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# Salesperson communication effectiveness in a digital sales interaction[1]☆

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ABSTRACT

B2B buyers are exhibiting an increased preference to transact digitally with vendors. A topic which has yet to receive sufficient academic attention in this modern selling environment is salesperson communication effectiveness. Accordingly, this article: 1) defines digital sales interactions (DSIs) as technology-enabled, face-to-face buyer-seller exchanges; 2) proposes a typology of DSIs to set the stage to examine salesperson communication effectiveness; 3) introduces a framework that reifies the sender's auditory and visual cues that can influence receivers' thoughts (i.e., cognition, affect, intention) and activity (i.e., purchase behavior, advocacy); 4) suggests theoretical lenses that can illuminate various aspects of the salesperson's communication barrage; 5) advances how machine learning can be applied to understand what constitutes effective communication in a digital interaction by asking: to what extent does *what* a salesperson says (auditory cues) and *how* s/he says it (visual cues) impact her/his effectiveness in a DSI?; and 6) concludes by noting promising future research directions for B2B marketing researchers.

## 1. Introduction

Technological advancements are ushering in the fourth industrial revolution (Schwab, 2016). Whereas the steam engine, mass production, and the internet were responsible for providing the foundation for innovation in past eras, the case is being made that economies and industries will be disrupted by technologies which permit the blending together of the digital, physical, and biological worlds (e.g., artificial intelligence, quantum computing, 3D printing, and the internet of things).[2] In brief, the new technologies are predicted to change the way that we live, work, and interact (Syam & Sharma, 2018).

A notable shift that is transpiring is that business exchanges (among suppliers, intermediaries, customers, and other constituencies) are increasingly being carried out in digital environments (Hoffman & Novak, 1996; Turkle, 2017; Yadav & Pavlou, 2014). In a world marked by greater connectivity and interactivity, digital interactions have emerged as a dominant mode for buyer-seller exchanges (Steinhoff, Arli, Weaven, & Kozlenkova, 2019). This assertion is supported in studies reporting that:

- 68% of B2B buyers prefer doing business online versus with a salesperson (Hoar, 2017) because the digital channel offers greater convenience, price transparency, and access to product information and customer reviews (Caitlin, Harrison, Plotkin, & Stanley, 2016).
- B2B buyers considering a purchase spend 17% of their time meeting with potential suppliers and 27% of their time researching sources independently online (Gartner, 2019).
- Owned media (a company's website) and digital inbound marketing (e.g., webinars, white papers, and blogs) play a pivotal role for B2B sellers in acquiring new business customers (Vieira et al., 2019).

To better align themselves with the demands of digital commerce so as to achieve competitive advantage, selling firms are modernizing their sales strategy and pursuing digital sales interactions (DSIs), which we

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☆ The authors benefitted from helpful comments from: our anonymous reviewers, session participants at the 3rd Annual *Industrial Marketing Management* Summit at the Fox School of Business at Temple University, and suggestions on our earlier thinking provided by Jagdish N. Sheth.

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[2] We thank Audhesh Paswan for suggesting that we address broader societal changes to contextualize the prevalence of digital exchanges. We believe that the COVID-19 pandemic is yet another force that is likely to further accelerate the adoption of digital commerce.

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define as technology-enabled, face-to-face buyer-seller exchanges. Although the digital sales channel holds potential to drive topline revenues and/or conduct sales interactions more efficiently (Sheth & Sharma, 2008; Thaichon, Surachartkumtonkun, Quach, Weaven, & Palmatier, 2018), some open questions remain before those business gains are to be realized (see, e.g., Singh et al., 2019; Organizational Frontline Research (OFR), 2019). Central to this article is salesperson communication effectiveness in a DSI.

It has long been understood that effective communication is a fundamental determinant of salesperson performance outcomes (e.g., Singh, Brady, Arnold, & Brown, 2017; Spiro & Weitz, 1990; Webster, 1968; Weitz, 1981). Furthermore, it is well established that a sender's verbal (e.g., Peterson, Cannito, & Brown, 1995) and nonverbal (e.g., Bonoma & Felder, 1977; Lim, Lee, & Foo, 2017) cues matter in face-to-face encounters. However, the extent to which the earlier findings on salesperson communication effectiveness hold in a less rich, digitally-enabled medium is not yet fully known.

Two promising developments facilitate studying the next frontier in sales communication effectiveness. First, digital commerce generates a continuous stream of video footage (OFR 2019). Instead of narrowly studying a single aspect of a salesperson's communication in isolation as was historically done (e.g., does “service with a smile” matter in shaping customer-related outcomes?), researchers are now in a position to couple the salesperson's auditory and visual cues with moment-by-moment customers' mindset and/or behavioral data for more holistic predictive and prescriptive purposes (Marinova, Singh, & Singh, 2018). Second, advances in artificial intelligence (AI) permit capturing and analyzing the massive amount of unstructured and structured data from the video footage not previously possible (Syam & Sharma, 2018). Whereas, for instance, the current literature that examines the “service with a smile” maxim relies on human raters to manually code the facial expressions of frontline employees (Du, Fan, & Feng, 2011; Pugh, 2001; Wang et al., 2017), recent efforts deploy convolutional neural networks to automate the facial coding process, extract the sender's facial expressions, and subsequently associate visual and/or verbal signals with business outcomes (Choudhury, Wang, Carlson, & Khanna, 2019; Liu, Shi, Teixeira, & Wedel, 2018).

These developments (i.e., the availability of video footage of seller-buyer interactions and state-of-the-art AI techniques) coupled with the increased interest in the digital sales channel among business buyers and sellers yields interesting opportunities for scholarship. Our discourse can offer researchers a path to address Marketing Science Institute's (MSI 2018–20) paramount research priority to deploy technological advances to capture and analyze audio and video data to improve marketing communications. The approach described is also pragmatically useful as it can provide guidance to firms on ways to improve salesperson communication effectiveness in DSIs, and in turn, drive key performance metrics.

In this article, we first propose a typology of buyer-seller interactions that can transpire in a digital medium to provide a starting point to assess salesperson communication effectiveness in this modern selling channel.[3] We then introduce a comprehensive framework that reifies the totality of the salesperson's auditory and visual cues directed towards a customer that can influence buyer outcomes. Subsequently, we advance how machine learning can be applied to better understand what constitutes effective communication in a digital interaction: to what extent does *what* a salesperson says (auditory cues) and *how* s/he says it (visual cues) impact her/his effectiveness in a DSI? We conclude by noting future research possibilities.

## 2. Digital sales interactions (DSIs)

Exchange is a foundational concept in marketing —it has been described as “the crux of marketing” (Kotler & Levy, 1969, p. 57) and as “a fundamental framework for viewing marketing” (Bagozzi, 1974, p. 77). The exchange system refers to “sets (of parties) in which interactions occur which serve to define the boundaries of the set” (Alderson & Martin, 1965, p. 125), and recognizes that the macro-environment in which the dyad is embedded is an important consideration (Hunt, 1983).

The increasing prevalence of buyer-seller communications and transactions being conducted remotely via a screen-to-screen interface marks an evolution from the traditional in-person, face-to-face exchange (Kopalle, Kumar, & Subramaniam, 2019; Salesforce, 2019; Verhoef & Bijmolt, 2019; Yadav & Pavlou, 2014). The fact that digital technologies can fundamentally alter marketing processes (Kannan & Li, 2017; Kumar, Sharma, Vatavwalla, & Kumar, 2020) provides the impetus to study the efficacy of a salesperson in a technology-enabled, face-to-face buyer-seller exchange, or what we deem a digital sales interaction (DSI). Akin to an in-person face-to-face interaction, a DSI can occur at any point along the B2B buying journey, spanning from pre-sales communications to actual sales transactions to post-sales activity.[4]

Scholars opine that digital technologies can alter the customer experience (Kannan & Li, 2017; Kumar et al., 2020). This means that even though leading firms are innovating their sales channel in an attempt to deliver a superior customer experience across the entire customer journey (see, for example, Moorman & Lemon, 2020), and in turn, drive topline revenues and/or conduct sales interactions more efficiently (Sheth & Sharma, 2008; Thaichon et al., 2018), salesperson communication effectiveness in a DSI is not yet fully understood.

One way to begin thinking about salesperson communication effectiveness in a DSI is to consider the nature of the sales communication in conjunction with its temporal aspect.[5] A seller's interaction with an institutional buyer can be scripted or tailored, and it can transpire in real-time or without temporal synchronization. Whether the communication is *adaptive* (i.e., the seller tailors the message) versus *standard* (i.e., the seller conveys a scripted message) or *synchronous* versus *asynchronous* can be used to formulate Table 1, which contains an exemplar digital exchange in each cell. For illustration, we juxtapose a one-to-one interaction and a one-to-many interaction to highlight how these require differing theories to illuminate the DSI.

A key implication arising from Table 1 is that a researcher interested in comparing a pair of cells will require different theoretical lenses to explicate the determinants of salesperson effectiveness. Take, for instance, a researcher interested in understanding the emotions displayed during an adaptive, synchronous DSI in relation to a standard, synchronous one. Assuming that the former is a one-to-one interaction, the DSI provides the researcher access the facial expressions of both sides of the dyad. This permits employing emotional contagion theory to examine the extent to which a facial expression by a seller (e.g., a smile) results in the buyer mimicking the viewed facial expression and experiencing a positive affect towards the seller (Chartrand & Lakin, 1993; Hatfield, Cacioppo, & Rapson, 1994). In contrast, a standard, synchronous DSI may involve a one-to-many interaction. This means that the researcher has access only to the seller's facial display. In this instance, one possibility is to construe the facial expression as a signal that the seller manipulates in order to achieve a desired response from a buyer (e.g., whether to smile, and if so, how broadly and for how

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[3] We thank Raj Agnihotri for this suggestion.

[4] We acknowledge that a DSI is not suitable for all instances. In a straight rebuy situation, for instance, it is more efficient for both the buyer and seller to have the repurchase of a known, required input transpire via the click of a button on a sales platform. Additionally, an in-person, face-to-face interaction may be required to lay the foundation for a relationship with a promising prospect in a complex new buy situation or a follow-up visit may be required at a strategic account for a modified rebuy . We thank an anonymous reviewer for this suggestion.

[5] We thank an anonymous reviewer for this suggestion.

**Table 1**
DSI exemplars.

| | Adaptive Communication | Standard Communication |
|---|---|---|
| Synchronous Communication | A seller conducts an online face-to-face chat to resolve a buyer's technical issue(s) and provides a customized solution. | A seller live-streams an informational webinar about a new product line to prospects in real-time. |
| Asynchronous Communication | A seller records a set of pre-recorded instructional videos to respond to a buyer's request to resolve a technical issue requiring a customized solution. | A seller posts on its website an informational webinar about a new product line, and prospects can access the content 24/7. |

long?). The emotions as social interaction (EASI) model (van Kleef, 2009, 2016) can provide the theoretical scaffolding to construe the seller's facial behavior as a signal. The seller can consciously determine which facial expression to display and the intensity of the emotion (e.g., slight versus broad smile) in order to elicit the desired response from the buyer.

In the next section, we expand on the cues that are available from a DSI. In addition to facial expressions, the researcher can access other nonverbal and verbal cues. As there are multiple cues, we provide a framework to conceptualize the sender's barrage of communications. For ease of exposition, we focus on a standard, synchronous communication in a one-to-many setting.

## 3. Conceptualizing salesperson effectiveness in DSIs.

A communication in an exchange system involves a sender conveying a plethora of signals to the receiver. Akin to a face-to-face meeting, the sender transmits auditory and visual signals in a DSI. However, other cues – such as touch and smell – are not as salient because the sender and receiver do not occupy the same physical space. Thus, we construe a receiver's appraisal of a sender in digital interaction to be shaped by the sender's auditory and visual signals, and the screen-to-screen interface makes it a less rich medium than an in-person, face-to-face interaction, yet richer than a telephone encounter in which only the sender's words and the delivery (i.e., auditory cues) play a pivotal role in shaping customers' appraisals (Bharadwaj & Roggeveen, 2008).

Ekman and Friesen (1978, 2003) describe the abundance of auditory and visual signals from a sender as a “communication barrage.” Those authors suggest that the receiver can gather information from the sender's statements in terms of the content (i.e., words used) and delivery (i.e., rate of speech, loudness, tone, number of pauses, and disruptive words such as “umms” and “aahs” used). In addition, the receiver is subjected to a host of information from the visual channel. These cues can hail from the sender's facial expressions as well as their head and body movements. The audio and the visual channels, respectively, give rise to the verbal and nonverbal cues in a communication, and theories exist to conceptualize the receiver's affective appraisals and/or behavioral outcomes (see e.g., contagion theory (Hatfield et al., 1994; Hennig-Thurau et al., 2006; Pugh, 2001) and emotions as social information (van Kleef, 2009, 2016)). Fig. 1 depicts our conceptualization of the communication barrage in a DSI and possible customer outcomes.

It is well-established that how effectively a salesperson from a selling organization communicates with a buyer influences her/his success (e.g., Singh et al., 2017; Spiro & Weitz, 1990; Webster, 1968; Weitz, 1981), and the extant research on salesperson effectiveness has examined the sender's auditory and visual communication cues noted in Fig. 1. Below, we briefly mention some exemplar studies.

To investigate the impact of *what* is said (i.e., the words used), Singh, Marinova, Singh, and Evans (2018) develop dictionaries of words to operationalize salesperson competence (e.g., in resolving customer queries such as need specification and transaction clarification) and warmth (e.g., relating/emoting in attending to customer queries). The authors' analysis of words demonstrates the primacy of salesperson competence in retaining a customer's interest, which in turn, drives customer purchase intent. In their paper evaluating the salesperson delivery-effectiveness relationship, Peterson et al. (1995) begin with the premise that *how* a sales message is communicated may be as important is *what* is communicated. They examine specific voice characteristics as determinants of customers' purchases, and find rate of speech (i.e., arguing that a rapid speaker is perceived as more knowledgeable and trustworthy) fundamental frequency contour (i.e., mean, variability, and contour), and loudness variability to be associated with higher sales. To assess visual cues, Pugh (2001) manually evaluates observational data from 106 actual bank teller-customer service encounters, and finds that the seller's positive facial expressions (i.e., happiness as conveyed by a smile) can influence the perceived quality of the service received. In their study of head and body activity, Pauser, Wagner, and Ebster (2018) rely on two trained observers to utilize the body action posture (BAP) coding system – which classifies 141 behavioral variables into 12 categories (e.g., head action, arm action) – to manually assess sales presentations, and find that symmetric movements (asymmetric movements) have a greater impact on attitude towards the salesperson in a low-gesture culture (high-gesture culture).

While the aforementioned sample of studies (as well as a large body existing research) can provide meaningful insight into the auditory and verbal cues summarized in Fig. 1, the individual aspects are studied in isolation. What is needed is a broader examination of the relationship between sales success and effective communication in a DSI. Such a study could shed insight into an important, open question: to what extent does *what* a salesperson says (auditory cues) and *how* s/he says it (visual cues) impact her/his effectiveness in a digital sales interaction?

## 4. Holistically assessing salesperson effectiveness in DSIs

The volume and variety of data created at an increased velocity by the sender's barrage of digital communications that are digitized pose unique challenges. The structured and unstructured data are massive, which taxes human abilities to collect, store and process (Bharadwaj & Noble, 2017; Marinova et al., 2018; McAfee & Brynjolfsson, 2012). They are also high dimensional, and situations in which $p > n$ require new methodologies and computational capabilities.

Wedel and Kannan (2016) equate such big data to the “oil” of the digital economy. We see this as a fitting comparison because, just like crude oil, it is necessary to refine unstructured (i.e., audio, video, images, or text) data and structured (i.e., organized by variables or numeric values) data to extract meaning. Given that roughly 80% of data available to firms are unstructured (Rizkallah, 2017), this suggests a rich, untapped reservoir of insights. For instance, deep learning can be used to detect the presence of a face in a given frame of the video footage and neural nets can then be used to transform the information from the face into a field of weighted pixels in order to extract the salesperson's facial expressions.

The aforementioned implies potential insights on both customers and sellers (MSI 2018), which raises two questions: how can firms harness and refine this data, and what potential insights can emerge? Recent developments in artificial intelligence (AI) can aid in this regard.[6]

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[6] AI is technology that mimics human intelligence and cognitive functions such as perception and reasoning (Russell & Norvig, 2014). For a more in-depth treatment, we direct the interested reader to Paschen, Kietzmann, and

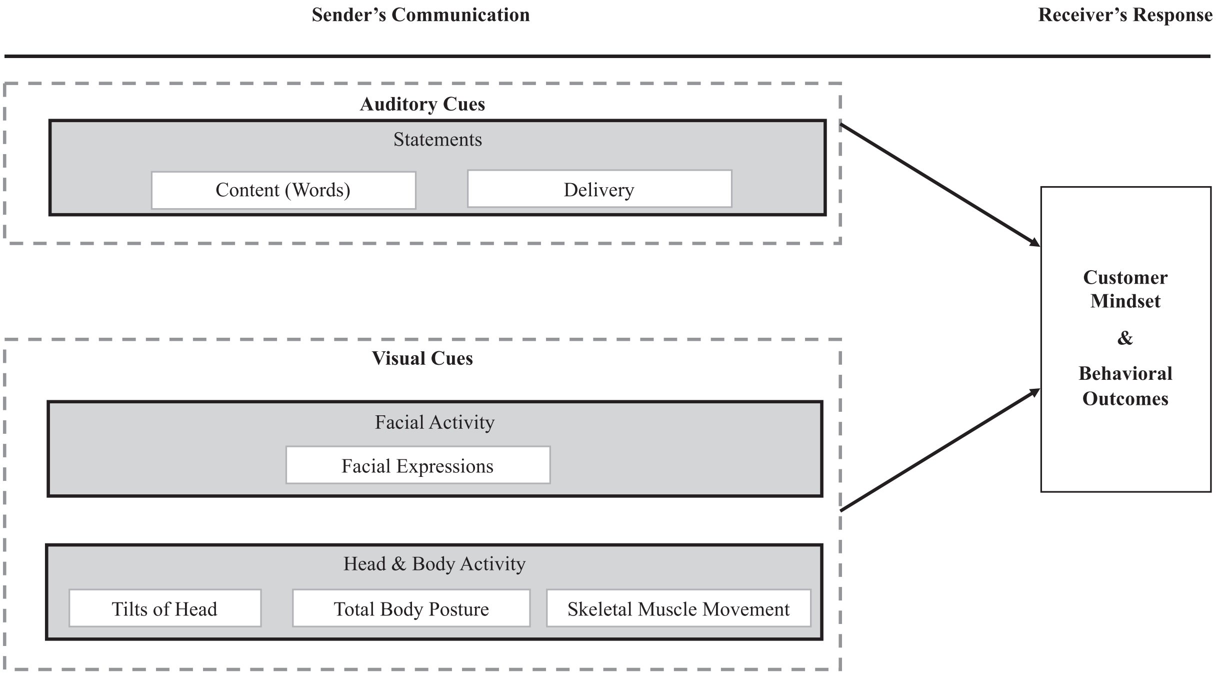

**Fig. 1.** The salesperson's communication barrage and buyer outcomes.

### 4.1. A primer on machine learning

Unstructured data, specifically audio and video, have successfully been structured and analyzed using methods from the field of artificial intelligence (Arandjelovic & Zisserman, 2017; Balducci & Marinova, 2018; Li, Shi, & Wang, 2019). AI is an umbrella term for any technology or program that attempts to make decisions without explicitly being programmed to do so. AI mimics human cognition using algorithms, which allows a computer to structure unstructured data, analyze multiple features of the data simultaneously, and estimate an equation that will best fit the available data.

Machine learning, a subfield of artificial intelligence, focuses on the mathematical and statistical modeling of a particular task allowing a computer program to make inferences or decisions. Machine learning can be divided into two general types of learning: supervised and unsupervised. Supervised learning is described as observing input-output pairs and then creating a function that maps input to output (Russell & Norvig, 2014). It is important to note that a supervised learning program will require “correct” input-output pairs—this is covered thoroughly by Syam and Sharma (2018). Alternatively, an unsupervised machine learning program will learn the patterns of the data set based on the inputs with no output feedback (Russell & Norvig, 2014).

The utility of machine learning comes from its ability to adjust the weighting of variables as more data becomes present. Because of this, machine learning provides an opportunity to derive a holistic prediction. Consider salesperson-customer interaction wherein the salesperson says something polite but uses a sarcastic tone. If the seller's tone of voice is not considered in tandem with the content of his message, it could register as a positive communication (and predict a successful sale outcome). However, including tone of voice along with additional cues (e.g., eye contact, arm movements) should make the prediction more accurate. In this way, the algorithm can learn what variables are important in predicting the outcome of an interaction (rather than having a researcher set parameters a priori).

### 4.2. Applying machine learning to assess a salesperson's communication barrage

Prior to describing strategies to assess distinct components of the auditory and visual cues noted in Fig. 1, we begin providing the basic intuition as to how those individual aspects can influence customers' outcomes. To this end, we suggest theoretical lenses that prior researchers have used to illuminate the individual components of the salesperson's communication barrage. We then mention studies from the nascent stream of research that apply state-of-the-art machine learning techniques to analyze the auditory and/or visual cues from the video footage.

Psycholinguistic theory (Pennebaker, 2011) offers a novel approach to evaluate *what* a sender says. In brief, quantifying the proportion of certain words used in relation to the total words used in the discourse can capture important aspects of the sender's communication, including the underlying sentiment of the message sent (i.e., positive emotion and negative emotion) and the thinking style that underlies those words: narrative thinking (i.e., the sender's message is characterized in a free-flowing, stream-of-consciousness manner with minimal structure), formal thinking (i.e. the sender's message consists of big words in an attempt to put on a performance to be consumed by the receiver), and analytic thinking (i.e., the sender's message is marked by a detailed analysis of the situation in an attempt to convey cause and effect). Bharadwaj, Noble, Tower, Smith, and Dong (2017), for instance, use Linguistic Inquiry and Word Count (LIWC) to extract the aforementioned 24 variables from words conveyed by movie critics in their evaluations of movies (i.e., one variable for positive emotion, one variable for negative emotion; eight variables for narrative thinking; eight variables for formal thinking; and six variables for analytic thinking). Peterson et al. (1995) draw on linguistic theory to extract *how* a sender conveys his message, and the characteristics of the sender's delivery yield another set of variables (e.g., rate of speech, fundamental frequency contour, and loudness variability). To assess facial activity, researchers (e.g., Liu et al., 2018) rely on Ekman and Friesen's (1978) Facial Action Coding System (FACS) to categorize a set of emotional displays (e.g., happiness, sadness, anger). The presence of the face in a video and the six basic emotions generated in FACS yields distinct 7 variables. Lastly, the body action posture (BAP) coding

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(*footnote continued*)
Kietzmann (2019).

system mentioned earlier captures the sender's head and body activity, and yields 141 behavioral variables.

Digital commerce generates a continuous stream of video footage, and allows researchers to move beyond narrowly study a single aspect of a salesperson's communication. The auditory and visual cues mentioned in the preceding paragraph, for instance, generate 175 predictor variables in each video frame. Assuming that there is on average 30 min of video footage for each sales interaction and the unit of analysis is a frame that is captured every second, the pixels from 315,000 frames for each salesperson must be analyzed. Given the large-scale nature of the analysis, the task must be automated, and a set of parallel computers (instead of human coders) trained to execute it.[7] Johnson, Ogihara, Ren, and Lee (2019), for instance, process the raw content data by the CNN parts, then the CNN features (outputs from the CNN layers) are fed into the LSTM (long-term short-term) layers, and the fully connected CNN layers fuse together the data and generate the prediction.

## 5. Future research directions

Although digital sales interactions (DSIs) have emerged as a dominant mode for buyer-seller exchanges, some open questions remain regarding salesperson communication effectiveness in this modern selling environment. To begin to understand the knowledge gaps, this article defines digital sales interactions (DSIs); proposes a typology of some exemplar DSIs to set the stage to examine salesperson communication effectiveness (in Table 1); presents a framework (in Fig. 1) that reifies the sender's auditory and visual cues that can influence receivers' thoughts (i.e., cognition, affect, intention) and activity (i.e., purchase behavior, advocacy); and advances how machine learning can be applied to further understand what constitutes effective communication in a digital interaction.

The preceding discourse regarding sales effectiveness in commercial exchanges raises a host of issues in need of inquiry. In Table 2, we identify a sample of possible research questions organized around five main promising avenues for B2B researchers: (1) the cues that can shape a customer's perceptions of a salesperson's digital communication effectiveness; (2) training and recruiting the digital salesperson; (3) organizational strategy and structure to support their digital selling transformation; 4) the suitability of digital selling; and (5) the potential negative effects of digital sales interactions.

The cues available in digital sales interactions (see Fig. 1) can allow buyers and sellers to digitally simulate face-to-face interactions; however, these interactions are not as information rich as traditional face-to-face sales interactions. In an environment where the visual cues of body language and verbal cues of intonation can be out of sync, buyers and sellers can be deprived of information that could otherwise inform back-tracking or rapport building behaviors. Without the more subtle communication cues of traditional face-to-face interactions, a key starting point is to test the synchronous communications noted in Table 1 with their in-person, face-to-face counterparts. For instance, are the cues from the sender's communication barrage valued differently in digital sales interaction? What is the level of success that a salesperson is likely to achieve delivering the same standard script and call-to-action in a face-to-face sales interaction versus in a synchronous DSI (and versus asynchronous DSIs), and might those results generalize across a one-to-one and one-to-many situation? How might testing the counterfactual be influenced by the seller and/or buyer interfacing with multiple screens simultaneously? (see, e.g., cross-media consumption discussed in Bharadwaj, Ballings, & Naik, 2020).

Digital selling will likely require salespeople to possess an updated skill set in order to deliver a successful sales pitch (Angevine, Plotkin, & Stanley, 2018; Davenport & Westerman, 2018), and require large expenditures on sales training (Loechner, 2018). In this regard, machine learning and AI have the potential to completely change the way that firm's train their sales employees (Singh et al., 2019). In their pursuit of more effective salesperson training, how might machine learning and AI help firms: reduce the amount of time needed for sales professionals to hone their digital selling skills in synchronous and asynchronous exchanges?; aid digital immigrants (i.e., older salespeople not as well-versed with digital interaction) to be more at ease with screen-mediated interactions (akin to digital natives)?; and ascertain the optimal script for a standard, synchronous sales pitch versus a standard, asynchronous sales pitch? Firms can also harness AI and machine learning for hiring decisions as well. For instance, can the repertoire of verbal and nonverbal behaviors of the most successful salespeople be cataloged and aid in the selection of prospective candidates? How should firms train employees to address cultural differences? In other words, might differences between individualistic and collectivistic cultures change the way that sellers navigate DSIs?

Firms undergoing a digital selling transformation will also need to attend to a host of issues pertaining to organizational strategy and structure. One of the most important strategic questions that firms need to address is: which set of customers is/will be most valuable? Even though new digital customers may absorb more time and require higher initial acquisition costs, it will be prudent to develop an updated decision rule in order to prioritize the firm's customer portfolio based on customer profitability (see, e.g., Zeithaml, Rust, & Lemon, 2001). Firms can then rely on the algorithm to determine which customers require an in-person, face-to-face meeting and which can be relegated to some type of digital interaction. From a structural standpoint, firms are often organized around functional areas, which leads to coordination issues. In this regard, a key challenge that chief marketing officers (CMO) face is how to develop "the necessary capabilities…to design, deliver, and monitor the customer experience" (Moorman & Lemon, 2020). Stemming from this is: how can CMOs work with those leading other functional capabilities to develop an integrated value proposition and thereby drive favorable firm performance (see, e.g., Nath & Bharadwaj, 2020)? Relatedly, a firm's technological platform may be built to support a traditional salesforce calling on customers in person, and set up to suit the needs of separate functional areas. An important question that arises is: what might "legacy" firms be able to learn from their "born digital" counterparts in order to expedite their on ramping of online interactions? (see, e.g., Kopalle et al., 2019).

Another fertile area for future research is the suitability of digital interaction. It is estimated that DSIs have the potential to significantly reduce face-to-face interaction expenses (Laplana, 2017), but should the DSI be viewed as a substitute to the face-to-face sales force or a complement (see Angevine, Plotkin, & Stanley, 2017)? As acknowledged in Footnote 3, a fully digital salesforce may not be advantageous in all instances. The factors limiting a firm from fully converting to a digital salesforce could depend on many different factors (i.e., the customer's lifetime value to the firm, stage of customer relationship, strategic importance of product, nature of purchase (e.g., straight rebuy) etc.). With a variety of limiting factors, the question becomes: under what circumstances should firms opt for an in-person, face-to-face interaction? What factors may moderate this business strategy decision (e.g., technological readiness of seller; technological readiness of buyer)? With consideration to researchers and firms unable to access machine learning or AI technologies, Tóth, Henneberg, and Naudé (2017) discuss innovative techniques, such as fuzzy set qualitative comparison analysis (fsQCA), that facilitate analyzing complex data sets holistically.

Lastly, what are the potentially negative effects of a digital sales interactions? In order to utilize the data produced from digital sales interactions, firms will need to collect data on each sales interaction. In

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[7] The aforementioned audio and visual cues can be extracted using crowd-sourced lexicons developed in the *R* environment. The sentiment underlying the sender's spoken words can, for instance, be calculated the using the *Syuzhet* package and can reveal the valence of the communication over the passage of time, and *Soundgen* can quantify the qualities of the sender's delivery.

**Table 2**
Future research directions.

| | |
|---|---|
| Sender's Cues | ● Do the salesperson's actions (nonverbal cues) speak louder than her/his words (verbal cues) in: converting prospective customers into realized customers? growing existing customers into even more profitable customers?<br>● Are the cues from the sender's communication barrage (see Fig. 1) valued differently in a digital sales interactions (DSI)?<br>● The received view is that a "smile" is a pivotal facial expression that a salesperson ought to display during a sales encounter. How important is a salesperson's smile in relation to other emotional displays in shaping customer behavior in a DSI?<br>● Are some calls-to-action more appropriate for the DSI a given cell in Table 1 than in the other cells?<br>● Does the mixture of *what* a salesperson says (auditory cues) and *how* s/he says it (visual cues) differ in shaping a sender's communication effectiveness in one to-one DSIs in relation to one-to-many settings?<br>● Are visual (facial expressions, body language, head movements, etc.) and audio (speaking rate, speaking pitch, content valence, etc.) features valued equally in synchronous and asynchronous digital interactions? What about the importance of other cues (e.g., text which appears on the screen)? |
| Training & Recruiting | ● How might machine learning and AI help firms: reduce the amount of time needed for sales professionals to hone their digital selling skills?; aid digital immigrants (i.e., older salespeople not as well-versed with digital interaction) to be more at ease with screen-mediated interactions (akin to digital natives)?; and formulate the optimal script for a standard, synchronous sales pitch and a standard, asynchronous sales pitch?<br>● Can machine learning and AI be used to identify "best practices" from the most successful salespeople and cultivated across a firm's sales force?<br>● Can the repertoire of verbal and nonverbal behaviors of the most successful salespeople aid in the selection of prospective candidates?<br>● How should firms train employees to address cultural differences? For example, might differences between individualistic and collectivistic cultures change the way DSIs are approached? |
| Organizational Strategy & Structure | ● What should be a firm's decision-rule to guide the allocation of resources towards those preferring a digital buyer-seller interaction and/or an in-person, face-to-face visit?<br>● How should the organization be structured to facilitate Chief Marketing Officers (CMOs) to work with other functional heads to develop an integrated value proposition for digital customers?<br>● What might "legacy" firms be able to learn from their "born digital" counterparts in order to expedite their on ramping of online interactions? |
| Suitability of Digital Interaction | ● Should the DSI be viewed as a substitute to the face-to-face sales force or a complement?<br>● Under what circumstances should firms opt for an in-person, face-to-face interaction?<br>● What factors might moderate this business strategy decision (e.g., technological readiness of seller; technological readiness of buyer)?<br>● With many different strategies leading to the same outcome, how can researchers ensure their findings are not artifacts of other digital practices?<br>● For firms or researchers without access to machine learning or AI technologies, could fuzzy set qualitative comparison analysis allow for similar analyses to be performed on qualitative text data? |
| Dark side of DSIs | ● How might consumers react when they find out that firms are providing salespeople with real-time customer information and coaching to improve communication effectiveness, and in turn, business outcomes?<br>● How might customers react to firms collecting information on each interaction?<br>● Could employees' privacy concerns reduce the potential benefits of a digital salesforce?<br>● Could AI and machine learning mitigate or propagate biases? |

doing so, firms will be collecting video, text, and/or audio data of not only their customers but also their employees, which could pose considerable security and privacy concerns. How might some employees or customers react to firms collecting information on each interaction? How might consumers react when they find out that firms are providing salespeople with real-time customer information and coaching to improve communication effectiveness, and in turn, business outcomes? Could their reactions augment the cost-saving potential of a digital salesforce? Alternatively, could these privacy concerns reduce the potential benefits of a digital salesforce? How might these effects be moderated by other firm specific factors? Could AI and machine learning mitigate or propagate biases?

Firms are still grappling with a variety of challenges in this new communication forum, which opens up a host of questions in need of academic attention. We are hopeful that this article spawns greater empirical research that harnesses structured and unstructured data and machine learning to better understand marketing communication effectiveness in DSIs. Additionally, we hope that future research considers the varying effects of synchronous and asynchronous digital sales (both adaptive and standard) interactions as firms need more guidance on their digital salesforce transformation investments and initiatives.

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