaps the most common numeric variables are ratings, which indicate approval (e.g., stars, thumbs up) and engagement (e.g., likes, shares, and comments). Ratings appear in many customer reviews, but their use raises several concerns, linked to the lack of incentives for truthfulness and the potential for inflation (i.e., skewed distribution toward 4 or 5 stars). Approximately 61% of reviews on Amazon reportedly are fake (Marketing Land 2018), suggesting the threat of substantial errors in research that uses ratings as dependent (Villarroel Ordenes et al. 2017) or independent (Chevalier and Mayzlin 2006) variables. Furthermore, even though reviews that appear neutral (e.g., 3 stars) can have an impact (Tang, Fang, and Wang 2014), companies such as YouTube often use binary rating scales, without any neutral option. Such "like/dislike" or "thumbs-up/thumbs-down" scales raise an interesting question about how consumers who would choose a neutral rating respond to a binary choice.

In social media, other popular numeric variables are count measures, such as the number of likes, shares, and comments. They have been analyzed differently, using Poisson (Heimbach and Hinz 2016) or negative binomial (Villarroel Ordenes et al. 2019) regressions, as well as with a logarithmic transformation (Herhausen et al. 2019b) and Poisson log-normal mixture models (Jalali and Papatla 2019). Each approach treats the count distributions differently, so researchers might need to validate the results of any statistical results they gain if they choose to use different methodological approaches (Germann, Ebbes, and Grewal 2015).

Communication with Text

Text data include emails, reviews, and social media conversations, which offer relatively low media richness, in that they express in-depth feelings or emotions only with verbal cues. Text is unstructured and lacks predefined numeric assignments for constructs of interest. Therefore, it requires numeric values to be assigned manually or automatically prior to any analysis. For example, to determine the level of satisfaction expressed by a certain review text, a dictionary-based approach could assign the words in the review to different levels of positive, negative, and neutral emotions, then count their occurrences to determine the degree of expressed satisfaction (this is a simplification; for more detail, see Humphreys and Wang 2017; Villarroel Ordenes and Zhang 2020). Text data also are multifaceted, and each text might contain facets that reflect different word categories in dictionaries or distinct outcomes in various machine learning algorithms. Each facet could be selected and analyzed, depending on the desired insights. Researchers can draw on various theories and prior literature to identify facets of interest, so they might include only those that make logical sense for their research question.

A wide range of retail-relevant constructs—such as consumer sentiment (Schweidel and Moe 2014), frontline problem-solving, relational language (Marinova, Singh, and Singh 2018), and consumer personality traits (Adamopoulos et al. 2018)—have been operationalized with various text mining methods (e.g., dictionaries, supervised machine learning, topic models, word embedding, deep learning, language models). Beyond reflecting a construct of interest, text mining can support predictions, such as predicting the survival of restaurants (Zhang and Luo 2018) or bank-loan defaults (Netzer, Lemaire, and Herzenstein 2019). Research has started to compare the predictive ability of the different text mining methods (Hartmann et al. 2019; Vermeer et al., 2019) and their implications for marketing outcomes (Kubler, Colicev, and Pauwels 2020). Yet the availability of multiple dictionaries for marketing and retailing research (e.g., Vader, Linguistic Inquiry and Word Count

Table 3
Multimodality in Digital Communication.

Modality	Examples	Data Structure	Facets of Analysis	Selected Research
Numeric	Ratings, likes, stars, thumbs up	Structured: Numbers have a single/common structure	Numbers have a single facet of analysis	Chevalier and Mayzlin 2006; Tang et al. 2014; Villarroel Ordenes et al. 2017
Text	Emails, reviews, conversations in social media	Rather unstructured: The use of linguistics, punctuation, and grammar helps structure texts	Linguistic facets such as syntax, semantics, morphology, pragmatics, and speech acts	Herhausen et al. 2019b; Ludwig et al. 2013; Singh, Marinova, and Singh 2020; Villarroel Ordenes et al. 2019
Audio	Customer calls, exchange via smart speakers	Rather unstructured: The use of phonetics and linguistics helps structure it through phonemes and words.	Audio facets such as phonetics, acoustics, and cognitive psychology	Dawar 2018; Hildebrand et al. 2020; Huang and Labroo 2020
Image	Consumer images, consumption images	Unstructured: Rules for structuring are not as strict as in text or audio data. Semiotics and photography principles (e.g., rule of thirds) might help in structuring	Image facets such as color, brightness, saturation, image acts, and semiotics	Farace et al. 2020; Klostermann et al. 2018; Li and Xie 2020; Zhang and Luo 2018
Video	Video reviews, video chat with customers	Unstructured: The most unstructured form of data, due to multiple modes (audio, images, text) and facets	All text, audio, and image facets previously described. In addition, movement and speed features related to the video scenes.	Li, Shi, and Wang, 2019; Liu et al. 2018; Marinova et al. 2018; Schwenzow et al. 2020

[LIWC], Dictionary of Affect in Language, Evaluative Lexicon, SentiStrength), the variety of supervised machine learning algorithms (e.g., naïve Bayes, SVM, deep learning, ensembles), and the range of topic model approaches (e.g., latent Dirichlet allocation, latent semantic analysis, correlated topic models) suggest the need for comparisons of the results across methods.

Communication with Audio

Audio or voice data include customer calls and interactions through smart speakers. They have no predefined numeric representation, are multifaceted, and achieve rather high media richness. In addition to verbal cues, audio and voice data include pitch, speech rate, and intensity, all of which provide unique information about the speaker's feelings or emotions, beyond the words used (Hildebrand et al. 2020). This information expands the analytical possibilities for generating insights and points to potential synergies across the pitch, speech rate, and intensity that might inform the meaning of words. To date, virtually no marketing research has used purely audio data (Balducci and Marinova 2018), but the growing prevalence of voice interfaces implies that audio data will gain importance (e.g., Twitter recently introduced the idea of audio tweets). The analysis of audio data involves two main components: (1) sound, which pertains to intensities (e.g., voice pitch, prosody, intonation), and (2) natural language, determined according to the content of words, grammatical choices, meanings, and intentions. Relative to text, sound constitutes a simpler communication measure, with a single quantifiable facet (e.g., decibels of intonation). But this same quantifiable facet may be perceived very differently, depending on the words used, the sender, or the context. In addition, audio data could be assessed using supervised machine learning, such as if a researcher seeks to classify different speech tonalities into emotions (e.g., sadness, joy, surprise).

Communication with Images

Pictures embedded in social media brand content (Villarroel Ordenes et al. 2019), user-generated content in social media (Klostermann et al. 2018), customer reviews of product and services (Zhang and Luo 2018), and product and service offerings on online platforms (e.g., pictures of Airbnb houses; Zhang et al. 2017) all feature image data, which are unstructured, with no predefined numeric representation, multiple facets, and high media richness. State-of-the-art applications such as Google Vision AI and Amazon Rekognition can identify several objects or actions within an image with high accuracy (e.g., emotions, presence of brands). In addition, advances in deep learning and neuronal nets have contributed to the development of customized algorithms to identify specific image types or motives in which a researcher might be interested (e.g., rugged brands; Liu, Dzyabura, and Mizik 2020)

Studies that rely on click workers hire image coders to annotate image data. These annotations can be used as inputs for a construct operationalization (Villarroel Ordenes et al. 2019) or to train an image classifier with deep learning (Liu, Dzyabura, and Mizik 2020). Depending on the task at hand, researchers need to choose the most suitable platform for having human coders annotate of image data. For example, annotating the presence of a human might be easy, with high interrater agreement; it likely would be harder for annotators to agree if an image triggers mental involvement. The first task seems more appropriate to execute on a platform such as MTurk, and the second might better fit a platform such as Upwork, which hosts specialized image annotators whose understanding of a task can be tested before hiring. Overall, it seems important to agree on certain standards for large-scale image annotation processes. Furthermore, imputation methods probably are necessary to model such data. A researcher interested in studying emotions in images likely needs images of people, but the imputation value for images without any people also needs to be identified. Previous research using text data suggests imputing mean values and adding dummy variables (Berger and Milkman 2012).

Communication with Videos

Reviews on YouTube, promotional brand videos on Snapchat or TikTok, and video chats with customers all provide video data. Such data are unstructured, have no predefined numeric representation, are multifaceted, and offer high media richness. Videos capture nonverbal data over time, such as facial cues and gestures while talking, which expand analytical possibilities across data facets. Video data present the greatest measurement challenges though, due to their inclusion of multiple facets of sound, text (natural language transcription), and images. All the issues discussed for text, audio, and image data thus apply to video.

Video mining might offer a viable solution, according to recent business research (Schwenzow et al. 2020). Videos constitute sequences of images, from which some measurements or characteristics can be extracted, such as objective factors (e.g., resolution, brightness), identifications of subjects or objects (e.g., humans, text), and expressions (e.g., emotions). Video mining research also distinguishes visual variation from video content measures (Li, Shi, & Wang 2019). The former reveal changes in visual information in a video, according to how rapidly the video screen changes from one image to another (e.g., many different individuals, objects, places). The latter instead use deep neuronal nets to measure the presence of subjects or objects in a video, such as persons and specific products (e.g., shoes). Similar to machine learning for text, image, and audio data, these measures demand cross-validation to avoid overfitting or measurement error. A common practice relies on content validation by human annotators for a subsample of videos.

Challenges of Studying Multimodality in Digital Communication

Research that uses one or more modes of digital communication data encounters conceptual and methodological challenges. We focus on two conceptual issues and four methodological challenges, pertaining to measurement error, omitted variable bias, spillover effects, and selection bias. In addition to providing examples of each of these challenges, we suggest some ways to deal with them, conceptually and empirically.

Conceptual issues

At a conceptual level, previous research in multimodality faces two main challenges: (1) finding a theoretical lens to fit the focal mode (e.g., text, images, audio, video) and research facet (e.g., syntax, semantics, semiotics) and (2) articulating a good theoretical frame for studying two or more modes (and/or facets) jointly. Studies that deal with only text data tend to draw on linguistic and psycholinguistic theories (Humphreys and Wang 2017); those dealing with image data mostly rely on semiotics of photographic schemes (Farace et al. 2020; Zhang et al. 2017); and research that solely includes video data mainly draws on movement theory (Jia, Kim, and Ge 2020), consistent with the definition of videos as series of images. Few studies use audio data alone, and they mainly pertain to atmospherics (e.g., music, Huang and Labroo 2020). Thus, we note broad room to conceptualize audio data, starting from simple theoretical stances. For example, what is the basic unit of perception in phonetics? Tackling this question conceptually might help clarify the impact of phonetics on consumer perceptions and behaviors (Klatt 1979). Recent research also has hypothesized and demonstrated that audio and visual content likely have separate effects on the experience of consuming video content, yet their joint effect remains a conceptual and empirical question.

Measurement error

According to Rutz and Watson (2019), measurement error affects the precision with which researchers can estimate true relationships among constructs. Typical measurement errors have been discussed in relation to traditional data (e.g., survey data), but less attention has centered on the implications of measurement error for variables operationalized using text, images, or videos. Text data suffer from measurement error across all text mining methods, such as dictionaries or supervised and unsupervised machine learning (McKenny et al. 2018). Validation represents a particularly cumbersome step for operationalizing text-based measurements (together with cross-validation and predictive accuracy for machine learning), and several types of validity could be relevant (Berger et al. 2020).

In turn, we lack sufficient insights into the best correction mechanisms for measurement error caused by (1) dictionaries that use absolute term frequencies (e.g., LIWC) or term frequency together with term weight (e.g., Dictionary of Affect in Language); (2) dictionaries that treat missing values as null (e.g., LIWC) or leave them as missing (e.g., evaluative lexicon); and (3) log-transformations of text variables due to skewed distributions (Van Laer et al. 2019), using simple word frequencies (Villarroel Ordenes et al. 2017), or creating weighted dictionaries from topic models (Huang et al. 2018). Each alternative represents a source of potential measurement error, with unique modeling implications that need to be considered. Image, audio, and video measurements can suffer from measurement error too. When using image recognition software (e.g., Amazon Rekognition), researchers should pay attention to the thresholds for accepting the presence (absence) of objects or actions in images (Wulf et al. 2019). In the case of audio data, if machine learning predicts emotionality attributes (e.g., fear) from voice, researchers should make sure to cross-validate to avoid overfitting. Finally, for videos, all these measurement error concerns apply.

Omitted variable bias

A core advantage of digital communication data, their richness, is also a severe challenge to researchers. For example, if researchers focus on text, they omit information from pictures that may drive virality. Moreover, text transcriptions are not sufficient to capture the information provided by a voice conversation; analyzing ratings or reviews without considering the context of previous and subsequent ratings or review also can omit important information. To address potential omitted variable bias, researchers might adopt two remedies. First, they could include theoretically meaningful control variables in the model, as potential confounders of the relationship of interest. Thus, pitch, volume, rhythm, tone, and intonation might be candidates to be included in models that analyze voice conversations, and information related to previous and subsequent reviews represent important controls for understanding the impact of certain reviews on consumer decision making.

Second, it is almost impossible to account for all potential confounders of the relationships of interest. For example, product pictures on a website might influence the impact of reviews, and researchers might not be able to capture and analyze this information. Banner and display ads often combine text, pictures, and sound, which might influence their impact on consumer behavior when they appear at the same moment onscreen. Other important variables might be completely unobservable to researchers, such as screen size or the buying behavior of a certain consumer. These unobserved factors likely influence outcomes of interest (e.g., conversion rates) and thus could lead to biased parameter estimates. One approach to deal with unobserved heterogeneity would be to use a semiparametric approach (e.g., hazard model) to represent the intercept term and the error variance with a finite number of support points, represented by latent classes (e.g., different product pictures, display ads unobservable to the researcher).

Spillovers and interactions

People use language, gesture, posture, and other nonverbal modes simultaneously to communicate (Partan and Marler 2005). Similarly, digital communication is generally multimodal, and different digital communication data can be captured synchronously. A single customer review often contains summative heuristics (e.g., thumps up, star ratings), text, and images or videos; a social media post by a brand might include different data modes, such as superimposed images and promotional text. Jointly, rather than independently, these modes influence consumer decision making and provide insights, yet their interactions and spillovers in multimodal digital communication rarely have been studied.

For example, two online sales employees using the same words with a different prosody (i.e., speakers' vocal tone) might have distinct impacts on customers. Speaker intentions (i.e., speech acts) can be represented by prosodic signals, which in turn can determine the success of human interactions (Hellbernd and Sammler 2016). To account for this effect, researchers should account for whether a specific acoustic feature (e.g., duration, intensity, pitch, spectral features) spills over to the words used to sell a product or service. This type of analysis also might be necessary to understand eWOM, in that the shared content usually involves some combination of numbers, text, images, and video. To benefit from the abundance of digital communication data, retailers need to leverage the explicit information they capture but also account for information that was not captured or used in the analysis.

Selection bias

If a study focuses on one mode of communication, such as text to analyze social media data, to deal with multimodality it might (1) exclude data points that incorporate additional information, such as images or videos not captured by the text analysis (e.g., Herhausen et al. 2019b); (2) use a dummy variable to account for the presence of a different mode of communication (e.g., De Vries, Gensler, and Leeflang 2012); or (3) adapt a communication mode to another form (e.g., convert a video into an image or snapshot of its first scene; Villarroel Ordenes et al. 2019). These efforts are important; most digital communication data are multimodal. Researchers also might include only data points that incorporate additional information. For example, to study social media images, it might be pertinent to include only tweets from a brand that include images. In all these cases, selection bias arises, whether related to the selection of data points or the information that gets incorporated in the model.

Researchers thus might lose a lot of information; the selection of the data also represents a non-random decision. For example, customer complaints in social media that include an image or video might be challenging for retailers to gather and assess, but if they limit themselves to analyzing only less challenging, text-based complaints, it may produce misleading results. Faced with a non-random subsample of a larger population of digital communication data, researchers must account for the non-randomness of the selection. The selection bias also might feature both observable factors (e.g., complaint includes an image and thus is not fully captured) and unobservable factors (e.g., strategic behaviors by certain actors). A common approach to dealing with these various selection biases relies on Heckman selection models (Greene 2017) and propensity score matching (Li and Xie 2020), which can account for both sample selection and strategic behavior. For example, Johnen and Schnittka (2019) use a selection model to address a firm's decision to respond to a social media complaint, and Herhausen et al. (2020b) use one to address service firms' non-random decision to use images of their employees on their websites.

Accordingly, we suggest that it is imperative for retail managers to understand how each modality of digital communication, spanning numeric, text, audio, and video, used to capture consumer preferences affects performance outcomes. We discuss the scope of both dynamics and multimodality for the four digital communication domains in more detail next.

Scope of dynamics and multimodality in digital communication

Dynamics and multimodalities in digital communication reflect and affect consumers' perceptions, attitudes, behaviors, and shopping journeys. Conceptually, marketing is a process, in which evolutions and ongoing interactions determine exchange and consumption (Bartels 1968; Hunt and Morgan 1996). Thus, investigations of consumers' and retailers' digital communication at a given point in time need to be complemented by conceptualizations of how this communication changes dynamically. Practically, integrating such insights offers retailers a clearer understanding of the dynamic contexts of their own communication, as well as insights into developments in consumers' communication.

In addition, the multiple modes of digital communication pose great challenges and opportunities for marketing research. The growing interest in methods to study text (Berger et al. 2020), image (Villarroel Ordenes and Zhang 2019), audio (Hildebrand et al. 2020), and video (Schwenzow et al. 2020) data highlights the potential impact of research that can address previously ignored facets of consumer behavior. In addition, whereas marketing and consumer behavior research traditionally rely on theories sourced from psychology literature, the multimodality of digital communication offers access to new theoretical lenses, related to linguistics, semiotics, phonetics, and other fields, which might enable theoretical advances in business research. Advancing research through these theoretical lenses also may support the development of better analytical tools for exploring and analyzing big data—a pressing managerial need for firms that struggle to make sense of the spreading digital data landscape.

To date, early research insights pertain to the sequences of texts (Batra and Keller 2016; Herhausen et al. 2019b; Villarroel Ordenes et al. 2019), but we need studies of developmental properties within texts and the dynamics of audio, image, and video communication. Research on digital communication should incorporate dynamics and multimodality in its conceptual development, data collection, and data analysis. We summarize some key research directions, across the four domains of digital communication, in Table 4. With this backdrop, we next discuss the implications of current research, research gaps, and opportunities.

Retailer-to-Consumer Messages

Implications of current research

Retailers frequently message and advertise to consumers online. Conceptually, the design and structure of these messages (Burke 1962; Genette 1992) and the combination of formats used (Balducci and Marinova 2018) determine their impact. To cut through the clutter of digital information, retailers compelling content that they combine appropriately in an effective sequence in their digital messages (Villarroel Ordenes et al. 2019). Digital content managers would benefit from insights into how to communicate content that is more likely engage and convince consumers.

Research gaps and opportunities

A first major gap arises with regard to how the structural development of retailers' messages determines their impact. Current research tends to focus on the content of digital messages (or proxies for it); the way retailers should order or structure their messages to influence consumers is not well understood. Such insights are relevant; for example, more emotionally charged genres and a dramatic ordering of events in reviews informs their impact on consumers (Van Laer et al. 2019). The sequencing dynamics of retailers' messages also requires further investigation. Compositional considerations refer to formulations of individual messages, as well as how they fit within the communication stream (i.e., cross-message aspects; Batra and Keller 2016). Prior promotions and dynamic considerations might determine subsequent promotional efforts. Investigating how to build good cross-message patterns could provide novel, actionable insights into sequences of multiple messages that foster sharing and impact, beyond the effects of each individual message. As a third research opportunity, we note the multimodal nature of retailer messages. Automated text, audio, image, and video analyses offer unprecedented possibilities for opening communication black boxes and quantifying the implications of variations in message compositions. Specifically, we need evidence about the differential impacts of retailers' numeric, text, audio, image, and video messages. Finally, in many messages, text is inextricably linked to other communication modalities (e.g., pictures, videos), which might spill over onto one another. Thus, research should explore the best combinations of different modalities in messages.

Retailer–consumer Interactions

Implications of current research

Retailer–consumer interactions might feature human service employees or AI-powered technology (e.g., chatbots; Shankar 2018). They can occur on the retailer's own touchpoints or through digital intermediaries such as social media sites. Since the earliest theorizing on relationship marketing, the most critical relational perceptions for determining marketing success have been commitment, trust, relationship satisfaction, and relationship quality (Palmatier et al. 2013). Managing and improving these outcomes in digital interactions with consumers is critical for retailers to acquire new customers, retain existing ones, or recover service failures.

Research gaps and opportunities

Retailers' communication choices influence their interactions with consumers, and the implications of dynamics and modalities for customers' experience and their own performance have received limited research attention. First, any retailer–consumer interaction is inherently dynamic, spanning several turns. A disgruntled customer may start off voicing anger; in the best case scenario, the customer leaves the interaction happy. We need insights into how retailers or their representatives (service employees, chatbots) can encourage the positive development of interactions with consumers. Second, different developmental properties (e.g., trends, peaks, variations) over interactive turns may provide additional, useful indications of what a customer will do next (e.g., join, stay, leave) and call for (re)actions by the retailer. Therefore, we need to know how developmental patterns reflect consumers' perceptions, attitudes, and behaviors. Third, many text- or voice-based interactions are accompanied by images or videos (e.g., picture of a broken product). Yet retailers lack comprehensive understanding of how this multimodality, and the interplay across modalities, affects inter-

Table 4
Selected Research Directions across Digital Communication Domains.

Domain	Research on Communication Dynamics	Research on Communication Multimodality
Retailer-to-consumer messages	■ How does the developmental structure of retailers' content in digital messages influence consumers? ■ How does the sequencing of retailers' content across digital messages influence consumers?	■ What differential impacts do numeric, text, audio, image, and video messages have on consumers? ■ How should different modalities be combined in retailers' digital messages to influence consumers?
Retailer–consumer interactions	■ How should retailers or their representatives (e.g., service agents, chatbots) develop interactions with consumers? ■ Which development patterns determine performance outcomes? ■ How do developmental patterns reflect consumers' perceptions, attitudes, and behaviors? ■ Which patterns are useful indications of what a customer will do next (e.g., join, stay, leave)?	■ When interacting with a consumer, how do the mode (e.g., online vs. live service chat) and the presence of cues (e.g., images of service employees) influence performance outcomes? ■ How should consumer perceptions, attitudes, and behaviors be distilled from different interaction modalities? For example, are there differences in handling service failures across the different modalities?
Consumer-to-consumer messages	■ How does the message order or structure best reflect the communicating consumer's perceptions, attitudes, and behavior? ■ How do developments or dynamics over time in a consumer's messages determine the influence on other consumers?	■ How does the format (e.g., text, audio, image, video) of a consumer's message determine its effects on other consumers? ■ Are there any spillover effects of a consumer's use of several communication modalities in the same message on influences on the other consumers?
Consumer–consumer interactions	■ Do dynamic developments in consumer interactions reflect ongoing and future perceptions, attitudes, and behaviors? ■ How are dynamics reflective of consumers' relationship patterns? ■ How does the order or structure in consumer interactions relate to their impact (e.g., virality, influence on purchase)?	■ How can consumer perceptions, attitudes, and behaviors be extracted from specific formats (e.g., text, audio, image, video) or combinations of formats in consumer interactions? ■ How does content across various formats in consumer interactions combine to influence perceptions, attitudes, and behaviors?

action outcomes. For example, do the interaction mode (e.g., response in an online forum or live service chat) and presence of other cues (e.g., images of service employees) influence performance outcomes? Do the effects differ for a chat with an employee versus a chatbot? Fourth, retailers should (re)evaluate their customer interactions to determine the implications of different modalities and dynamics for customers' experience and their own performance. They thus need to learn how they can best gather consumer perceptions, attitudes, and behaviors from different communication modes. For example, we lack clear understanding of how service failure severity can be determined from different modalities, as well as how different methods for handling service failures might become optimal in different modalities.

Consumer-to-Consumer Messages

Implications of current research

Consumer-to-consumer messages, such as eWOM or consumer reviews, are powerful performance drivers (Lamberton and Stephen 2016). Conceptualizations of user-generated content suggest that its perceived diagnostic value is a primary reason for its relevance, to both consumers and retailers (Yadav and Pavlou 2014). Both the way consumers structure their digital messages dynamically over time and their choice of modality have relevant implications for their impact.

Research gaps and opportunities

The prevalent focus on the content of single messages needs to be expanded, to acknowledge how this content develops dynamically within and across messages. Researchers should investigate how the message development order or structure reflects the communicating consumer's perceptions, attitudes, and behavior. Most relevant concepts in consumer messages are measurable with scales and content coding, so the order in which this content is presented may add useful insights to existing measurement approaches. We also need a better understanding of how messages go viral within networks or brand communities, in particular as it relates to dynamics over time in messages from the same consumer (e.g., an influencer). This more detailed understanding can help anticipate the potential impact of both positive and negative messages from such sources. Furthermore, surprisingly little research considers communication modes other than text and ratings (Babić Rosario et al. 2019). We encourage additional research into the multimodality of user-generated content on review and rating sites to provide insights into how the modality of a consumer's message determines its effects on other consumers. Finally, images and videos are popular decision aids (Xu, Chen, and Santhanam

2015) and commonly accompany posts and reviews. Rapidly growing visual platforms such as YouTube, Instagram, Pinterest, Snapchat, and TikTok make the role of image and video more evident. Thus, it would be helpful to establish the spillover effects across several communication modalities in the same message, as well as their influences on other consumers.

Consumer–Consumer Interactions

Implications of current research

Consumer–consumer interactions are insightful for retailers. Interactions in social networks reveal how consumers communicate naturally, about themselves and their preferences (Yadav and Pavlou 2014). They use these digital interactions to express themselves and achieve desired goals, so such communication offers in-depth insights about them. Retailers should investigate reasons for dynamics in interactions among consumers (e.g., change in topics or sentiment), as well as choices of interaction formats (e.g., text- vs. image-based exchanges).

Research gaps and opportunities

Research thus far largely has focused on static characteristic of consumer interaction, so little is known about dynamic changes in interactions. First, we need further insights into how dynamic developments in consumer interactions reflect ongoing and future perceptions, attitudes, and behaviors. Second, we need evidence of how virality takes shape through consumers' ongoing interactions. Similar to interactions with retail representatives, the way consumer–consumer interactions unfold likely determine their subsequent impacts on consumer perceptions and shopping behavior. Third, to move beyond research that studies mostly text-based interactions, continued work should include images, videos, and their integration with text. More than 100 million pictures and videos are uploaded daily on Facebook and Instagram—information that typically is not included in research that examines social media. Determining how consumer perceptions, attitudes, and behaviors can be extracted from specific modalities or combinations of them is an important research direction. Fourth, related to the previous point, it is important to understand how content across various modalities combines to influence the perceptions, attitudes, and behaviors of consumers.

Conclusion

This article aims to draw attention to two critical but under researched factors associated with digital communication in four realms. First, it is important to understand the dynamic elements of digital communication. We focus on dynamics at three levels: the content of the message, the communicator, and the interaction. The increasing pace of digital communication (Roggeveen and Sethuraman 2020), approaching real-time updates and exchanges, suggests that dynamics will become even more important. Second, we need a better understanding of multiple modalities in digital communications. We particularly draw attention to the lack of research on the role of nontextual modalities and the importance of clarifying the synergies and spillovers among them. As retail technologies (Grewal et al. 2020a, 2020b) and virtual reality (Grewal, Roggeveen, and Nordfalt 2017) continue to expand their reach, the various modalities may take on even greater roles.

Our discussion of digital communication in retailing is by no means complete. Reflecting our focus on dynamics and multimodality, many research directions are possible. First, by drawing on cross-disciplinary research, we delineate six properties of dynamic developments (Table 2), but they constitute mainly a starting point for continued investigations of the dynamics of digital communication, perhaps using alternative or additional properties. Second, further research should address contingencies that determine the impact of multimodality during the shopping journey. It would be interesting to specify which modalities are most effective in which stages of the shopping cycle and why, or how the device type (desktop vs. mobile vs. wearable) might influence the effectiveness of different communication modalities. Third, the difficulties of tracking shoppers' footprints holistically, across the various devices, platforms, and retail websites they might use, along with issues surrounding behavioral attributions, highlight the need for research solutions for aggregating dynamic and multimodal data from several sources. Fourth, we have neglected other actors—manufacturers, platforms, general public—that could exert influences on digital communications between consumers and retailers. Overall, we hope that the research directions and questions outlined in Table 4 encourage scholars to pursue greater insights into multimodality and dynamics in digital communication data.

References

Adamopoulos, Panagiotis, Anindya Ghose and Vilma Todri (2018), "The impact of user personality traits on word of mouth: Text-mining social media platforms," *Information Systems Research,* 29 (3), 612–40.

Aggarwal, Praveen, Rajiv Vaidyanathan and Alladi Venkatesh (2009), "Using lexical semantic analysis to derive online brand positions: An application to retail marketing research," *Journal of Retailing,* 85 (2), 145–58.

Ariely, Dan and Ziv Carmon (2000), "Gestalt characteristics of experiences: The defining features of summarized events," *Journal of Behavioral Decision Making,* 13 (2), 191–201.

Arnould Andrew (2017), 4 Ways Social Media Influences Millennials' Purchasing Decisions, Forbes [Available from: https://www.forbes.com/sites/andrewarnold/2017/12/22/4-ways-social-media-influences-millennials-purchasing-decisions/#3cda7842539f].

Babić Rosario, Anna, Kristine de Valck and Francesca Sotgiu (2019), "Conceptualizing the electronic word-of-mouth process: What we know and need to know about ewom creation, exposure, and evaluation," *Journal of the Academy of Marketing Science,* 48 (May), 422–48.

Balducci, Bitty and Detelina Marinova (2018), "Unstructured data in marketing," *Journal of the Academy of Marketing Science,* 46 (4), 557–90.

Bartels, Robert (1968), "The general theory of marketing," *Journal of marketing,* 32 (1), 29–33.

Batra, Rajeev and Kevin L. Keller (2016), "Integrating marketing communications: New findings, new lessons, and new ideas," *Journal of Marketing,* 80 (6), 122–45.

Baumgartner, Hans, Mita Sujan and Dan Padgett (1997), "Patterns of affective reactions to advertisements: The integration of moment-to-moment responses into overall judgments," *Journal of Marketing Research,* 34 (2), 219–32.

Berger, Jonah, Ashlee Humphreys, Stephan Ludwig, Wendy W. Moe, Oded Netzer and David A. Schweidel (2020), "Uniting the tribes: Using text for marketing insight," *Journal of Marketing,* 84 (1), 1–25.

Berger, Jonah and Katherine L. Milkman (2012), "What makes online content viral?," *Journal of Marketing Research,* 49 (2), 192–205.

Bradlow, Eric T., Manish Gangwar, Praveen Kopalle and Sudhir Voleti (2017), "The role of big data and predictive analytics in retailing," *Journal of Retailing,* 93 (1), 79–95.

Burke, Kenneth (1962), *A Grammar of Motives, and a Rhetoric of Motives,* Cleveland, OH: World Publishing.

Chevalier, Judith A. and Dina Mayzlin (2006), "The effect of word of mouth on sales: Online book reviews," *Journal of Marketing Research,* 43 (3), 345–54.

Dawar, Niraj (2018), "Marketing in the Age of Alexa," *Harvard Business Review,* 96 (3), 80–6.

de Haan, Evert and Elena Menichelli (2020), "The incremental value of unstructured data in predicting customer churn," *MSI Working Paper Series,*,

De Luca, Luigi M., Dennis Herhausen, Gabriele Troilo and Andrea Rossi (2020), "How and when do big data investments pay off? The role of marketing affordances and service innovation," *Journal of the Academy of Marketing Science,*, 1–21.

Dekimpe, Marnik G. (2020), "Retailing and retailing research in the age of big data analytics," *International Journal of Research in Marketing,* 37 (1), 3–14.

DeKinder, Jade S. and Ajay K. Kohli (2008), "Flow signals: How patterns over time affect the acceptance of start-up firms," *Journal of Marketing,* 72 (5), 84–97.

De Vries, Lisette, Sonja Gensler and Peter S.H. Leeflang (2012), "Popularity of brand posts on brand fan pages: An investigation of the effects of social media marketing," *Journal of interactive marketing,* 26 (2), 83–91.

Duan, Wenjing, Bin Gu and Andrew B. Whinston (2008), "The dynamics of online word-of-mouth and product sales—An empirical investigation of the movie industry," *Journal of Retailing,* 84 (2), 233–42.

Farace, Stefania, Anne Roggeveen, Francisco Villarroel Ordenes, Ko De Ruyter, Martin Wetzels and Dhruv Grewal (2020), "Patterns in motion: How visual patterns in ads affect product evaluations," *Journal of Advertising,* 49 (1), 3–17.

Genette, Gérard (1992), , Univ. of California Press.

Germann, Frank, Peter Ebbes and Rajdeep Grewal (2015), "The chief marketing officer matters!," *Journal of Marketing,* 79 (3), 1–22.

Ghoshal, Tanuka, Eric Yorkston, Joseph C. Nunes and Peter Boatwright (2014), "Multiple reference points in sequential hedonic evaluation: An empirical analysis," *Journal of Marketing Research,* 51 (5), 563–77.

Greene, William (2017), *Econometric Analysis,* 8th edition.

Grewal, Dhruv, John Hulland, Praveen K. Kopalle and Elena Karahanna (2020a), "The future of technology and marketing: A multidisciplinary perspective," *Journal of the Academy of Marketing Science,* 48 (1), 1–8.

Grewal, Dhruv, Stephanie M. Noble, Anne L Roggeveen and Jens Nordfalt (2020b), "The future of in-store technology," *Journal of the Academy of Marketing Science,* 48 (1), 96–113.

Grewal, Dhruv, Anne L. Roggeveen and Jens Nordfalt (2017), "The future of retailing," *Journal of Retailing,* 93 (1), 2017.

Harrison, David A. and Katherine J. Klein (2007), "What's the difference? Diversity constructs as separation, variety, or disparity in organizations," *Academy of Management Review,* 32 (4), 1199–228.

Hartmann, Jochen, Juliana Huppertz, Christina Schamp and Mark Heitmann (2019), "Comparing automated text classification methods," *International Journal of Research in Marketing,* 36 (1), 20–38.

Heimbach, Irina and Oliver Hinz (2016), "The impact of content sentiment and emotionality on content virality," *International Journal of Research in Marketing,* 33 (3), 695–701.

Hellbernd, Nele and Daniela Sammler (2016), "Prosody conveys speaker's intentions: Acoustic cues for speech act perception," *Journal of Memory and Language,* 88, 70–86.

Herhausen, Dennis, Oliver Emrich, Dhruv Grewal, Petra Kipfelsberger and Marcus Schoegel (2020b), "Face forward: How employees' digital presence on service websites affects customer perceptions of website and employee service quality," *Journal of Marketing Research,* 57 (5), 917–36.

Herhausen, Dennis, Kristina Kleinlercher, Peter C. Verhoef, Oliver Emrich and Thomas Rudolph (2019a), "Loyalty formation for different customer journey segments," *Journal of Retailing,* 95 (3), 9–29.

Herhausen, Dennis, Stephan Ludwig, Dhruv Grewal, Jochen Wulf and Marcus Schoegel (2019b), "Detecting, preventing, and mitigating online firestorms in brand communities," *Journal of Marketing,* 83 (3), 1–21.

Herhausen, Dennis, Dario Miočević, Robert E. Morgan and Mirella H.P. Kleijnen (2020a), "The digital marketing capabilities gap," *Industrial Marketing Management,* 90, 276–90.

Hess, Nicole J., Corinne M. Kelley, Maura L. Scott, Martin Mende and Jan H. Schumann (2020), "Getting personal in public!? How consumers respond to public personalized advertising in retail stores," *Journal of Retailing,* 96 (3), 344–61.

Hildebrand, Christian, Fotis Efthymiou, Francesc Busquet, William H. Hampton, Donna L. Hoffman and Thomas P. Novak (2020), "Voice analytics in business research: Conceptual foundations, acoustic feature extraction, and applications," *Journal of Business Research,* 121, 364–74.

Holmlund, Maria, Yves Van Vaerenbergh, Robert Ciuchita, Annika Ravald, Panagiotis Sarantopoulos, Francisco Villarroel Ordenes and Mohamad Zaki (2020), "Customer experience management in the age of big data analytics: A strategic framework," *Journal of Business Research,* 116, 356–65.

Hsee, Christopher K. and Robert P. Abelson (1991), "Velocity relation: Satisfaction as a function of the first derivative of outcome over time," *Journal of Personality and Social Psychology,* 60 (3), 341.

Huang, Allen H., Reuven Lehavy, Amy Y. Zang and Rong Zheng (2018), "Analyst information discovery and interpretation roles: A topic modeling approach," *Management Science,* 64 (6), 2833–55.

Huang, Xun and Aparna A. Labroo (2020), "Cueing morality: The effect of high-pitched music on healthy choice," *Journal of Marketing,* 84 (6), 130–43.

Humphreys, Ashlee, Mathew S Isaac and Rebecca Jen-Hui Wang (2020), "Construal matching in online search: Applying text analysis to illuminate the consumer decision journey," *Journal of Marketing Research,*, forthcoming.

Humphreys, Ashlee and Rebecca Jen-Hui Wang (2018), "Automated text analysis for consumer research," *Journal of Consumer Research,* 44 (6), 1274–306.

Hunt, Shelby D. and Robert M. Morgan (1996), "The resource-advantage theory of competition: Dynamics, path dependencies, and evolutionary dimensions," *Journal of Marketing,* 60 (4), 107–14.

Jalali, Nima Y. and Purushottam Papatla (2019), "Composing tweets to increase retweets," *International Journal of Research in Marketing,* 36 (4), 647–68.

Jia, He, B.K. Kim and L. Ge (2020), "Speed up, size down: How animated movement speed in product videos influences size assessment and product evaluation," *Journal of Marketing,*, 0022242920925054.

Jin, Liyin, Bingyan Hu and Yangun He (2014), "The recent versus the out-dated: An experimental examination of the time-variant effects of online consumer reviews," *Journal of Retailing,* 90 (4), 552–66.

Johnen, Marius and Oliver Schnittka (2019), "When pushing back is good: The effectiveness of brand responses to social media complaints," *Journal of the Academy of Marketing Science,* 47 (5), 858–78.

Kanuri, Vamsi K., Yixing Chen and Shrihari (Hari) Sridhar (2018), "Scheduling content on social media: theory, evidence, and application," *Journal of Marketing,* 82 (6), 89–108.

Kern, Margaret L., Gregory Park, Johannes C. Eichstaedt, H. Andrew Schwartz, Maarten Sap, Laura K. Smith and Lyle H. Ungar (2016), "Gaining insights from social media language: methodologies and challenges," *Psychological Methods,* 21 (4), 507.

Klatt, Dennis H. (1979), "Speech perception: A model of acoustic–phonetic analysis and lexical access," *Journal of Phonetics,* 7 (3), 279–312.

Klostermann, Jan, Anja Plumeyer, Daniel Böger and Reinhold Decker (2018), "Extracting brand information from social networks: Integrating image, text, and social tagging data," *International Journal of Research in Marketing,* 35 (4), 538–56.

Kubler, Raoul V., Anatoli Colicev and Koen H. Pauwels (2020), "Social media's impact on the consumer mindset: When to use which sentiment extraction tool?," *Journal of Interactive Marketing,* 50, 136–55.

Lamberton, Cait and Andrew T Stephen (2016), "A thematic exploration of digital, social media, and mobile marketing: Research evolution from 2000 to 2015 and an agenda for future inquiry," *Journal of Marketing,* 80 (6), 146–72.

Lee, Ju-Yeon, Eric Fang, Jisu J. Kim, Xiaoling Li and Robert W. Palmatier (2018), "The effect of online shopping platform strategies on search, display, and membership revenues," *Journal of Retailing,* 94 (3), 247–64.

Lee, Thomas Y. and Eric T. Bradlow (2011), "Automated marketing research using online customer reviews," *Journal of Marketing Research,* 48 (5), 881–94.

Li, Xi, Mengze Shi and Xin Shane Wang (2019), "Video mining: Measuring visual information using automatic methods," *International Journal of Research in Marketing,* 36 (2), 216–31.

Li, Yiyi and Ying Xie (2020), "Is a picture worth a thousand words? An empirical study of image content and social media engagement," *Journal of Marketing Research,* 57 (1), 1–19.

Liu, Liu, Daria Dzyabura and Natalie Mizik (2020), "Visual listening in: Extracting brand image portrayed on social media," *Marketing Science,* 39 (4), 669–86.

Liu, Xuan, Savannah Wei Shi, Thales Teixeira and Michel Wedel (2018), "Video content marketing: The making of clips," *Journal of Marketing,* 82 (4), 86–101.

Ludwig, Stephan, Ko De Ruyter, Mike Friedman, Elisabeth C. Brüggen, Martin Wetzels and Gerard Pfann (2013), "More than words: The influence of affective content and linguistic style matches in online reviews on conversion rates," *Journal of Marketing,* 77 (1), 87–103.

Ludwig, Stephan, Ko De Ruyter, Dominik Mahr, Martin Wetzels, Elisabeth Brüggen and Tom De Ruyck (2014), "Take their word for it," *MIS Quarterly,* 38 (4), 1201–18.

Ludwig, Stephan, Dennis Herhausen, Dhruv Grewal, Liliana Bove, Sabine Benoit, Ko de Ruyter and Peter Urwin (2020), *Buying and selling in online freelance marketplaces,* Working Paper.

Marinova, Detelina, Sunil K. Singh and Jagdip Singh (2018), "Frontline problem-solving effectiveness: A dynamic analysis of verbal and nonverbal cues," *Journal of Marketing Research,* 55 (2), 178–92.

Marketing Land (2018), *Study Finds 61 Percent of Electronics Reviews on Amazon are 'Fake',* https://marketingland.com/study-finds-61-percent-of-electronics-reviews-on-amazon-are-fake-254055

McKenny, McKenny, Herman Aguinis, Jeremy C Short and Aaron H. Anglin (2018), "What doesn't get measured does exist: Improving the accuracy of computer-aided text analysis," *Journal of Management,* 44 (7), 2909–33.

Minnema, Alec, Tammo H. Bijmolt, Sonja Gensler and Thorsten Wiesel (2016), "To keep or not to keep: Effects of online customer reviews on product returns," *Journal of Retailing,* 92 (3), 253–67.

Murphy, Rosie (2019), *Local Consumer Review Survey,* BrightLocal [Available from: https://www.brightlocal.com/research/local-consumer-review-survey/]

Netzer, Oded, Ronen Feldman, Jacob Goldenberg and Moshe Fresko (2012), "Mine your own business: Market-structure surveillance through text mining," *Marketing Science,* 31 (3), 521–43.

Netzer, Oded, Alaine Lemaire and Michel Herzenstein (2019), "When words sweat: identifying signals for loan default in the text of loan applications," *Journal of Marketing Research,* 56 (6), 960–80.

Packard, Grant, Sarah G. Moore and Brent McFerran (2018), "(I'm) happy to help (you): The impact of personal pronoun use in customer–firm interactions," *Journal of Marketing Research,* 55 (4), 541–55.

Palmatier, Robert W., Mark B. Houston, Rajiv P. Dant and Dhruv Grewal (2013), "Relationship velocity: Toward a theory of relationship dynamics," *Journal of Marketing,* 77 (1), 13–30.

Partan, Sarah R. and Peter Marler (2005), "Issues in the classification of multimodal communication signals," *The American Naturalist,* 166 (2), 231–45.

Pauwels, Koen, Peter S.H. Leeflang, Marije L. Teerling and K.R. Eelko Huizingh (2011), "Does online information drive offline revenues? Only for specific products and consumer segments!," *Journal of Retailing,* 87 (1), 1–17.

Pollach, Irene (2012), "Taming textual data: The contribution of corpus linguistics to computer-aided text analysis," *Organizational Research Methods,* 15 (2), 263–87.

Reb, Jochen and Russell Cropanzano (2007), "Evaluating dynamic performance: The influence of salient gestalt characteristics on performance ratings," *Journal of Applied Psychology,* 92 (2), 490.

Roggeveen, Anne L., Jens Nordfält and Dhruv Grewal (2016), "Do digital displays enhance sales? Role of retail format and message content," *Journal of Retailing,* 92 (1), 122–31.

Roggeveen, Anne L. and Raj Sethuraman (2020), "Customer-interfacing retail technologies in 2020 & beyond: An integrative framework and research directions," *Journal of Retailing,* 96 (3), 299–309.

Rutz, Oliver J. and George F. Watson IV (2019), "Endogeneity and marketing strategy research: An overview," *Journal of the Academy of Marketing Science,* 47 (3), 479–98.

Schweidel, David A. and Wendy W. Moe (2014), "Listening in on social media: A joint model of sentiment and venue format choice," *Journal of Marketing Research,* 51 (4), 387–402.

Schwenzow, Jasper, Jochen Hartmann, Amos Schikowsky and Mark Heitmann (2020), "Understanding videos at scale: How to extract insights for business research," *Journal of Business Research,* 123, 367–79.

Shankar, Venkatesh (2018), "How artificial intelligence (AI) is reshaping retailing," *Journal of Retailing,* 94 (4), vi–xi.

Shankar, Venky (2019), "Big data and analytics in retailing," *NIM Marketing Intelligence Review,* 11 (1), 37–40.

Shankar, Venkatesh and Sridhar Balasubramanian (2009), "Mobile marketing: A synthesis and prognosis. Tenth anniversary special issue," *Journal of Interactive Marketing,* 23 (2), 118–29.

Shankar, Venkatesh, Kirthi Kalyanam, Pankaj Setia, Alirez Golmohammadi, Seshadri Tirunillai, Tom Douglass, John Hennessey, J.S. Bull and Rand Waddoups (2020), "How technology is changing retail," *Journal of Retailing,*, forthcoming.

Singh, Sunil K., Detelina Marinova and Jagdip Singh (2020), "Business-to-business e-negotiations and influence tactics," *Journal of Marketing,* 84 (2), 47–68.

Tang, Tanya (Ya), Eric (Er) Fang and Feng Wang (2014), "Is neutral really neutral? The effects of neutral user-generated content on product sales," *Journal of Marketing,* 78 (4), 41–58.

Van Dolen, Willemijn M., Pratibha A. Dabholkar and Ko De Ruyter (2007), "Satisfaction with online commercial group chat: The influence of perceived technology attributes, chat group characteristics, and advisor communication style," *Journal of Retailing,* 83 (3), 339–58.

Van Laer, Tom, Jennifer Edson Escalas, Stephan Ludwig and Ellis A. Van Den Hende (2019), "What happens in vegas stays on tripadvisor? A theory and technique to understand narrativity in consumer reviews," *Journal of Consumer Research,* 46 (2), 267–85.

Vermeer, Susan A.M., Theo Araujo, Stefan F. Bernritter and Guda van Noort (2019), "Seeing the wood for the trees: How machine learning can help firms in identifying relevant electronic word-of-mouth in social media," *International Journal of Research in Marketing,* 36 (3), 492–508.

Villarroel Ordenes, Francisco, Dhruv Grewal, Stephan Ludwig, Ko De Ruyter, Dominik Mahr and Martin Wetzels (2019), "Cutting through content clutter: How speech and image acts drive consumer sharing of social media brand messages," *Journal of Consumer Research,* 45 (5), 988–1012.

Villarroel Ordenes, Francisco, Stephan Ludwig, Ko De Ruyter, Dhruv Grewal and Martin Wetzels (2017), "Unveiling what is written in the stars: Analyzing explicit, implicit, and discourse patterns of sentiment in social media," *Journal of Consumer Research,* 43 (6), 875–94.

Villarroel Ordenes, Francisco and Shunyaun Zhang (2019), "From words to pixels: Text and image mining methods for service research," *Journal of Service Management,* 30 (5), 593–620.

Wedel, Michel and P.K. Kannan (2016), "Marketing analytics for data-rich environments," *Journal of Marketing,* 80 (6), 97–121.

Wu, Xiaoyue, Liyin Jin and Qian Xu (2020), "Expertise makes perfect: How the variance of a reviewer's historical ratings influences the persuasiveness of online reviews," *Journal of Retailing,*, forthcoming.

Wulf, Jochen, Tobias Mettler, Stephan Ludwig and Dennis Herhausen (2019), "A computational visual analysis of image design in social media car model communities," in *European conference on information systems* Working Paper.

Xu, Pei, Liang Chen and Radhika Santhanam (2015), "Will video be the next generation of e-commerce product reviews? Presentation format and the role of product type," *Decision Support Systems,* 73, 85–96.

Yadav, Manjit S. and Paul A. Pavlou (2014), "Marketing in computer-mediated environments: Research synthesis and new directions," *Journal of Marketing,* 78, 20–40.

Zhang, Jonathan Z. and Chun-Wei Chang (2020), "Consumer dynamics: Theories, methods, and emerging directions," *Journal of the Academy of Marketing Science,*, 1–31.

Zhang, Mengxia and Lan Luo (2018), "Can user generated content predict restaurant survival: deep learning of yelp photos and reviews," in *Advances in neural information processing systems 28*, [available at: https://ssrn.com/abstract=3108288].

Zhang, Shunyuan, Dokyun Lee, Param Vir Singh and Kannan Srinivasan (2017), *How much is an image worth? Airbnb property demand estimation leveraging large scale image analytics,* [available at: https://ssrn.com/abstract=2976021].